Intelligent On-Line Transformer Monitoring, Diagnostics, and Decision Making

by

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Abstract

The failure of a large power transformer is an area of significant concern since it can result in millions of dollars in costs as well as a possible interruption of power. Therefore, it is desirable to detect the existence of abnormal or anomalous changes in the transformer's internal condition which could indicate an incipient failure. This thesis proposes and tests an anomaly detection scheme that is based on both spatial and temporal information and ultimately integrates intelligence into the detection process. It was developed from experience gained from field-deployed monitoring systems that currently monitor several 345/115 kV autotransformers in a large utility transmission system. The scheme is extensively tested with data from the field-deployed systems. Results indicate that nuisance or false alarms are virtually eliminated while the sensitivity to anomalous changes is preserved. Failure data from a 450 MVA shell-form autotransformer are analyzed and results indicate that the proposed detection scheme would have raised an alarm, indicating an abnormal rate of change of the gas residual, 8 days prior to the actual failure.

The interest in transformer monitoring has accelerated over the last few years due to structural changes in the electricity industry. This thesis examines the existing and potential incentives for the acquisition, utilization, and commercial development of transformer monitoring systems. Potential benefits are calculated based on capital cost avoidance, environmental cost avoidance, and operational benefits. The cost of a monitoring system is estimated using three scenarios. From a commercial standpoint, both a transformer monitoring system as a product and a fee-based transformer monitoring service appear to be viable business opportunities.

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Contents

List of Figures

List of Tables

Chapter 1

Introduction

Restructuring of the Electric Utility Industry is aimed at expanding competitive opportunities in the electric power sector in the United States. The Energy Policy Act of 1992 opened access to the transmission lines, meaning that wholesale marketers and traders could buy energy from any producer offering the most favorable conditions [1]. The outcome has led to both competitive suppliers (generation) and "competitive" or efficient transportation (transmission). Therefore, restructuring has provided incentives for performance improvements and cost minimization to both utilities and other organizations involved in the generation and transmission of electricity. These incentives are resulting in new tools and techniques for monitoring, diagnostics, and advanced controls that can be applied at the level of the individual component, the subsystem, and the power system as a whole.

Over time, electric power system control has evolved towards increased use and dependence upon computer based logics. In the past, a limited amount of information has been available concerning the real time performance characteristics of the power system components, and most of this has been limited to generator operating behavior. Only recently have transformers been monitored, while there has been virtually no experience in monitoring other components, except for electric machinery. The development of high speed communications and better data handling has allowed the movement of data from the source to central control stations, nonetheless, data utilization has remained virtually unchanged since the time of the implementation of state estimators.

New monitoring technologies and breakthroughs in information technology allow the development of a new generation of performance monitoring and control systems which will increase the physical and economic efficiency of the system. This will provide more reliable service at a lower total system cost. Nevertheless, the present status is of total information "overload" with increasing speeds in communications and improved sensing techniques which allow far more data to be collected than can presently be handled and reduced to useful form. It is possible and desirable to increase component and subsystem monitoring with the introduction of localized intelligence. By reaching increasingly deeper into the transmission and distribution system to monitor components, data may be taken and then abstracted to useful information at the lowest levels. Hence only information is passed up to the supervisory levels which reduces the data overload problem.

Transformer monitoring can be thought of as a paradigm for the same type of monitoring that currently exists on other power equipment such as breakers, FACTS devices, and storage. In particular, this thesis focuses on performance monitoring at the level of the transformer. Monitoring the condition of large power transformers is an emerging technology that will become critical in the Electric Utility Industry in the United States in future years. This practice will ultimately produce a more reliable and economic supply of electricity. Section 1.1 contains the motivation for this thesis. It sets the stage for why on-line transformer monitoring is beneficial from both the economic and policy viewpoints. A thesis overview is presented in Section 1.2.

1.1 Motivation

In the Electric Utility Industry, the tendency of large power transformers to fail catastrophically is a major concern. The failure rate of power transformers in the 400-500kV range has been estimated at 2% per year [2]. For suppliers and transporters of electricity, this raises not only questions concerning reliability and safety, but also monetary issues. In addition to general operating costs, the capital costs associated with repairing or replacing a large power transformer that has suffered a catastrophic failure are considerable. Catastrophic failures are often accompanied by fire and/or spillage of flammable and environmentally hazardous fluid. This raises concerns over costs and potentially dangerous situations to people, other equipment and property, and the local environment. The (tremendous) costs associated with a transformer failure often force utilities to purchase spare transformers and install redundant equipment, tying up capital and manpower better utilized elsewhere. Also, equipment may be over designed in order to be able to re-route power around failed nodes again resulting in additional costs.

1.1.1 Economic Forces

Economic incentives are the driving forces behind most, if not all decisions in business. In the restructured environment, generators of electricity must look not only to prevent loss of expensive equipment, but also to increase productivity without compromising the reliability and safety of the electricity supply. Therefore generators must be able to provide high quality power while minimizing total (short and long run) costs. Restructuring is also impacting regulated companies with profit motives, such as TransCo International [3]. TransCo either owns or leases all of the transmission facilities within a specific market. It charges for services either as a function of capital or as a function of the throughput of the system. It would welcome opportunities to achieve higher throughput without a decrease in reliability.

The implementation and use of the monitoring and diagnostic systems will have a (tremendous) economic impact. They will reduce both long- and short-run marginal costs through improved operating performance. Improved utilization of the physical assets of the transmission system will result in lower investment requirements. Long-run marginal costs are reduced as a result of delaying investment or eliminating the need for specific future investments. Improved on-line monitoring of the condition of the individual components will permit them to be maintained or repaired prior to failure. Also, better monitoring will permit individual components to operate closer to their actual capabilities rather than at their name plate ratings. This will reduce the need for new investment as demand on the network increases.

The replacement energy costs are a more severe financial burden than the capital costs of the components. By monitoring the real time condition of the components and subsystems, appropriate decisions can be made that allow the operation of the components in such a manner as to reduce the total system operating cost. On-line monitoring will permit the system as a whole to be operated closer to its margin, thus reducing short-run marginal costs.

1.1.2 Policy Forces

The operation of utilities is regulated by both the state and federal governments. Most of these regulations occur at the state rather than the federal level. Only "interstate transfers", i.e., bulk power sales between utilities in different states are regulated by the Federal Energy Regulatory Commission. Changes in government regulations have forced the utilities to develop internal policies that reflect the external policies of the regulating agencies. Changes could include total government deregulation of the industry, tighter environmental regulations, or added safety restrictions. Policy making becomes a multi-attribute function in this variable environment.

Today, changes in regulation are shaping the overall market structure resulting in various levels of demand for on-line transformer monitoring and diagnostic systems described in this thesis. Even if the transformer is owned by the regulated part of a partially deregulated system, there will still be economic incentives for acquiring a monitoring system just as if the transformer was owned by a deregulated (competitive) business. Both would be interested in a monitoring system if it economically reduces the overall cost of providing power. Besides the cost of providing power, utilities must consider issues such as meeting the demand for power and public perceptions of safety and environmental concerns. Policy decisions are vital to keep up with these changes.

The on-line monitoring and diagnostic systems will raise many issues in the area of public relations. These issues range from environmental to public welfare concerns. For instance, safety becomes a major concern when transformers fail catastrophically in residential areas and the possibility of spilled oil or fire results. Even the issue regarding the continuity of power to customers, especially ones such as hospitals, is important. This raises the question of measuring the real utility of the on-line monitoring and diagnostic systems if their use predicts or prevents transformer failures with some probability. This may generate pressures on both corporate and public policy makers to require the installment of the systems in cases that may not be entirely economically driven. Utilities and independent power producers will expect government officials to make decisions in these areas. The major implication is that utility policy makers will face issues raised by the on-line monitoring and diagnostic systems that may or may not be purely economic.

Therefore, the ability to identify the existence of incipient failures of in-service transformers before the failures become catastrophic has become extremely attractive. The conflicting requirements to operate the transformer at higher levels of utilization, defer or avoid capital expenditures, reduce maintenance costs, and maintain reliability can be realized by acquiring significant status and control information on the transformers. This thesis uses recent technological advances that presently permit early stage failure detection of in-service transformers by using information obtained from an on-line monitoring system in order to resolve the conflicting requirements.

1.2 Thesis Overview

This thesis concentrates on the monitoring of transformer performance. In particular, it presents the design and development of an advanced diagnostic system that will act as an advisor to electric utility personnel to aid in decision making concerning the maintenance and operation of large power transformers. Several field installations of MIT's on-line transformer monitoring system currently collect data and information which is examined and analyzed by humans to form a manual diagnosis, which is the identification of the cause of anomalous conditions from the observable effects it has on the behavior of the transformer. This thesis examines the acquisition and structuring of knowledge that is necessary for an automated diagnostic and decision-making advisory system. The diagnostic system will have the capability to make on-line appraisals of a transformer's condition, while assessing the type and magnitude of problems. It uses an artificial intelligence based approach, integrating traditional techniques with the use of model-based monitoring, which incorporates extensive additional information. This approach is superior to those typically based on traditional off-line transformer diagnostic techniques, namely dissolved gas analysis. This thesis concludes with an analysis of the costs, benefits, and implications of a system capable of detecting and diagnosing incipient failures of in-service transformers. An overview of the thesis is described below.

Chapter 2, Traditional Transformer Monitoring and Diagnostics, provides an overview of monitoring techniques, new sensor developments, and related work. In-service transformer monitoring is not a new phenomenon, but has focused primarily on the use of information revealed through (infrequent) off-line oil sample analyses or more recently from on-line real-time sensing that fails to provide any sort of guide to the meaning of the data. The chapter presents a case study of a situation that occurred with a transformer at Deer Island, in Boston, Massachusetts. It was developed to reveal the shortcomings of traditional techniques in order to provide a motivation for this thesis. The chapter concludes with examining the most recent trends in transformer monitoring.

Chapter 3, Overall MIT On-Line System Structure, describes the basics behind and presents the conceptual overview of the on-line adaptive model-based power transformer monitoring system developed in the MIT Laboratory for Electromagnetic and Electronic Systems (LEES). It summarizes prior work at MIT and then describes current implementation and use of prototype field installations. As a long term research goal, an overall transformer performance monitoring system was designed and is presented. It allows for the detection, diagnosis, and prognosis of the condition of the transformer while providing useful capability for users.

Chapter 4, On-Line Monitoring and Diagnostic Basics, develops the basic terminology and analysis steps that emerged from the use of the MIT on-line monitoring system as a real-time diagnostics tool. This type of information is necessary for designing and implementing an advanced diagnostics system. Flow diagrams were constructed that illustrate how diagnostic information is processed. Two examples, the Gas Module and the IEEE Thermal Module, were developed and are presented to highlight these concepts.

Chapter 5, Knowledge Acquisition and Structuring, outlines the general structure and basic concepts associated with a knowledge-based system. It describes the methods by which knowledge is acquired and then presents the results of several knowledge elicitation sessions in the form of an overall diagnostic graph. The main result of this chapter was that a diagnostic system could not be implemented until a better anomaly detection scheme was devised.

Chapter 6, Intelligent Anomaly Detection, proposes and examines the use of an anomaly detection scheme that is based on both spatial and temporal information. It ultimately integrates more intelligence into the anomaly detection process than is currently implemented in the field-deployed monitoring system. It presents the scheme in general and detailed form, along with numerous examples which verify its potential and usefulness.

Chapter 7, Transformer Monitoring Incentives: Effect of Restructuring, presents the benefits and the costs of an on-line monitoring system. It discusses policy implications and incentives that will potentially emerge in the unregulated environment.

Conclusions and Recommendations are contained in Chapter 8. Specific conclusions and contributions to the field of transformer monitoring are summarized. Recommendations are made for future work in the area of transformer monitoring and diagnostics.

Chapter 2

Transformer Monitoring Techniques and Trends

The monitoring and diagnostics of electrical equipment, in particular transformers, has attracted considerable attention for many years. A power transformer costs millions of dollars and a failure could cause an interruption of power and costly repairs. Therefore, it has been desirable to detect potential failures and dangerous operating conditions as early as possible. This interest has accelerated over the last few years due to structural changes in the electricity business.

This chapter provides an overview of transformer monitoring techniques and their uses. In-service transformer monitoring is not a new phenomenon, but has focused primarily on the use of information revealed through (infrequent) oil sample analyses or more recently from on-line real-time sensing that fails to provide any sort of guide to the meaning of the data. Section 2.1 briefly examines the causes of transformer failures and presents traditional monitoring techniques. Section 2.2 examines the most widely used on-line sensors and presents recent developments in sensor use and technology. Commercial monitoring systems are described in Section 2.3. A Case Study is given in Section 2.4 that was developed to show just how difficult monitoring and diagnostics can be even in the simplest situations. It is used to provide a motivation for this thesis. Section 2.5 examines the most recent trends in transformer monitoring.

2.1 Failures and Traditional Monitoring Techniques

A transformer failure is normally defined as a disturbance that causes complete coil/core and permanent insulation damage that requires transformer replacement. Inadequate maintenance is the main contributing factor of transformer failures. Both design and field maintenance experience have shown that a properly maintained power transformer should have a life of 50-75 years, while insurance agents generally consider transformer reliability to be questionable after 20 years [4]. A utility directly affects a transformer's life through improper or insufficient maintenance, overloading, operator errors, and poor shipping, handling, and installation procedures. A transformer manufacturer affects the transformer's life by the quality of the design and workmanship. External events or forces such as lightning strikes, earthquakes, animals, through-faults, and excessive line surges can precipitate a failure. Some transformer designs are more capable of handling these types of events than others.

Transformer aging or gradual degradation is due to a number of chemical reactions that affect the mechanical and dielectric strength of the insulating system. The mineral oil can be processed and cleaned to yield oil that can be as good as, or better than, new oils. The solid insulation has an aging characteristic that is irreversible. Therefore if the cellulosic or insulation paper is neglected, any loss in mechanical and electrical strength can never be regained, thus making it the determining factor of transformer life.

Catastrophic failures are sometimes preceded by a series of small, short-duration indicators of "incipient failures". Many efforts involving off-line techniques have been made to detect incipient failures and alarm their onset. Much literature has been devoted to these techniques through the years. A thorough treatment is given in [4] and a relatively up to date summary in [6]. This chapter does not focus on these off-line techniques, but emphasizes primarily on-line techniques and systems.

Fault gases, dissolved in oil, are the first signs of a developing transformer failure. Analysis of gases dissolved in the oil is the most established detection and diagnostic method for transformers. The analysis is based on the fact that many important failure types generate gases in predictable ways. The gases produced in the greatest quantities are hydrogen (H_2), nitrogen (N_2), carbon monoxide (CO), carbon dioxide (CO_2), oxygen (O_2), methane (CH_4), ethane (C_2H_6), ethylene (C_2H_4), and acetylene (C_2H_2). Dissolved gas analysis can distinguish between different types of failures because each type of failure tends to produce the various gases at different rates. For instance, arcing leads to generation of acetylene, whereas carbon oxides are formed by overheated cellulose.

Traditionally, the gases are extracted from oil samples taken manually at regular intervals, normally every six months to two years, depending on the importance of the transformer. This analysis technique is well accepted and established due to its capability to detect a wide range of failure types. Several different methods have been proposed for interpreting the dissolved gas data, with the Key Gas [4] and the Rogers Ratio Methods [7, 8] the most widely used.

For a complete description of the major failure processes of oil-filled transformers, see [4, 6]. They chronicle the primary roles of moisture, oxygen, and heat in the degradation of the insulating system and discuss the stresses that drive the deterioration that ultimately triggers a failure. In addition, they present a complete discussion of traditional off-line and on-line monitoring techniques and diagnostic methods.

2.2 On-line Sensors and Recent Developments

Transformer monitoring equipment today is on-line and permanently attached to the transformer. The equipment generally consists of sensors that supply a warning signal based on a yes/no type of determination and without any real on-line analysis or diagnosis. This allows maintenance to be condition-based rather than time or periodic-based. The most common types of on-line sensors are described below.

2.2.1 Gas Sensors

Analysis of gases dissolved in oil is the most established diagnostic method for transformers. For a number of years, on-line sensors for detecting hydrogen, mainly indicative of partial discharge, have been available commercially. These types of sensors are described below.

Hydran® 201R

One particular sensor that gives a continuous indication of the level of hydrogen dissolved in the oil is the Hydran® 201R sensor from Syprotec, Inc. in Pointe-Claire, Quebec, Canada [9]. The Hydran® 201R is a transformer fault prevention device that provides a direct and continuous combustible gas-in-oil digital reading. It is sensitive to hydrogen, carbon monoxide, acetylene, and ethylene. The reading, R, reflects 100% of the hydrogen concentration, 15% of the carbon monoxide, 1% of the ethylene, and 8% of the acetylene. This can be represented as $R = k(H_2 + 0.15CO + 0.01C_2H_4 + 0.08C_2H_2)$ where k is a scaling factor. It contains two adjustable gas alarm set points and operates over a wide temperature range for all-weather outdoor operation. The alarms are regarded as warning signals and it is recommended by Syprotec, Inc. that a conventional gas-in-oil analysis be performed after an alarm. However, the risk of missing an incipient fault due to long sampling intervals is considerably reduced.

AMS 500

Another device is the AMS 500 by Morgan Schaffer Systems in Montreal, Quebec, which monitors only hydrogen. In this device, dissolved gas is extracted from a continuously circulating oil sample through permeable teflon tubes and hydrogen is detected by a thermal conductivity probe that changes resistance in the presence of hydrogen. It is reportedly capable of responding to a step change in 20 minutes and warning signals can be transmitted by an existing SCADA system [1, 10].

Hydran® 201*i*

In 1995, Syprotec introduced the Hydran® 201*i* monitoring system that is an intelligent dissolved gas monitor that contains the same essential characteristics as the Hydran® 201R with additional features. These features include adjustable hourly and daily gas trend computation with alarming, history logging of data and events with date and time stamping, serial communications with a host computer, networking capabilities and modem control, etc. This system now allows an operator to perform historical data analysis and an on-line survey of the alarm status [9].

Multi-Gas Sensors

Recent efforts have aimed at the development of on-line sensors that measure individual concentrations of several gases. These sensors are early warning systems, but they will give a better indication of the type of fault, and will give warning for heating of the cellulose that the present sensors do not. Examples are developments made by ABB (metal oxide technology) and by Micromonitors (metal insulator semiconductor technology) [1].

2.2.2 Partial Discharge Detectors

Other recent work has been directed toward partial discharge (PD) monitoring. A PD is a transient electric discharge which only partially bridges the insulation gap between two conductors. This is opposed to a breakdown which completely bridges the gap. Detection of PDs is important since they indicate a loss of dielectric strength of the insulation or an increase in electric stress, such as might occur if two conductors move closer together by through-fault forces. They also cause deterioration of the insulation system. Many arrangements of acoustic and electromagnetic sensors have been under development but have various problems associated with them [5, 1, 11].

2.2.3 Temperature Sensors

The load capability of the transformer is limited by the "hot spot" of the winding. Conventional temperature measurements are not direct since temperature sensors are attached to the outside of the transformer tank. The "hot spot" temperature is calculated indirectly from measurements of oil temperatures and of load current. Direct temperature measurements may be obtained from expensive fiber optic temperature sensors installed in the winding when the transformer is manufactured. These sensors consist of fibers which measure the temperature in one point or consist of distributed fibers which measure the temperature along the length of the fiber [1].

2.2.4 Load Tap Changer

The load tap changer (LTC) monitor, known as LTC-MAP (formerly DataWatch), is made by J. W. Harley^{TM} Inc. It is one of the most successful applications of transformer monitors. The LTC-MAP evolved from a device that monitored only temperature to one that monitors control relay timing and sequencing, tap position, load and motor current signatures, voltage, and tap position. Installation is easy as temperature sensors are attached with magnets to the outside of the transformer and LTC tanks. A control box calculates needed data and communicates it to a central office where the tap-changer condition is calculated with simple software. The LTC enables maintenance intervals to be extended, providing cost savings that easily justifies the cost of the monitors [10].

Barrington Consultants Inc. in Santa Rosa, California produce a similar system known as TDM-2L. It has no local controls at the substation and can be arranged to feed three temperatures directly into the SCADA (Supervisory Control and Data Acquisition) unit at the remote terminal unit (RTU) substation or a single alarm signal when the temperature difference between the RTU and the main transformer tank exceed a preset value.

2.2.5 Other Types of Sensors

Other types of on-line sensors have been developed and investigated. These include moisture content of the oil [15], static charge in oil [16, 17], pump monitoring [1], etc. Oftentimes, status indicators such as oil level or vibration are monitored. Efforts must be made to make these types of sensors more reliable, less expensive, and directly linked to important and frequent failure modes. New sensor developments must be accompanied by better and more advanced models and both the sensors and models must be extensively tested before they will add value as on-line monitoring tools.

2.3 On-Line Monitoring Systems

Recent research and commercial efforts have been aimed at real-time on-line monitoring of multiple transformer measurements and parameters. This has come in response to the utilities need for optimal asset management through the use of better monitoring equipment. Four systems have been or are commercially available to utilities in varying stages of capability and usefulness in transformer monitoring. These are briefly described below, after which their deficiencies are discussed.

2.3.1 Westinghouse TMS

The Westinghouse Transformer Monitoring System (TMS) was the first effort at providing a continuous on-line monitor of transformer performance. Developed circa 1981, the TMS monitors the top oil temperature, cabinet temperature, winding current, relative corona, gas in oil, and status inputs such as oil level, oil flow, cooling equipment contactors, etc. The system indicates a problem if any of these measured parameters violates a strict factory set threshold or if warnings on other monitored parts of the system occur. For example, if the top oil temperature exceeds 120°C or if the oil level drops too low, the system would indicate a problem. The TMS does not perform any diagnosis of an indicated problem, but it does attempt to classify the performance of the transformer and recommend associated actions. See [6, 18] for a complete description.

2.3.2 J. W. Harley^{TM} TPAS^{TM}

J. W. Harley^{TM} Inc., based in Twinsburg, Ohio, developed and markets the Transformer Performance Analysis System (TPAS^{TM}). It was based on technology developed at and licensed by MIT in 1989. The system was designed to sense quantities that are indicators of transformer condition and to detect potential problems. The system includes acoustic partial discharge detectors, water-in-oil sensor, gas-in-oil sensor, current sensors, and top oil, bottom oil, and ambient temperature sensors. It stores data once per minute at the remote computer, downloads data nightly to the master computer from the remote computer, maintains a long-term database, monitors up to three alarm limits and rate of change for each data point with automatic call feature to alert the master computer of alarm conditions. The TPAS^{TM} collects data effectively, but any analysis or diagnostics must be performed by a human. It provides graphing capability on the order of a few days, which severely limits the analysis and diagnostics a human can perform. It does not provide any adaptive modeling or diagnostics. Several utilities have installed TPAS^{TM} on large power transformers and are actively taking and storing data [19, 20].

2.3.3 QualiTROL SENTRY^{TM} Substation Transformer Monitor

The SENTRY^{TM} Substation Transformer Monitor System was developed and marketed in the mid 1990s by QualiTROL Corporation based in Fairport, NY. It provides a base platform with basic monitoring capability, automatic alarm notification, remote access to present and historical data, local displays, controls and alarms, and outputs for SCADA and future higher level systems. The SENTRY^{TM} sensors are non-intrusive to the transformer tank and when used in conjunction with existing instruments, permit easy installation. Available sensors include ambient temperature, liquid (oil) temperature, simulated winding temperature, liquid levels, secondary load voltage, primary and secondary load current, rapid pressure rise, static pressure, and gas accumulation. It also supports remote monitoring of many third party sensors, such as the Hydran® 201R. It is equipped with a modem for remote communication via a standard telephone line. It comes with QUALOG^{TM} Analysis Software which provides a basic set of tools to plot, analyze, and print reports of recorded measurements. It logs historical data for long term trend analysis and automatically reports when alarm conditions occur.

The SENTRY^{TM} provides an effective method by which transformer data may be collected and stored for future purposes. Any analysis or diagnostic use of the data must be done by a human, although it does provide a method for utilities to manually analyze transformer behavior without travel to the site. Any resource planning or problem situations must be decided by the utility. As of 1996, only a handful had been installed by utilities [21, 22].

2.3.4 USI "Transformer Monitor"

Underground Systems, Inc. based in Armonk, New York, has developed a transformer monitor that gathers data from any relevant sensors attached to the transformer and then runs a set of models for all dynamic aspects of the transformer. The manufacturer says several have been sold to utilities and their earliest installations have been running successfully since 1993. Only their thermal model has been extensively field tested, while all other models are presently running blind as no sensors are attached to provide inputs to these models. A portable version, installable in one to two hours, has also been developed. Further details are not available [23].

2.3.5 Deficiencies of Existing Systems

There are many problems with these commercial systems. They function primarily as data acquisition and storage systems, as no automatic analysis of the data is being performed. Conventional transformer expertise does not know what to do with or how to handle on-line data sampled every few minutes. For a utility, it is difficult to use all of the data because there is no "guide" to the meaning of the data. In addition, the utility personnel do not have countless hours to "watch" data from many transformers on a regular basis. In general, these systems do not relate the on-line measurements to operating conditions. The systems do not take into account the effects of transformer loading, the cooling state, or the ambient temperature on the transformer measurements. The USI system does incorporate dynamic models, although the details by which to judge its capability are not available.

The state of on-line monitoring in real-time is underdeveloped. Reliable monitoring equipment is necessary for getting access to relevant data, but without well developed methods for interpreting this data or for giving recommendations, there is limited practical value in installing such equipment. It is now important that detection, diagnostic, and prognostic techniques be developed which match the sensors and monitoring systems installed on the transformers. The following Deer Island Case Study emphasizes these issues.

2.4 Deer Island Case Study

This case is based on an actual experience described by Ann Hueston of Boston Edison [24]. It outlines the steps a transformer expert used in performing classical transformer diagnostics. More importantly, it shows just how difficult diagnostics can be without an on-line monitoring system utilizing model-based diagnostics.

On February 28, 1994, Boston Edison had a Hydran® 201R reading drift up, higher than normal, on a transformer at Deer Island in Boston, Massachusetts. A high reading of this type was an immediate concern as it could indicate a transformer problem. This particular transformer was only two years old, lightly loaded, and served as the backup supply for the Massachusetts Water Resources Agency (MWRA).

2.4.1 Anomaly Detection

During a monthly survey, the Hydran® 201R reading was found to be 1200 parts per million (ppm), clearly indicative of anomalous behavior. Twenty minutes later the reading had risen to 1340 ppm. The operator made one final reading which was 1900 ppm. There was an increase of 700 ppm in the course of a day. For this particular unit, the Hydran® 201R reading had stayed normally near 50 ppm, but always below 100 ppm. For these low levels the Hydran® 201R is not very accurate. Here the changes have occurred quite rapidly. The anomaly time scale, reflecting the triggering mechanism of the anomaly involved, was minutes-to-hours. The concern was not only the high reading, but also the rate of increase of the reading.

At this point, possible diagnoses included Hydran® 201R sensor failure or a problem with the transformer itself. Based on past experience, these types of sensors cannot always be trusted. On the other hand, there could be something seriously wrong with the transformer.

2.4.2 Determine Course of Action

At this point, the operator determined the maximum reaction time or time allotted for response to the detected anomaly. In this particular case, the detected anomaly appeared to be serious. The behavior of the Hydran® 201R reading corresponds to a "large" anomaly case, in the dissolved-gas characteristic of the transformer, which is indicative of a potentially serious problem.

The Hydran® 201R reading of 1200 ppm was extremely high, requiring immediate action. The normal procedure for readings between 100 and 200 ppm is to monitor the Hydran® 201R with two surveys per month rather than the normal monthly survey. For readings over 200 ppm, an oil sample is typically requested, but with less urgency than the case at hand. In normal situations, this anomaly would need attention within a couple of hours. Due to its location at Deer Island, it would require about four hours for proper personnel to respond. Therefore the minimum reaction time was approximately four hours.

At this point, the operator tried to piece together any available information in order to make a diagnosis. Oftentimes, external events may be related to or cause the anomaly. This particular transformer is located outdoors on Deer Island. It is in a very hostile environment as it experiences tremendous amounts of wind, salt spray, and pollution. In addition, no recent maintenance had been performed. There were no unusual loading conditions or incidents on the system that would have affected it.

The operator then checked other sensors and available measurements for a possible correlation. This step can be done very rapidly in hopes that additional information currently available will help in the diagnosis. Boston Edison did the following:

A. Push Test Button: This is a test on the electronics and will tell if an operational amplifier (op amp) is burned out. It does not test the sensors. This test is always done anytime there is a suspected problem. In this instance, it showed the Hydran® 201R ramp up, and then back down. This type of response from the Hydran® 201R was unusual.

B. Check Top Temperature: The top oil temperature was 5°C, a normal reading for this transformer. The Hydran® 201R reading should have held steady or possibly decreased for this temperature. Therefore, there was no reason for the Hydran® 201R to be rising indicating an increase in gas content, given this temperature.

C. Check Winding Temperature: The winding temperature was 30°C. It showed that the transformer was energized.

D. Check Sudden Pressure Relay: It had not tripped.

E. Check Combustible Gas Relay: The reading was 0.

F. Check Pressure Release Devices: They showed no alarm.

G. Check for Noise inside Transformer: No noise was heard, which was a good sign. Noise could mean arcing or bad partial discharges.

2.4.3 Initial Diagnosis

Based on the previous checks and measurements, the operator tried to determine the cause or the possible causes. Failure modes no longer suspected can be eliminated.

In this case the original candidate diagnoses included possible sensor failure or a potentially serious transformer problem. The sensor failure diagnosis was eliminated since the behavior observed did not seem to match the past failure modes of the Hydran® 201R. The Hydran® 201R behavior, namely the actual reading level and the rate of rise, did not look like past sensor failures. A potentially serious problem with the transformer cannot be ruled out at this time.

2.4.4 Determine Recommended Mode of Action

Courses of action recommended at this point are based on the initial diagnosis, reaction time, anomaly severity, transformer location, company policy, etc. Prior to this step in the process, the operator's diagnostic decision process was based entirely on information that was readily available. The decision was made to seek additional input and the course of action became:

A. Schedule Dissolved Gas Analysis: Due to the severity of the anomaly, this was scheduled the same day since results were needed within hours. Had the anomaly not appeared serious this would have been done the next day, thus avoiding overtime pay to workers. Results from the Chemistry Lab revealed that the Hydran® 201R was 20 ppm higher than previous readings and all other combustible gases were lower than normal. The hydrogen level was reported to be 32 ppm by the chemistry lab. Based on these results, it was definitely a problem with the Hydran® 201R sensor. This type of anomaly was different and had not been encountered before. Based on the Dissolved Gas Analysis, no new diagnoses were added to the initial list, although the sensor failure diagnosis cannot be eliminated from the list as was previously done. The recommendation is now to take Action B.

B. Send System Electronics Lab to Site: System Electronics Lab personnel were sent out the same day to see if they could figure out what was wrong with the Hydran® 201R. They measured the test points which are used as trouble shooting guides. Any other tests done by the lab were not reported and were unavailable. They thought it might be either (a) Heat in the Thermal Enclosure or (b) a Resistor in the Electronics Board. Final results of other lab tests or actions were unavailable by the end of the four hour reaction time. Therefore, Action C was taken and the transformer remained in service.

C. Continue Operation: The transformer continued operation and stayed in service while more results were anticipated from the System Electronics Lab. For this particular utility shutting the transformer down was never an option, although other utilities at this point might remove their transformers from service. A Canadian firm had a similar sort of problem and actually ordered a shutdown. This points out the need for user settable parameters for the monitoring and diagnostic systems.

2.4.5 Final Diagnosis

At the end of the four hour reaction time, a unique final diagnosis was not determined, although it did appear to be a malfunctioning Hydran® 201R sensor. Boston Edison decided to leave the transformer in service and wait for more information from the System Electronics Lab. Several months later Boston Edison determined that is was a Hydran® 201R sensor failure.

2.4.6 Conclusions

If Boston Edison had installed an on-line monitoring system running diagnostics on this transformer, this problem could have been diagnosed with some degree of probability. It could have potentially saved a lot of worry and manpower. In these critical situations, time is money. This case emphasizes how difficult diagnostics can really be without an on-line monitoring system. Boston Edison and other utilities now realize that monitoring and diagnostics are a method by which the number of catastrophic failures of transformers may be reduced. In addition, maintenance costs may be reduced, forced outages may be prevented, and existing equipment may be pushed harder and longer. The next Section examines the newest trends in transformer monitoring and how MIT and this thesis attempt to meet these trends.

2.5 Trends in Transformer Monitoring

Since the inception of expert systems in the late 1960s and early 1970s, diagnosis and interpretation have been favorite application areas. The implementation of expert systems for use with different aspects of transformer monitoring has been slowly evolving.

One of the first systems was the Transformer Oil Gas Analyst (TOGA) system [25] which is an expert system that is mostly an implementation of one of the standard dissolved gas analysis codes, such as Rogers Ratio Method [7, 8]. Another system, Exformer [26], is also an expert system that implements the IEC code for dissolved gas analysis through the use of fuzzy logic. Since these earliest systems, many others have applied fuzzy expert system approaches to the problem of interpreting the dissolved gas analysis results [27, 28]. Others have tried neural networks and other polynomial networks, but mainly to the interpretation of dissolved gas analysis results [29]. A recent thesis at MIT [30], examined the use of neural networks with dissolved gas data taken from an on-line transformer monitoring system.

Based on our field experiences with on-line monitoring systems, a fuzzy logic based approach to performing anomaly detection was chosen. It would allow the experience gained to be applied in an insightful and logical manner that neural networks and other types of polynomial networks do not allow. One prior attempt was the application of fuzzy set theory to on-line monitoring of power transformers [31]. The approach was based on a system operators' expert knowledge. It collected data every 10 seconds, but processed all of the data once every 24 hours. There are several flaws to this approach. First, a system operator does not have expert knowledge for use with an on-line monitoring system. Data collected every 10 seconds is severely oversampled for the dynamics of a large power transformer where time constants range from 100 to 600 minutes. It was unclear why trend analysis is performed once every 24 hours, rather than on some other time schedule.

This thesis presents a reasonable and sound approach for fuzzy-based detection and diagnostics. It is based on the knowledge gained from nine transformer years of experience. This came from monitoring five 345/115kV autotransformers in a large utility transmission system on a 24 hour a day basis. The fuzzy logic-like detection and diagnostic scheme described in this thesis significantly improves the intelligent sensing of anomalous behavior while simplifying system setup and facilitating the direct generation of alarms.

2.5.1 Future Trends

Transformer monitoring is now moving toward on-line systems in contrast to off-line techniques and stand alone on-line sensors that were primarily used for years. The rapid development of new technologies and cheaper and reliable computers has facilitated this shift. The system aspect has become much more important as multiple sensors are being combined to provide better on-line monitoring and diagnostic information. The transformer is now being thought of as a system, rather than a series of individual components.

In general, on-line sensors and monitoring systems by themselves have limited value. Much research is needed to interpret and understand the output from the sensors and monitoring systems used in real-time. On-line experience with these sensors and systems is critical for developing new types of knowledge that consist of interpretation skills and diagnostic methods. Chapter 4 examines the basic concepts behind on-line monitoring and diagnostics that emerged as MIT personnel monitored transformers on a 24 hour a day basis. Those doing the research will become new types of experts where the area of expertise is on-line transformer monitoring. Knowledge bases must be created, structured, and maintained that reflect this on-line experience. This thesis is the first known attempt at really structuring on-line transformer and sensor knowledge. This is the focus of Chapter 5, Knowledge Acquisition and Structuring.

Other trends are geared towards diagnostics. Here the shift is from off-line, human-intensive diagnostics to on-line, machine-intensive analysis and diagnostics. While off-line diagnostics will remain important, it will be used to provide additional information when the on-line systems make this type of recommendation. Diagnostic methods must be developed that can be used without taking the transformer out of service. In Chapter 3, the design of a diagnostic system that shows the relative importance of combining different diagnostic methods is presented. Chapter 6 presents an intelligent detection scheme that has passed the proof of concept test with real data taken from an on-line system. It forms the basis for future diagnostic capabilities. In the end, on-line monitoring when combined with diagnostics is a way utilities can remain competitive in today's business environment.

Chapter 3

MIT Monitoring System Structure

The Deer Island Case Study in Chapter 2 revealed many conceptual issues and constraints that must be taken into account in order to develop an effective and useful diagnostic system. This chapter examines the basics behind the Massachusetts Institute of Technology Laboratory for Electromagnetic and Electronic Systems' (MIT-LEES) Adaptive Transformer Monitoring System and its use as a platform for diagnostic purposes. Section 3.1 describes prior research at MIT that led to the development of the system, the basics behind the MIT-LEES' approach, and a conceptual overview of the system. Section 3.2 describes a field-deployed version of this system and discusses its use as a platform for diagnostic purposes. Section 3.3 presents block diagrams for the design of a Transformer Performance Monitoring System which allows for the detection, diagnosis, and prognosis of the condition of the transformer while providing useful capability for users. Its detailed design and implementation is one of MIT-LEES' long term research goals.

3.1 MIT-LEES' Approach

Researchers at MIT-LEES have been involved in the development of an Adaptive Transformer Monitoring System since 1984. A prototype system has been in operation in the MIT-LEES' Pilot Transformer Test Facility since April 1988. A field-deployed version of this system was implemented and tested in the Pilot Facility in late 1994 and early 1995, and was first installed at an electric utility in March 1995. At the time of this writing (May 1998), five 345/115kV autotransformers in a large utility transmission system are being monitored on a 24 hour basis.

3.1.1 Model-Based Monitoring

The MIT approach uses model-based monitoring in which the transformer is considered a system and its operation is monitored with on-line measurements and modeled with mathematical equations. This approach is typically used in control theory applications [6, 32].

State and parameter estimation are used in conjunction with the equations and the on-line measurements to determine the condition of the transformer. To accomplish this, the estimated state of the transformer, as predicted by the models, is compared to the actual state of the transformer, as represented by the on-line measurements. Here the transformer condition remains constant if the transformer is operating normally while the transformer state is constantly changing in response to exogenous ambient and operating conditions. Abnormal differences between the measurements and the predictions are indicative of anomalous operation, which may be caused by incipient failure conditions.

Figure 3-1, Monitoring System Fundamental Operation, shows a graphical representation of this concept. The expected normal behavior of the transformer is reflected in the adaptive mathematical models. These models use external factors such as load (primary current), ambient temperature, and cooling state as data inputs in predicting the output of a particular sensor. Each mathematical relationship models the behavior of a particular measurement. The model output is called the prediction. This is represented in the figure by feeding the data inputs into the mathematical models. These are the same inputs that determine the actual transformer operation and are represented as such. By comparing the actual transformer behavior with the predicted, a residual or error term may be computed. The residual (error) is given by

$$residual = measurement - prediction. \tag{3.1}$$

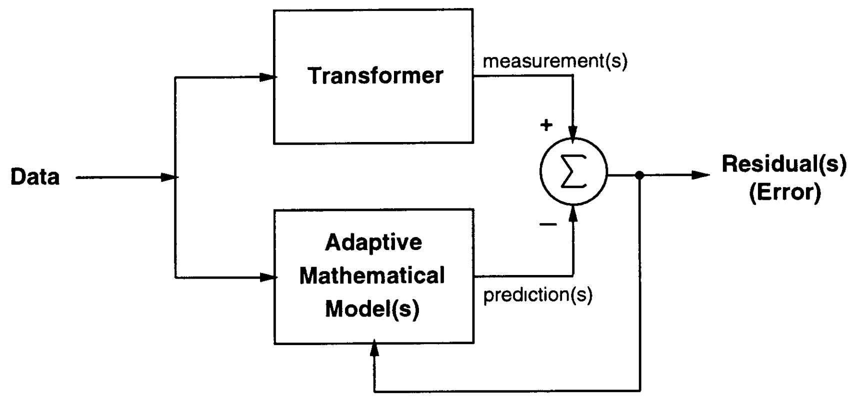

Figure 3-1: Monitoring System Fundamental Operation

If the transformer is behaving normally, the residual should be small due to only modeling errors and noise. If the transformer is behaving abnormally then the residual should become significant. These are indications that the observable quantity is sensitive to the particular failure mode in effect [6].

3.1.2 Module Block Diagram

The mathematical models are adaptable to a particular transformer by using actual data from the transformer to estimate the parameters of the model. By tuning the models to each specific transformer, the sensitivity to incipient failures is dramatically increased while removing the need to set transformer specific alarm levels. After parameters are estimated, the residual or error term may be computed as described above. It reflects the deviation of the transformer from its own normal state in the short term. If the parameters of a model are periodically re-estimated, long-term tracking of the condition of that particular signature may be accomplished. The concepts of adaptability and short- and long-term tracking are embodied in the Module Block Diagram, implemented primarily in software and shown in Figure 3-2 [6].

Sensor signals are passed to the Signal Processor where any necessary data preparation or reduction steps are performed. The processed data then passes through the Measure-

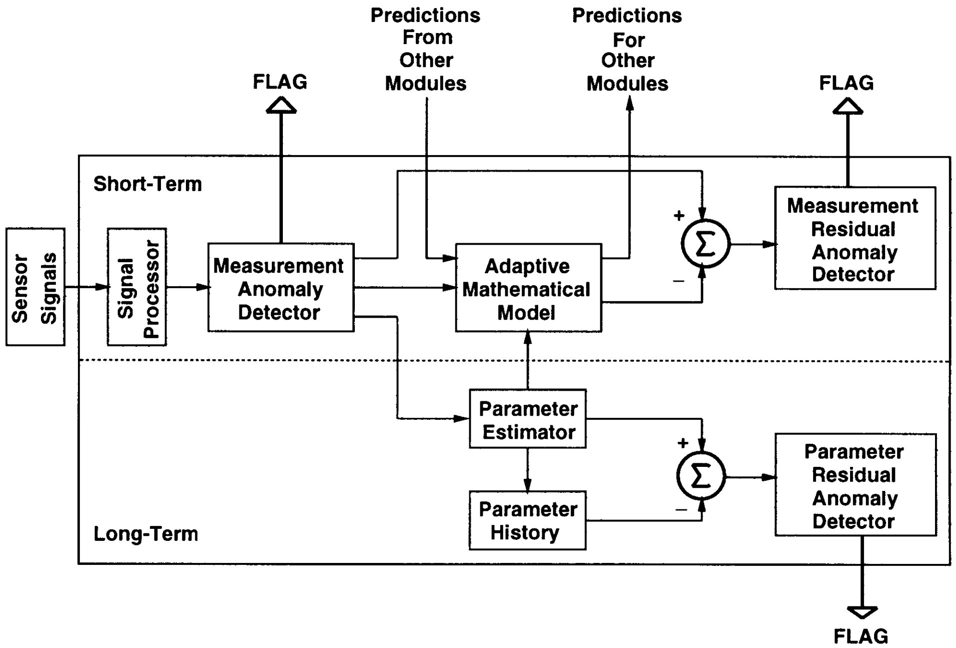

Figure 3-2: Module Block Diagram

ment Anomaly Detector where threshold checks for abnormal levels and rates-of-change of data are made and indicated by a "flag". Validated data is used as the input to an Adaptive Mathematical Model which predicts the values that are expected based on the inputs. Predicted values are compared to the measured values in the Measurement Residual Anomaly Detector. If abnormal residual levels and/or rates-of-change are detected, a "flag" is raised. Periodically, the parameters of the mathematical equation which make up the Model are updated through the operation of the Parameter Estimator to insure that the Model remains accurate. The Parameter Residual Anomaly Detector checks for anomalous levels and rates-of-change in the parameters and raises a "flag" if a violation occurs. For a complete description see [6, 33].

3.1.3 System Block Diagram

A module exhibits sensitivity to incipient failures which affect the condition of a particular signature. This is provided by the adaptive models, continuous real-time operation, and

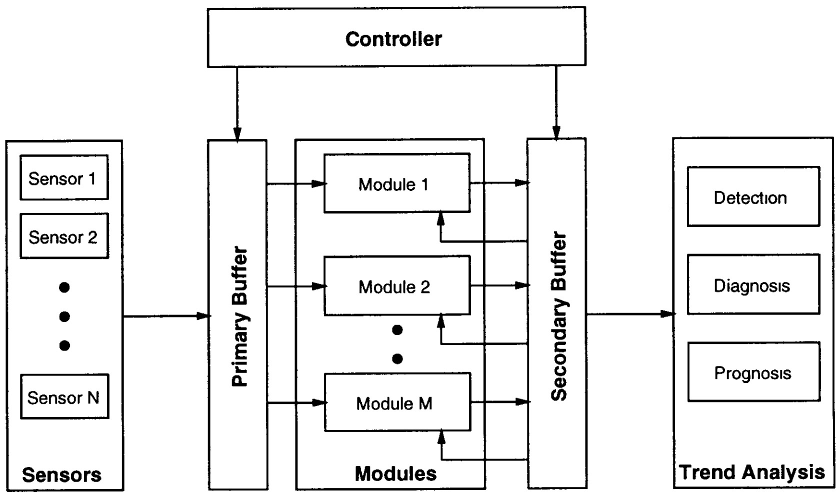

Figure 3-3: Monitoring System Block Diagram

the differential comparison technique that produces residuals. The sensitivity to incipient failures can be increased by cross-correlating the inputs and outputs of multiple modules. In order to do this, the modules are combined in a system which controls and schedules the data acquisition, information organization, module operation, detection, diagnosis, prognosis, communications and interfacing with the operation. The Monitoring System Block Diagram incorporating several modules, is shown in Figure 3-3 [6].

This system is implemented as a combination of hardware and software. Sensors acquire raw data that is organized in a time-correlated format in the Primary Buffer and then becomes available to any portion of the system. The Modules run the appropriate models and flag any anomalous behavior while outputting relevant information into the Secondary Buffer for use by the rest of the system. The organization and scheduling of various tasks of the system are provided by the Controller. Trend Analysis is performed on raw data and relevant information from the modules to detect anomalies in the transformer being monitored. Detection is presently being performed by the generation of "flags". Current and future research are focused on improving the detection scheme and adding the diagnosis and prognosis pieces. Diagnosis is the act of identifying a failure from the observable effects it has on the behavior of the transformer. Prognosis is the act of estimating the future condition of the transformer based on the diagnostic results. For a complete description of the above topics, see [6] for further details.

3.1.4 Thermal, Gas, and Electrical Modules

Early research in LEES led to the development of adaptive mathematical models of transformer behavior. The two most important models for monitoring the condition of transformers are the thermal and gas models. They predict the expected thermal performance and the combustible gas content of the transformers. Crowley [6] developed an analytical framework and complete description of the operation of these models, which form the basis for the Thermal and Gas Modules. An Electrical Module is also implemented, but does not consist of a model at the present time. Its use is discussed later in this section.

Thermal Module

The primary purpose of the thermal module is to detect changes, particularly excess heating, in the thermal system of the transformer. The secondary purpose is to predict unmeasurable temperatures such as the hot spot or winding temperature in the transformer.

At the heart of the thermal module is a top oil temperature model based on the widely used model of the "IEEE Loading Guide" specified in IEEE/ANSI C.57.115 (1991) [34]. The form of this static, adaptive, and recursive model implemented in the field installation, described in Section 3.3, is shown in Equation (3.2). It predicts the current generic top oil temperature, $\widehat{T}_{topoil}[k]$, which is the temperature of the oil in the space above the transformer. The prediction is based on the previously predicted top oil temperature, $\widehat{T}_{topoil}[k-1]$ and previously measured ambient temperature, $T_{ambient}[k-1]$, as well as the presently measured ambient temperature, $T_{ambient}[k]$, and primary current, $I_{primary}[k]$.

$$\widehat{T}_{topoil}[k] = K_1 * (\widehat{T}_{topoil}[k-1] - T_{ambient}[k-1]) + K_2 * I_{primary}[k]^{K_4} + T_{ambient}[k] \quad (3.2)$$

The top oil and ambient temperatures are in degrees Kelvin and the primary current is in Amperes. The time step index is given by k. The parameters K_1 and K_2 are estimated from observed data by using linear least squares techniques since both parameters appear linearly in the model [35]. K_4, the exponent in the thermal model, is a fixed parameter determined by oil flow. Experiments roughly indicate that this parameter is 1.6 [5]. The model has the capability of handling multiple cooling states (i.e., OA-FOA-FOA) with multiple parameter sets as given by the adaptive parameters, K_1 and K_2, in the model.

This equation captures the basic idea that an increase in the loading or primary current of the transformer will result in an increase in the losses within the device and thus an increase in the overall oil temperature. Likewise an increase in ambient temperature will cause an increase in the overall oil temperature. The time constant depends on the heat capacity of the transformer (i.e. the mass of the core, coils, and oil) and the rate of heat transfer out of the transformer (i.e. present cooling state) [5].

Every time the thermal module runs, the predicted top oil temperature is compared with the corresponding measured value, as given by Equation (3.3). Here the top oil temperature residual, $R_{topoil}[k]$, is computed by subtracting the predicted from the measured, at time k. The residual is quite useful in diagnostics. The residual becomes positive if the measured value rises with respect to the predicted value, and more negative if the measurement falls below the predicted. Thus, the residual is positive if the top oil is "too hot" and negative if the top oil is "too cold" based on the primary current, ambient temperature, and cooling state. A residual of statistical significance may possibly indicate an incipient failure condition. Residuals allow a dynamic sensitivity that strictly measurements cannot.

$$R_{topoil}[k] = T_{topoil}[k] - \widehat{T}_{topoil}[k] \tag{3.3}$$

The IEEE model, while sufficient under most conditions, does not properly account for variations in ambient temperature. The transformer temperature, which is responsive to ambient temperature as well as internal dissipation, will lag behind the daily cycle of ambient temperature changes since the thermal time constants of the different cooling states are on the order of 100 to 600 minutes. Improvements in this model are the basis of future research [5].

Gas Module

The purpose of the gas module is to detect anomalous changes in the dissolved gas content of the oil. This simple model developed at MIT and used in the field installation, described in Section 3.3, is partially black-box, partially physically-based, and is intended for use with the Syprotec, Inc. Hydran® 201R combustible gas sensor. This sensor is most commonly installed in an oil flow loop that is separate from the main cooling circuits as shown in the center portion of the Back View in Figure 3-5 to be discussed later. This sensor allows for the continuous monitoring of the content of a mix of combustible gases in the transformer oil. It is sensitive to hydrogen, carbon monoxide, acetylene, and ethylene. These gases are produced by overheating and by partial discharges, two conditions that could lead to transformer failure if left uncorrected. Therefore continuous monitoring of the Hydran® 201R sensor is useful in detecting incipient failure mechanisms in a transformer.

The gas module implements a static and adaptive model whose form is shown in Equation (3.4). It predicts the combustible gas content, $\widehat{Gas}$, in ppm and uses the measured temperature of the oil in the Hydran® 201R sensor (loop oil) in degrees Kelvin as its input [6]. Here T_{oil} is measured in the oil flow loop as it passes the Hydran® 201R sensor. The model has the capability of handling multiple cooling states (i.e., OA-FOA-FOA) with multiple parameter sets as given by the adaptive parameters, A, B, and C, in the model. The parameters are estimated from observed data by using linear least squares techniques since the parameters appear linearly in the model [35].

$$\widehat{Gas}[k] = A + B * T_{oil}[k] + C * T_{oil}^2[k] \tag{3.4}$$

Every time the gas module runs, the predicted gas content of the transformer oil is compared with the corresponding measured value, as given by Equation (3.5). Here the gas residual is computed by subtracting the predicted from the measured. The residual is quite useful in diagnostics. The residual becomes positive if the measured value rises with respect to the predicted value, and more negative if the measurement falls below the predicted. Thus, R_{Gas} is positive if the gas content of the oil is "too high" and negative if the gas content is "too low" based on the present ambient and operating conditions. A residual of statistical significance possibly may indicate an incipient failure condition. Residuals allow a dynamic sensitivity that strictly measurements cannot. Typically, positive residuals are more worrisome than negative ones.

$$R_{Gas}[k] = Gas[k] - \widehat{Gas}[k] \tag{3.5}$$

The gas model has worked reasonably well in the field installations. Several complications have been encountered when using a Hydran® 201R, including a severe problem known as "sensor starvation", which results in abnormally low (and incorrect) readings [32].

Electrical Module

The present purpose of the electrical module is to detect transformer trips and overloading. A transformer trip, indicated by a primary current of 0 amps, indicates that the transformer is off-line. This could be the result of an instantaneous failure, but normally is caused by a manual action when the utility needs to perform some type of off-line maintenance that requires the transformer to be de-energized. Transformers are often overloaded due to high electricity demands during peak periods, improved technology, and business economics. Overloading causes overheating which is extremely detrimental to the transformer as it adversely affects the oil and paper insulation system leading to premature thermal aging.

Presently, the electrical module does not implement any type of behavioral model. A physically-based model of the transformer's electrical characteristics should be developed that takes into account the winding resistance and inductance as well as the core magnetization and loss. It should also have appropriate links to the thermal model. This type of model requires an expanded research and industry effort.

Ideally, sensors for primary voltage, secondary current, and secondary voltage should be installed and monitored. In this way, the efficiency of the transformer and the consistency of one form of the fundamental transformer equation, shown in Equation (3.6), can be checked. This equation states that the current ratio is inversely proportional to the voltage ratio, with

I_1 and I_2 representing the primary and secondary currents, and E_1 and E_2 representing the primary and secondary voltages. These additional quantities are not routinely monitored on-line due to the high costs.

$$\frac{I_1}{I_2} = \frac{E_2}{E_1} \tag{3.6}$$

3.2 Prototype Field Installations and Use

After the catastrophic failure of two large power transformers at an electric utility during 1994, a new effort was undertaken by the Transformer Monitoring Group in LEES in order to create a fully functioning fieldable version of the Adaptive Transformer Monitoring System. The Adaptive Monitoring System was upgraded in an intensive effort from a research tool to become almost a marketable product. Currently the group monitors five 345/115kV autotransformers in a large utility transmission system on a 24 hour basis. The field deployed version and its use are described below.

3.2.1 Field Version

Figure 3-4 shows, in highly schematic form, the Monitoring System Field Version [41]. The transformer to be monitored is fit with a commercially available Data Acquisition System (DAS). Both the J. W. Harley Transformer Performance Analysis System (TPAS) and the QualiTROL SENTRY have been used successfully for data acquisition purposes in field installations. A Fiber Optic Communications Link supplies requested packets of data from the DAS to the MIT Monitoring Computer. The Monitoring Computer is a 486 (or better) PC running the monitoring software under UNIX. The computer contains Local Terminals for logging in at the station, but it is designed to be accessed remotely through a High Speed Modem from Remote (Computer) Terminals, as it is primarily used in unattended substations. Data is backed up daily on a Tape.

During on-line operation, data is received by the Monitoring Computer from the DAS once per minute, then time correlated and stored. The modules/models process time corre-

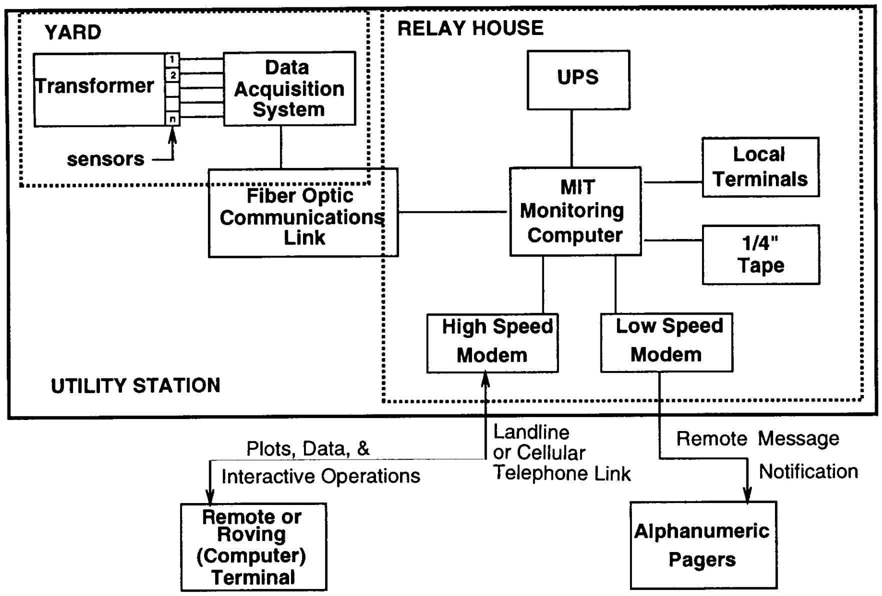

Figure 3-4: Monitoring System Field Version

lated data once every five minutes. Next, the measured data are compared with the model predictions to obtain a residual or error signal. Flags are generated once every five minutes if any data value and/or residual in the system exceeds a preset threshold and/or if its rate of change between successive measurements changes too fast. Any anomalous behavior generates a "flag" (error message) that is transmitted, after some modifications, over a Low Speed Modem, to a commercial pager company and then to MIT personnel carrying alpha-numeric pagers [32].

A field installation requires a minimum of 6 sensors and 2 models. The sensors are primary current, ambient temperature, top oil temperature, Hydran® 201R oil (loop oil) temperature, Hydran® 201R dissolved gas content, and cooling state. In the present field installation only the models in the Thermal and Gas Modules previously described are used.

Figure 3-5 shows the Layout of one 345/115kV autotransformer currently under Surveillance. The Front View shows the location of the ambient temperature sensor which is placed three feet from the tank to avoid temperature effects from the tank. The Back View shows the location of the oil bypass flow loop on which the Hydran® 201R sensor and Hydran®

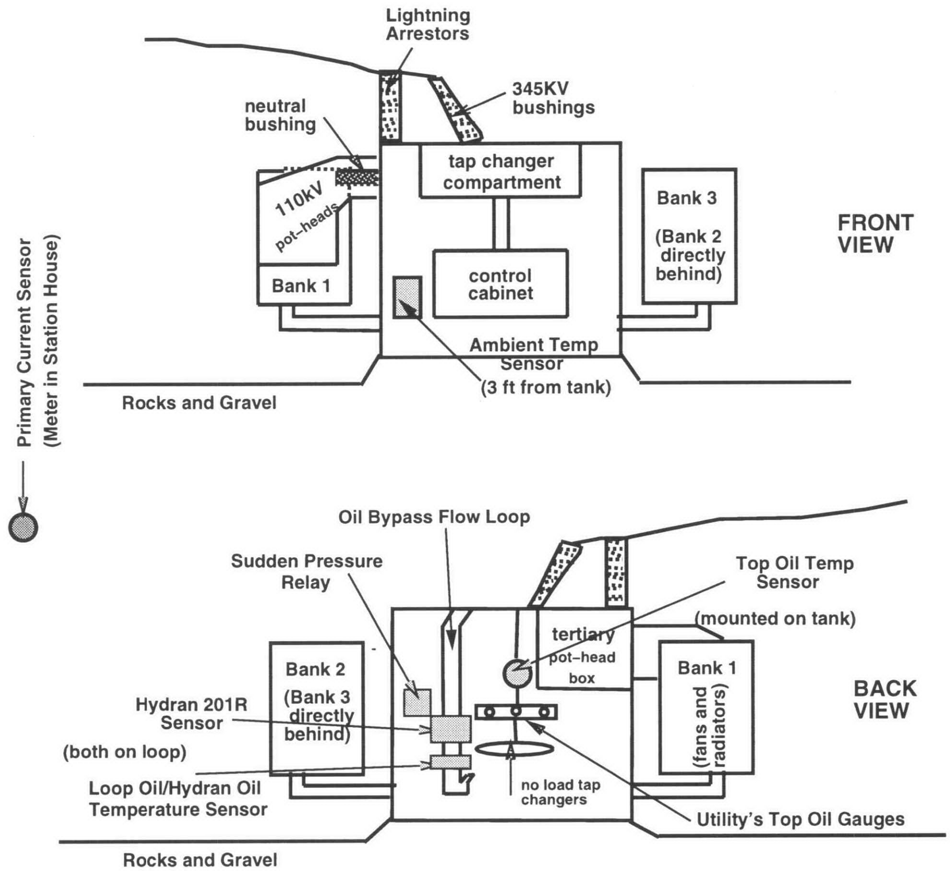

Figure 3-5: Layout of one Transformer under Surveillance

201R oil sensor are placed. The top oil temperature sensor is mounted on the tank as indicated. This is separate from the utility's top oil gauges. This particular transformer only has three banks of pumps and fans since it is a little transformer (280MVA) and does not require the extra cooling capacity. Transformers larger than this rating would have four banks. The primary current sensor is located in the utility's station house. The location of sensors and the transformer configuration must be taken into account when analyzing anomalous events and recommending actions to the utility.

3.2.2 Manual Analysis/Diagnosis

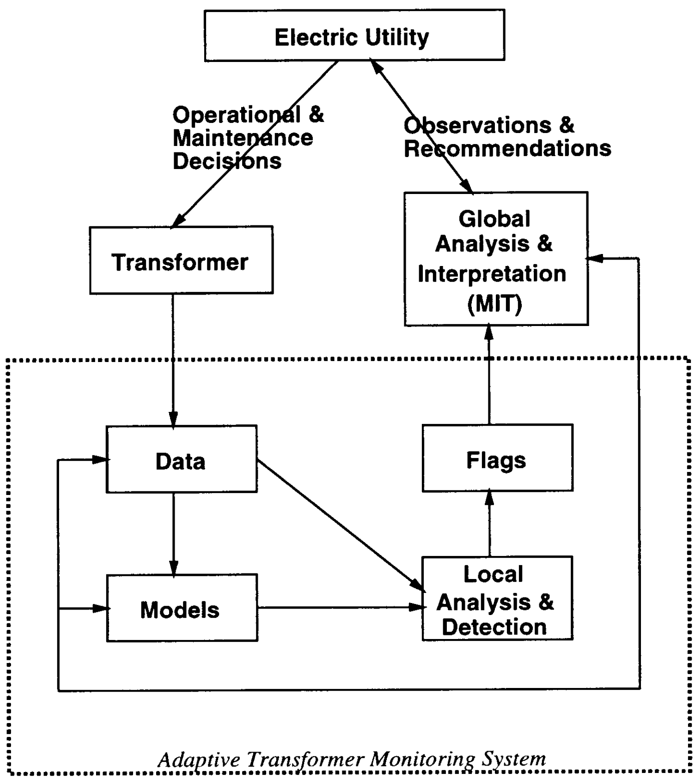

Figure 3-6: Transformer Operation and Maintenance Decision Support System

```
ie3mod(3/19 7:55): gtoil has changed too fast! (28.6 -> 2.86)
etmod(3/20 6:45): priamp is out of range, threshold A! (0)
gasmod(3/21 12:25): gas is out of range, threshold A! (99)
gasmod(3/21 12:30): gas is out of range, threshold A! (100)
gasmod(3/21 12:35): gas is out of range, threshold C! (150)
gasmod(3/21 12:35): gas has changed too fast! (100 -> 150)
gasmod(3/21 12:35): rgas has changed too fast! (14.59161 -> 68.03491)
ie3mod(3/21 12:35): rgtoil is out of range, threshold A! (13.3483)
gasmod(3/21 12:40): gas is out of range, threshold C! (150)
ie3mod(3/21 12:40): rgtoil is out of range, threshold A! (13.2085)
gasmod(3/21 12:45): gas is out of range, threshold C! (150)
ie3mod(3/21 12:45): gtoil is out of range, threshold A! (100.3948)
ie3mod(3/21 12:45): rgtoil is out of range, threshold A! (13.3733)
etmod(3/23 13:25): /monitor/mod.elec/et.acm: No new data
```

Figure 3-7: Example of Monitoring System Flags

The field deployed system can be thought of as a Decision Support System for Transformer Operation and Maintenance as shown in Figure 3-6. It provides simple anomaly detection capabilities as evidenced by the generation of "flags". Diagnostic and prognostic information is obtainable only through human analysis of pertinent information. Anomalous behavior is "flagged" in the Local Analysis & Detection block. A list of typical flags is shown in Figure 3-7. Each flag contains information concerning which module generated it, the date and time of generation, and a brief description that may include which threshold was exceeded and the value(s) that caused the flag. A multiple threshold scheme is implemented based on the design of the anomaly detectors in Figure 3-2. Thresholds are set according to the transformer's nameplate and/or from other knowledge specific to the particular transformer. Multiple levels (A, B, C, etc.) are used to partition the abnormality into varying degrees of either real or perceived seriousness. For example, C is more critical than B, while B is more critical than A. The current field deployed system does not identify if an abnormality is either an upper or lower violation of the present thresholds.

The first flag, "ie3mod(3/19 7:55): gtoil has changed too fast! (28.6 $\rightarrow$ 2.86)", shown in Figure 3-7, was raised by the (IEEE) Thermal Module, indicated by "ie3mod" on March 19 at 7:55. This occurred when the generic top oil temperature, indicated by "gtoil", changed from 28.6 to 2.86°C in 5 minutes. This flag requires only a sanity check as experience indicates that the DAS generated a decimal point error. The second flag, "etmod(3/20 6:45): priamp is out of range, threshold A! (0)", shown in Figure 3-7, was raised by the Electrical Module, indicated by "etmod" on March 20 at 6:45. This occurred when the primary current, indicated by "priamp", went to 0 amps. This flag indicates that the transformer is off-line and would require communication with the utility to determine the cause which would then be entered into a maintenance log for reference purposes. The third flag, "gasmod(3/21 12:25): gas is out of range, threshold A! (99)", shown in Figure 3-7, was raised by the Gas Module, indicated by "gasmod", on March 21 at 12:25. This occurred when the "gas" (Hydran® 201R reading) content of the oil violated threshold A when it went to 99 ppm. This would require an analysis and diagnosis of the present condition of the transformer.

Other examples are provided in Figure 3-7 and should be self explanatory. Here "rgas" refers to the gas residual generated by the Gas Module and "rgtoil" refers to the top oil residual generated by the Thermal Module. All flags are logged by the Monitoring System in an "errors" file for documentation and further use. Other types of housekeeping messages and system errors are logged either in the "errors" file or in the "stderr" file. These are dealt with accordingly.

In the effort with the electric utility, flags are immediately prepared by condensing the message and attaching a transformer specific identifier. The identifier would specify the utility, the station, and the transformer by name and/or number. For example, a flag raised by the transformer in the MIT Pilot Facility as:

ie3mod(3/19 7:55): gtoil has changed too fast! (28.6 $\rightarrow$ 2.86),

would be transmitted to the pagers as:

MIT PILOT ie3mod(3/19 7:55): gtoil 2fast! (28.6 $\rightarrow$ 2.86).

The message is sent to personnel on call who evaluate the (condensed) flags based on established procedures, transformer expertise, and a knowledge base developed from previous experience. If more information is required for analysis and manual diagnosis, MIT personnel login from a remote or roving (computer) terminal to the computer at the substation to access data and information within the monitoring system, to download plots and/or data, to query files containing transformer, sensor, and monitoring system history, or to directly monitor any part of the system in real time. Therefore a Global Analysis & Interpretation phase is performed based on the present transformer condition, site-specific and general transformer and sensor knowledge, specialized on-line monitoring knowledge, and any available operational or maintenance information. This diagnosis may identify a pending (or imminent) failure or other problems. When appropriate, MIT conveys any serious observations and recommendations concerning the transformer to the electric utility. The utility may request more information from MIT or order off-line tests before making operational and maintenance decisions.

There is a definite procedure that is followed in the Global Analysis & Interpretation phase as the human employs previously learned knowledge to make an informed decision. Also, the human learns from each experience, as part of the analysis process involves structuring and cataloging newly developed knowledge. This knowledge will be critical at future stages of this work.

3.2.3 Knowledge Base

The eventual goal is to remove MIT from the analysis and diagnostic processes. In order to develop an automatic diagnostic system, an on-line model-based transformer monitoring knowledge base must be developed. This allows the integration of on-line experience with general and specific transformer knowledge, sensor knowledge, and transformer anomaly knowledge. Obtaining knowledge (knowledge elicitation) of this type is a very complex and tedious task and is accomplished either by direct interview sessions or from highly structured event reports generated by MIT personnel. To date, more than 35 separate on-line cases have been documented from over 9 transformer years of experience accumulated to date. The elicited knowledge is then formalized and transformed into a readable and useful structure, referred to in this work as diagnostic graphs. This is the focus of Chapter 5.

In creating the knowledge base and from the real-time experience gained from evaluating the flags transmitted to the pagers, it has become apparent that a better anomaly detection scheme is required before a diagnostic system can be implemented. The "flag" scheme is simple but experience shows that a point-wise determination of the transformer condition creates a large number of nuisance flags that result from harmless changes in external conditions not related to the health of the transformer. A novel detection scheme is presented in Chapter 6.

3.3 Transformer Performance Monitoring System (TPMS)

This section presents block diagrams for the design of a Transformer Performance Monitoring System (TPMS) which allows for the detection, diagnosis, and prognosis of the condition of the transformer while providing useful capability for users. Its detailed design and implementation is one of MIT-LEES' long term research goals.

3.3.1 Motivation

A system used for monitoring transformers deals with real-time data, operates continuously, and must assist and support the utility in choosing the right information in order to make informed decisions. In traditional or conventional monitoring systems the major effort has been devoted to collecting and displaying process data while very little has been done to aid the utility in better understanding the overall process output. The major goal of this work is to provide an automated method for searching through large amounts of interrelated process data to identify causes for deviations from normal operating conditions, while providing a mechanism for user input and output to the system.

There will be different types of users of the TPMS at an electric utility. Direct users include research, engineers, maintenance, and the control room. Management is an indirect user and will be informed of all developments by appropriate communication with the engineers, maintenance, and the control room.

The Human Interaction with the TPMS is shown in Figure 3-8. Each user will have different needs and requirements as shown in this figure. Research will make enhancements to the TPMS and receive operational analyses from the system. The engineers will rec-

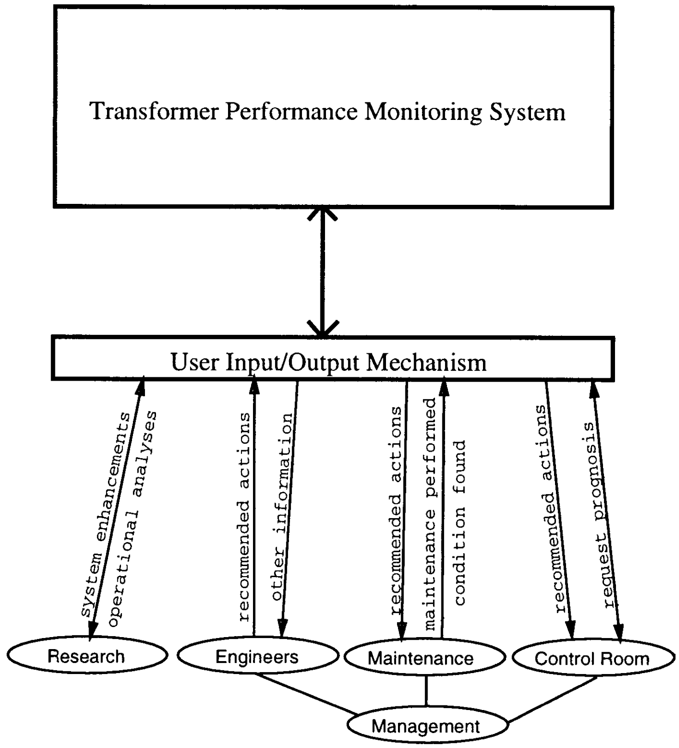

Figure 3-8: Human Interaction with TPMS

ommend actions to be taken and enter these into the system. They will also receive other types of information in order to stay informed of all situations. Maintenance will receive recommended actions from the system. These could include fixing broken sensors or even performing off-line tests. Any maintenance performed, conditions found, and the results of tests will be entered into the system for use in analysis and diagnostics and as an entry in a maintenance log. This is useful in keeping accurate records of maintenance procedures and results in order to correlate information. The control room will receive recommended actions, such as lower the load or turn on the cooling. It will eventually have the capability to request and receive prognosis information.

3.3.2 TPMS Architecture

Designing a Transformer Performance Monitoring System must be done with great care and with foresight of future needs. An intelligent and useful system must possess several properties which are outlined below.

- Expandable system
- Modular system design and development
- Cooperating modules
- Multiple analytic and reasoning techniques
- Global access to data and information

Taking these requirements into consideration, the major components of the Transformer Performance Monitoring System at a very global level are shown in Figure 3-9. These include On-Line Monitoring and Detection, Diagnosis, Prognosis, Local Information Storage, Operator, Peripherals, Control and Scheduling, and External Communications.

The On-Line Monitoring and Detection block already exists and is completely functional. It was described in Sections 3.1 and 3.2. Upgrades are currently in progress to provide a "Call Director" and a "Software Toolbox" for use with this existing system. This will allow a central mechanism for data handling and information flow into and out of the entire system, while providing the capability for easily handling addition and subtraction of users, modules, and methods of communication.

A major piece of this work is to add Diagnosis, which is the focus of this thesis. Generally, diagnosis includes knowledge-based information processing, reasoning, and decision making. These are described in more detail later in this thesis. Prognosis, or estimating the future condition of the transformer on diagnostic results, will be implemented at a future date.

Peripherals are devices that make the system more useful. These include items such as terminals, printers, floppy drives, and tape drives. External Communications allow connection with LANS, WANS, SCADA, Modems, and Multiple Databases. The multiple databases are used mainly for archived storage and retrieval of many different types of data indicated in the Figure 3-9. Other types of data are kept locally in the Local Information Storage. These include recent on-line data, transformer parameters, model-based predictions and residuals, anomaly detection criteria, anomaly reports, and information requested from external data bases. The Operator can modify and control schedules when necessary. The Control and Scheduling maintains a type of order, scheduling, and managing of events.

The approach for implementing this type of design is discussed below.

3.3.3 AI Approach

An AI-based approach was chosen since it provides separation of knowledge from reasoning and is therefore superior to conventional programming. It also allows both classical transformer diagnostic techniques and model-based monitoring to be used in developing a solution to a problem. The motivation for this is that:

- Building a complete rule set is a massive task
- Large numbers of rules are necessary to verify sensor data
- Complete rule sets rapidly become obsolete

General Blackboard Model

The "blackboard model" or architecture is a particular model of problem solving that allows many and varied sources of knowledge to be used in the development of a solution to a problem [39]. In this type of architecture, the blackboard is globally accessible working memory where the current state of understanding is stored. Knowledge of the application domain is divided into modules or knowledge sources (KSs) which contain knowledge relating to a particular task. KSs are independent and may communicate by reading from or writing to the blackboard. The general blackboard architecture is illustrated in Figure 3-10, entitled The Blackboard Model.

The blackboard model was chosen since it provides a framework for integrating knowledge from several sources. It can represent multiple levels of problem decomposition and incrementally develop the solution to a problem. It allows for divide and conquer and opportunistic problem solving. Different types of reasoning strategy may be mixed as appropriate in order to reach a solution. In the event a complete solution is unachievable, all partial solutions will appear on the blackboard and may be of some use to users [39, 43].

The blackboard model adapted for transformer diagnostics will contain the following knowledge sources that are briefly described below. Figure 3-11 shows the integration of

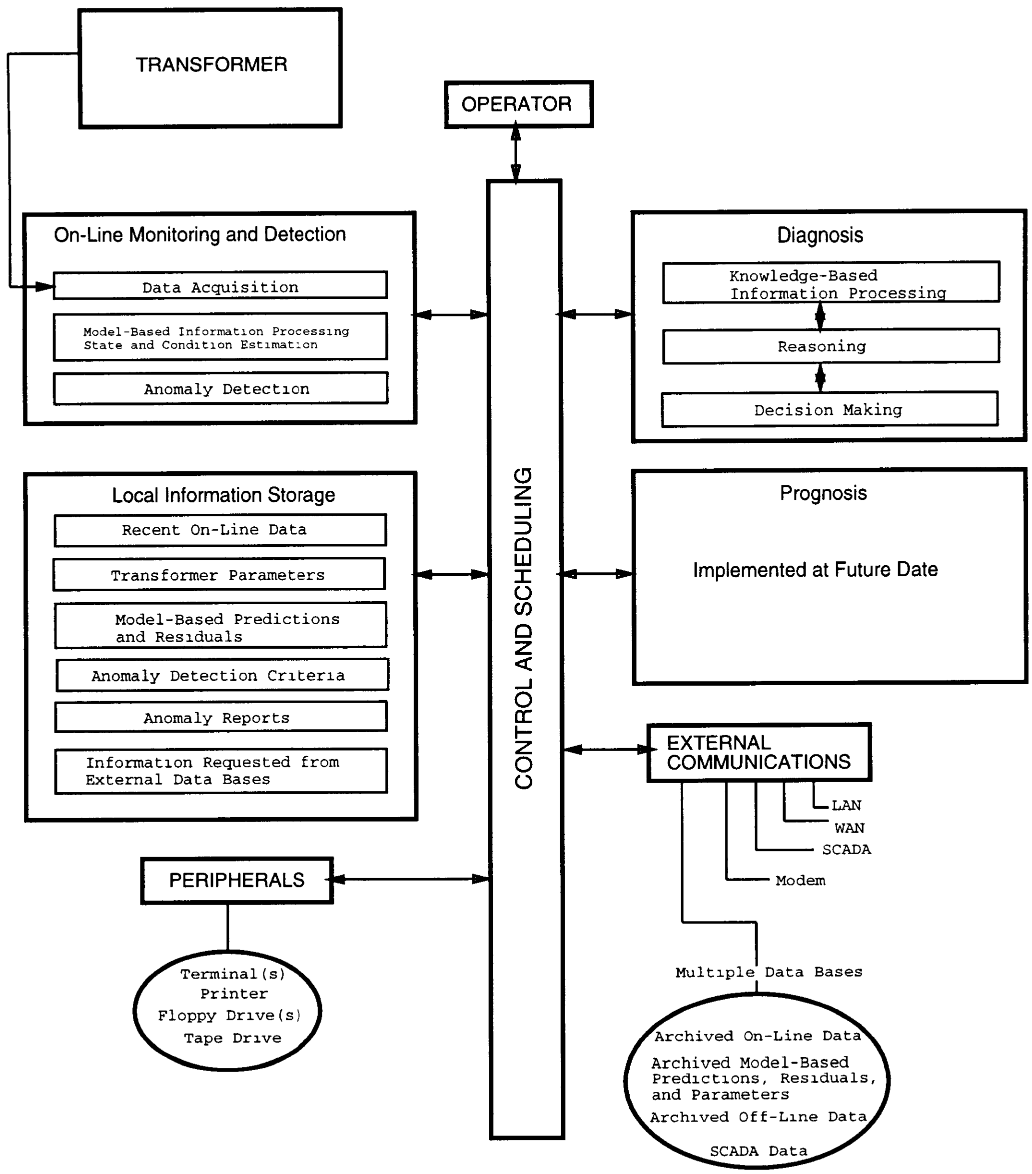

Figure 3-9: Performance Monitoring System Block Diagram

multiple KSs in the blackboard environment.

Knowledge Sources

The knowledge needed to solve the problem is divided into knowledge sources (KSs) which are independent, although they communicate via the blackboard. They participate in the problem solving process by creating, modifying, and deleting entries in a global database, namely the blackboard. Several types of KSs exist which include rule-based, model-based, neural network, object-oriented, and procedural. At the present time, the knowledge sources shown in Figure 3-12 are needed for transformer diagnostics. An appropriate KBES tool will be selected for each in the future, but for now they are only briefly described in general below.

The Intelligent Detection KS takes data and information contained in the flags and generates alarms which in the future will be placed on the blackboard and coordinated with the Supervisor KS. In the future, it will post on the blackboard the present state/input matrix, error messages, the location of the anomaly as well as related information. It organizes these items and calls appropriate routines to display portions of the blackboard as well as plots of related transformer measurements on the computer screen for users to view the state of the system.

The On-Line KS will use measurements and information obtained from the MIT On-Line Monitoring System. Information concerning model behavior, data analysis, and rules of thumb will be combined to provide diagnostic results.

The Classical KS will integrate traditional transformer monitoring and diagnostic techniques. Specifically it will use data and information from off-line tests for diagnostics purposes. For example, it might use the Rogers Ratio Method for interpreting the results of a dissolved gas analysis.

The Sensor KS will apply a series of tests or relations to provide information concerning sensor operation. It will be used to predict sensor failure versus transformer failure.

The Strategy KS will examine the present information on the blackboard and suggest the next course of action to be taken. A goal processor will be used to determine the overall or general attack the system will pursue against the current problem. It will determine which KSs should be activated or scheduled and in what order based on priority ordering heuristics. It will place the scheduled list on the blackboard. An anomaly will initially trigger this KS which will then determine a course of action.

The Statistical Analysis KS will provide all of the statistical analysis capability needed by the entire diagnostic system. In addition, it will allow the analysis stages, namely Sanity Check, Behavioral Classification, Correlation Checks, Statistical Trending, and Data Base Comparison, to be implemented. For research purposes, it will involve *statit* sold by Statware, Inc. and possibly some routines from *Numerical Recipes*.

The Data Conversion KS is activated when data or files need to be converted from one type or format to another. For example, measurements stored from the on-line monitoring system will be converted by this KS to a format required by the Statistical Analysis KS.

The Utilities KS (Graphics) will be defined in greater detail in the future. Presently, it will consist of *pl* or *plop* for plotting transformer data and may contain other plotting functions.

The User KS is an interface between the user and the blackboard system. The user may specify the course of action or input information pertaining to the solution. The User KS provides a method by which knowledge from the user is supplied to the blackboard. For example, the results of a dissolved gas analysis may be entered by the user.

The Diagnostic-Recommended Action KS will interpret the data, information, and results residing on the blackboard. It will draw global conclusions based on the present state of the blackboard any time it is activated. Its diagnostic conclusions will be followed by appropriate recommended actions.

The Supervisor KS will perform many tasks. Generally these include what knowledge source to apply and when and to what part of the blackboard to write the results. The supervisor will use knowledge generated by the individual knowledge sources to make decisions concerning scheduling, KS activation, etc. The supervisor's tasks are described briefly as follows. The Monitor looks for events or changes to the blackboard. After an activated KS has performed its task, the results and the time of the results are posted on the black-

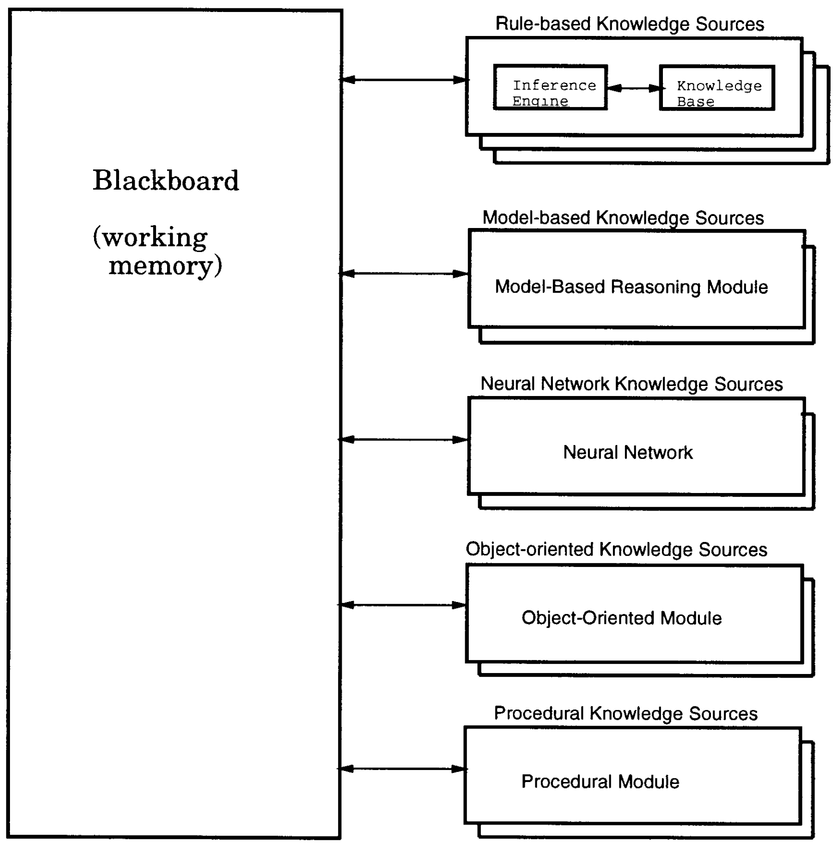

Figure 3-10: The Blackboard Model

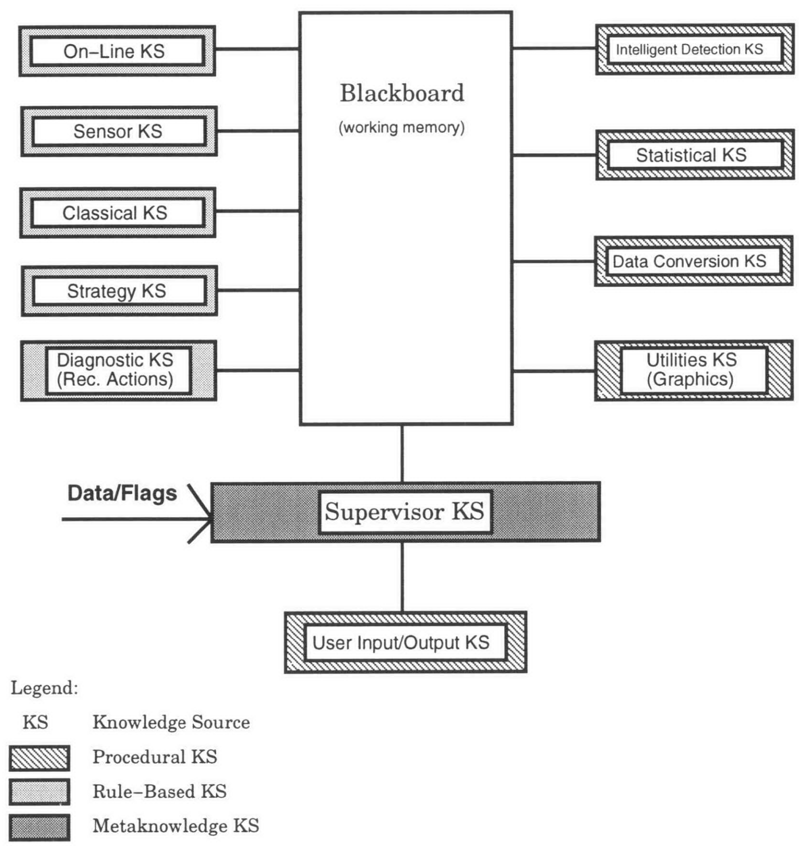

Figure 3-11: Blackboard Architecture: Integration of Multiple KSs

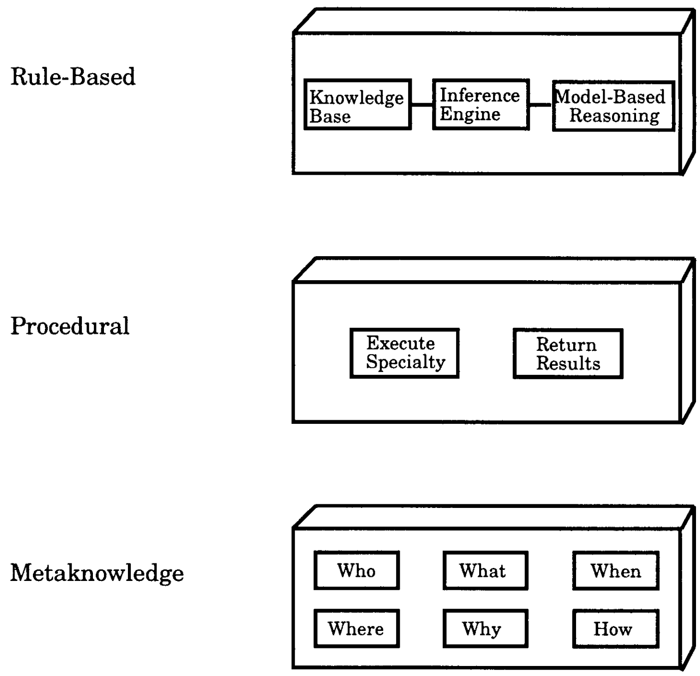

Figure 3-12: Types of Knowledge Sources

board. This Posting of Findings/Time of Posting may be done by the individual KSs, the supervisor, or a combination of both. This will probably be accomplished by having the KS that modifies the blackboard to notify the monitor that it has made a change(s) and the location(s) of the change(s). The Control information is used by the supervisor to determine the focus of attention. This indicates the next thing to be processed as posted on the blackboard by the Strategy KS. The control mechanism takes the appropriate steps to activate the knowledge sources. These steps are referred to as KS Trigger/Activation Conditions. Information on how this, along with Scheduling and Dispatch, will be achieved is known by the supervisor. The blackboard Organization is known entirely by the supervisor. It will know the specifications and layout of the various panels making up the blackboard. In addition, it will know the locations the KSs are allowed to change. The capability to provide blackboard Maintenance must exist. The ability to delete or remove outdated or incorrect results must be allowed. Maintenance may include posting of results, data, error messages, control information, etc., whether by the individual KSs or the supervisor as previously discussed. Time Constrained Reasoning or Decision Making is important if catastrophic failure of the transformer could be imminent. This corresponds to the case of a large anomaly where a rapid response time is critical. The supervisor must be able to manage KS activation or deactivation while keeping in mind the maximum reaction time available. On the other hand, the small anomaly case allows a longer response time and more information processing before recommended actions are suggested. Learning and Knowledge Constrained Reasoning or even the Use of Incomplete Knowledge is oftentimes associated with the supervisor. But, with the outlined architecture, this will best be accomplished or implemented by the individual KSs.

The On-Line, Sensor, Classical, Strategy, and Diagnostic-Recommended Action KSs are considered Ruled-based KSs. These may be rule-based with a hybrid inference engine or a rule-based hypothesis generating KS. The Intelligent Detection, Statistical, Data Conversion, Graphical, and User KSs are considered Procedural KSs. When a Procedural KS is activated it simply runs a procedure and is then deactivated. The Supervisor KS is considered a Metaknowledge KS as it is all knowing. See Figure 3-12 for a complete look at these. There may be a need to redefine some of these KSs as Object-oriented or as Neural Network KSs. More research in these areas will define the best approach for handling the varied types of knowledge outlined above.

See Figure 3-13 for a complete Information Management Diagram. This combines the concepts of the Blackboard Model with the On-Line Monitoring System with the concept of the User. This diagram is the combination of several aspects of prior diagrams. Chapters 4, 5, and 6 focus primarily on the acquisition, structuring, and use of knowledge for detection and diagnostic purposes.

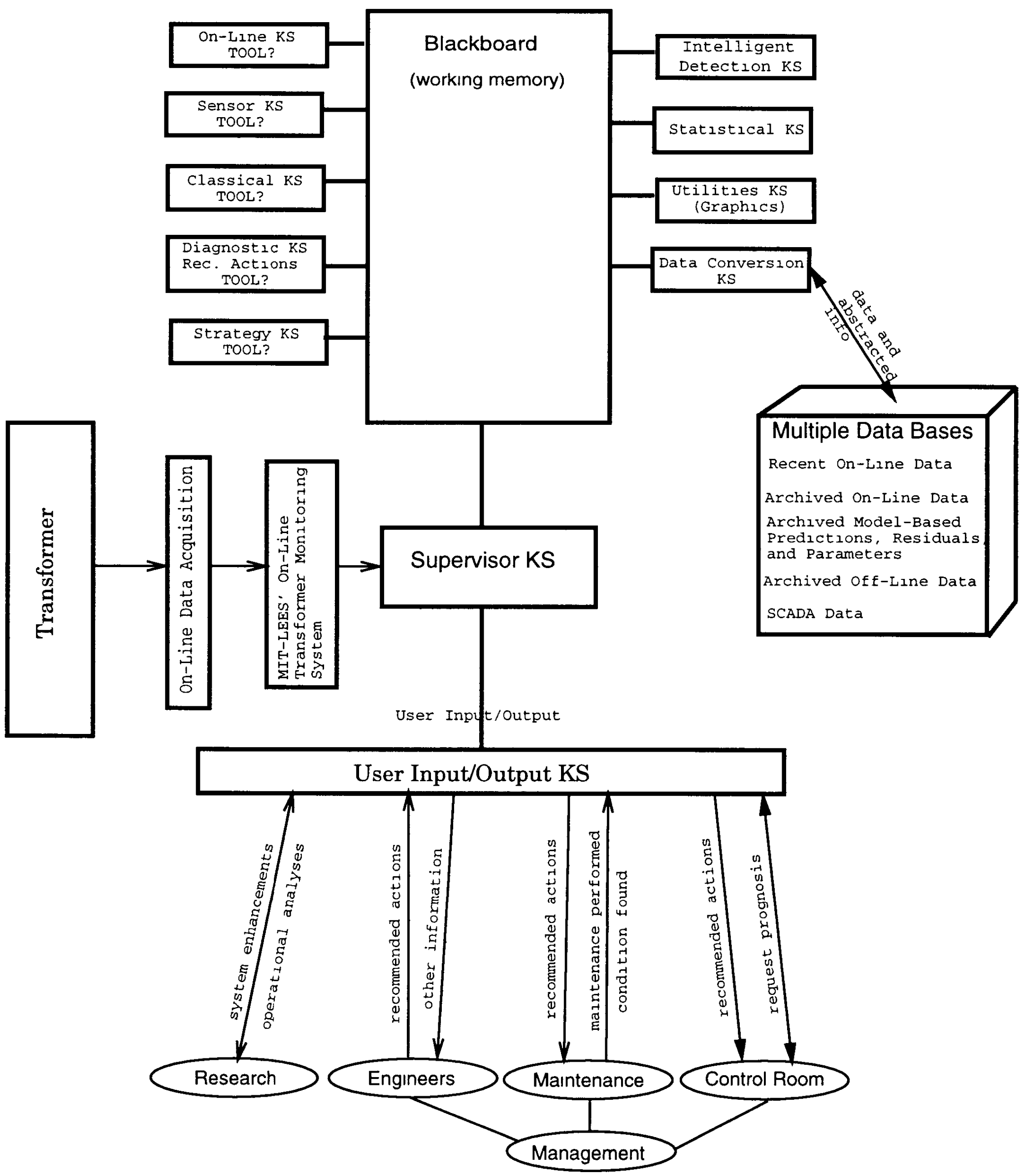

Figure 3-13: Information Management Diagram

Chapter 4

On-Line Monitoring and Diagnostic Basics

This chapter determines and structures the basic concepts and methods that are necessary for designing an advanced diagnostic system for large power transformers. It identifies what is important in constructing the diagnostic system, starting with how the operation of the system will be triggered and continuing with how to analyze multiple information streams operating on different time scales. In essence, the diagnostic system must be able to use on-line information provided by an adaptive model-based monitoring system as well as information provided by off-line or sampled-data tests. Finally, the system must be able to draw conclusions about the condition of a transformer and then make recommendations to electric utility personnel concerning operation and maintenance.

It should be kept in mind that the diagnostic system under development is not only a research tool, but also a system that utilities presently need. Therefore the user is taken into account in designing the diagnostic system. From MIT-LEES' perspective, the system must:

- Develop/abstract information from raw on-line data
- Present information to the user in a useful form
- Point the user at prioritized information

- Present the user with initial diagnostic/control recommendations

Section 4.1 examines the overall Diagnostics and Alarm Hierarchy and develops a discrete structure for identifying and examining problems. Section 4.2 restructures this information as flow diagrams that reveal how information is processed. The concepts developed in this section are then applied to two problems in Section 4.3.

4.1 Diagnostics and Alarm Hierarchy

Figure 4-1 shows a discrete, three category view of the overall Diagnostics and Alarm Hierarchy [40]. This is a highly simplified view since in reality there will be no pre-classification of anomalies. This figure is included since it is a good starting point in understanding the issues involved in anomaly detection, diagnostics, and decision-making. It identifies how a problem is detected, how serious the problem appears, and how fast the problem occurred. It also indicates a time for reaction, the particular action to be performed, the identification of the problem cause, and then a recommended action. These are examined in greater detail in the following subsections.

4.1.1 Apparent Problem Level

The apparent problem level can be discretely identified as either "large", "medium", or "small". These levels can be directly correlated with a very serious, moderate, or minor problem that is occurring with a particular transformer.

4.1.2 Indication

The indication of a problem, or anomalous behavior in a transformer, can occur in several ways. First a measurement level or rate of change, may violate a set range or threshold. For a severe violation, the problem is termed large. On the other hand, if the measurement level or rate of change is only at or near some predetermined limit, the problem is identified as medium. A medium problem may also include significant residuals produced by the model-based detection system where a residual is simply the difference between the measured

Apparent Problem Level	Indication	Diagnostic Action	Time Scale of Problem	Reaction Time	Identification of Cause	Recommended Action
Large	Measurements out of Range* (temp, gas, etc)	Sanity Check (sensor or transformer)	Minutes to Hours	Immediate	No	Shutdown Replace Sensor
Medium	Measurements at or near Limits* or Significant Residuals	Sanity Check Cross Correlations	Hours to Days	Hours	Yes, Events (overheating, PD, arcing, etc)	Perform other Tests Schedule Shutdown Closer Observation
Small	Significant Parameter Trends and/or Significant Residuals	Sanity Check Cross Correlation Statistical Trending Data Base Comparison	Days, Weeks Months	Days	Yes, Root Cause (hot cellulose, electrification, abrasion, etc)	Continued Observation

Figure 4-1: Diagnostics and Alarm Hierarchy

and predicted value. A small problem is identified by significant parameter trends and/or significant residuals.

4.1.3 Time Scale of Problem

The time scale indicates how rapidly a problem has occurred and reflects the underlying triggering mechanism. A large problem will develop very rapidly, indicated by a time scale of minutes to hours. A medium problem occurs on the time scale of hours to days while a small problem occur over several days, weeks, or even months.

4.1.4 Reaction Time

The reaction time is the maximum time allotted to the diagnostic system and/or human to respond to the particular problem. For instance, if the diagnostic system is unable to recommend a course of action in the allotted time, a human must make a decision based on all currently available information. In general, a large problem requires an immediate reaction, possibly on the order of minutes. A medium problem may be responded to over the course of several hours, while a small problem may be dealt with over several days.

4.1.5 Diagnostic Action

Diagnostic actions are a series of analysis steps that take several forms. For large problems, the only action taken is a sanity check to try to determine if there is an actual problem with the transformer or some type of sensor failure. For medium problems, a sanity check is performed followed by cross correlation of behaviors observed in different transformer subsystems. Small problem require several levels of analysis. They start with the basic sanity and cross correlation checks, and then utilize various types of statistical trending and data base comparisons.

4.1.6 Identification of Cause

The identification of the cause of the problem is ideally sought. In some situations, the reaction time may not be sufficient enough to allow determination with a certain degree of accuracy or there may not be enough information available to do so. For a large problem, no cause is identified. For a medium problem, a particular event, such as overheating, partial discharge, arcing, etc. is identified. For a small problem, the root cause is identified and may include items such as hot cellulose, electrification, abrasion, etc.

4.1.7 Recommended Action

A recommended action(s) is based on the information provided and the results of any analysis performed. It takes into account reaction time, severity of problem, and any other information available. A large problem requires the most urgent action. Urgent actions may include a transformer shutdown or a sensor replacement. Medium problems allow additional time for action. This allows time for other tests to be performed, shutdowns scheduled, or the transformer may be observed more closely than is usually done in normal operation. Small problems may only require closer and continued observation.

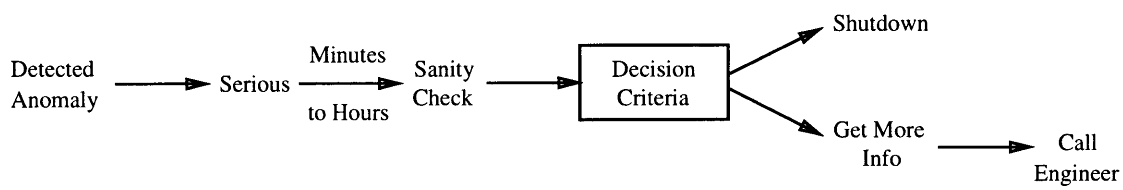

Figure 4-2: Information Processing Flow Diagram for a Large Anomaly

4.2 Information Processing Flow Charts

An identified problem activates a series of steps as outlined in Figure 4-1. This section clarifies some of the terminology previously used and develops a hierarchical scheme for handling problems of varying severity. The result is three flow diagrams that specify the processing of large, medium, and small problems and the final result is a general structure of the Overall Diagnostics System [42]. Problems will henceforth be referred to as anomalies.

4.2.1 Large Anomaly

A large or most severe anomaly will require a fast response to avoid a possible catastrophic failure of the transformer. This is shown in Figure 4-2 [42]. In this situation, the operation of the transformer has gone out of preset limits by a large amount. Here the detected anomaly that triggered the diagnostic system operation is assumed to be serious since the deviation from the normal is large and the time scale involved was minutes to hours. This may have been either physically or temporally based, that is a measurement level or rate of change criteria was greatly exceeded. In this case, the diagnostic process is the simplest since less information processing is required. The only information processing or analysis step necessary is a Sanity Check which is based on Outlier Detection. If the sanity check indicates an actual problem with the transformer, a shutdown message is sent to the Control Room. If the problem appears to be a gross sensor failure or an undetermined problem that cannot be identified with high enough certainty, an engineer is called to obtain more information. This course of action might be followed by some utilities in the face of a large dissolved-gas reading anomaly, where catastrophic failure of the transformer might be imminent [37].

4.2.2 Medium Anomaly

Figure 4-3 shows the required information processing for a medium or moderate anomaly [42]. It is the response to an anomaly that develops more slowly, or is evidenced by a smaller deviation from normal. This type of anomaly will develop over a period of hours to days and will not require the same rapidity of response as a large anomaly. This situation allows and requires more information processing and a correspondingly longer time to arrive at a recommended course of action. In addition to performing the basic sanity check, it is necessary to classify the behavior of several signals produced by the monitoring system. The Behavior Classification stage will attempt to identify behaviors such as pulses, steps, ramps, lags, increased noise, etc. Coupled with this will be the Correlation Checks stage that will auto-correlate behaviors observed in individual transformer subsystems and cross-correlate behaviors observed in different transformer subsystems. Based on these results and a set of prespecified decision criteria, a recommended action is made. A recommended action at this level may include closer observation, a message to perform other tests, or a message to schedule a shutdown. These messages or recommendations may go to engineering, maintenance, or the control room. The results of any off-line or sampled-data test are entered into the system for interpretation.

4.2.3 Small Anomaly

Figure 4-4 shows the required information processing for a small or minor anomaly [42]. This response is for situations developing over a period of days, weeks, or months and includes everything in Figures 4-2 and 4-3, plus Statistical Trending and Data Base Comparison. These additional analysis stages employ progressively finer-grained analysis of the available

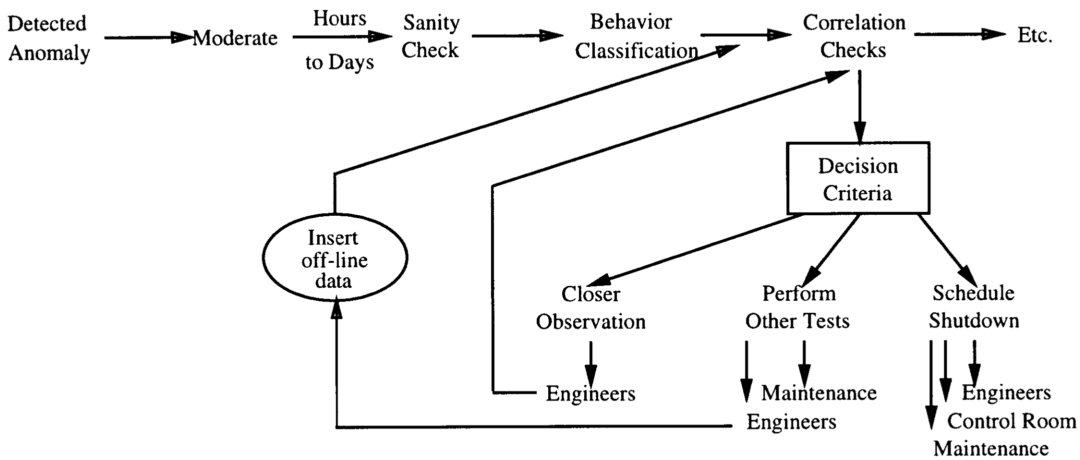

Figure 4-3: Information Processing Flow Diagram for a Medium Anomaly

information, including the integration of knowledge residing in external data bases. This knowledge may contain parameter trending information for a class of similar transformers.

4.2.4 The General Case

In actuality, there will be no pre-classification of anomalies. There will only be triggering events and the diagnostic system must be able to respond to a continuum of severity levels. Figure 4-5 provides a compact Overall Diagnostics System Block Diagram and Figure 4-6 shows the Analysis Stages in the order in which they are utilized [42]. In this generalized diagram following each analysis stage, if the cause of the anomaly can be identified with some degree of certainty, a Recommended Action is made based on some set of Decision Criteria. These are shown in decreasing urgency. On the other hand, should the cause not be identified, a different Recommended Action is made based on a different set of Decision Criteria. The action Abstract More Information, causes the diagnostic system to perform

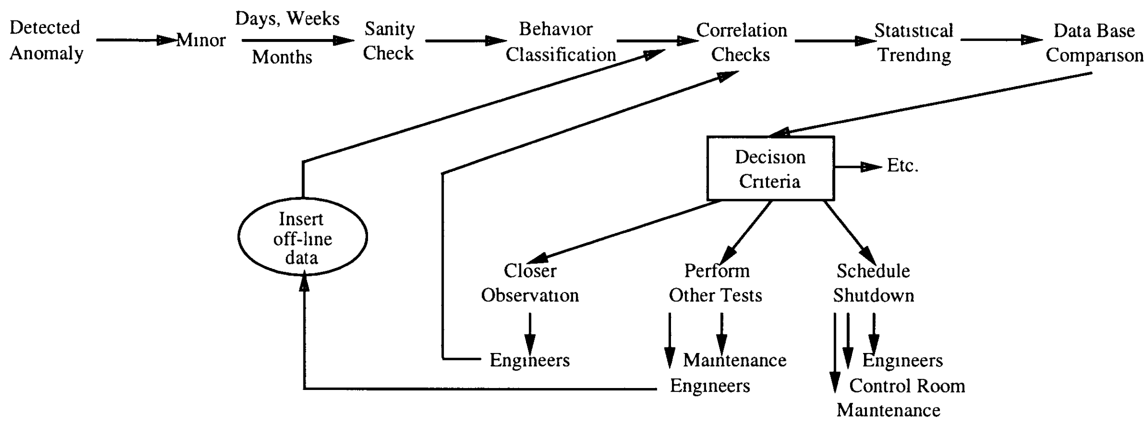

Figure 4-4: Information Processing Flow Diagram for a Small Anomaly

the next analysis stage before a final decision is made.

4.3 Diagnostic Examples

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Two examples were developed in order to determine the diagnostic system strategy and the steps necessary for the cause identification of detected anomalies. These examples use and illustrate the underlying concepts developed in Sections 4.1 and 4.2 and allow the formalization of a solution strategy necessary to develop a robust knowledge-based diagnostic system. This process will allow diagnostic system development to occur in a orderly and timely manner, and ensure that it will interface with the Adaptive Model-Based Transformer Monitoring System previously developed at MIT [6, 33, 35].

These examples are developed from experiments performed at MIT and discussed in [6]. They involve data and information taken from the Adaptive Model-Based Transformer Monitoring System at the MIT Pilot Test Transformer. The state of these examples is

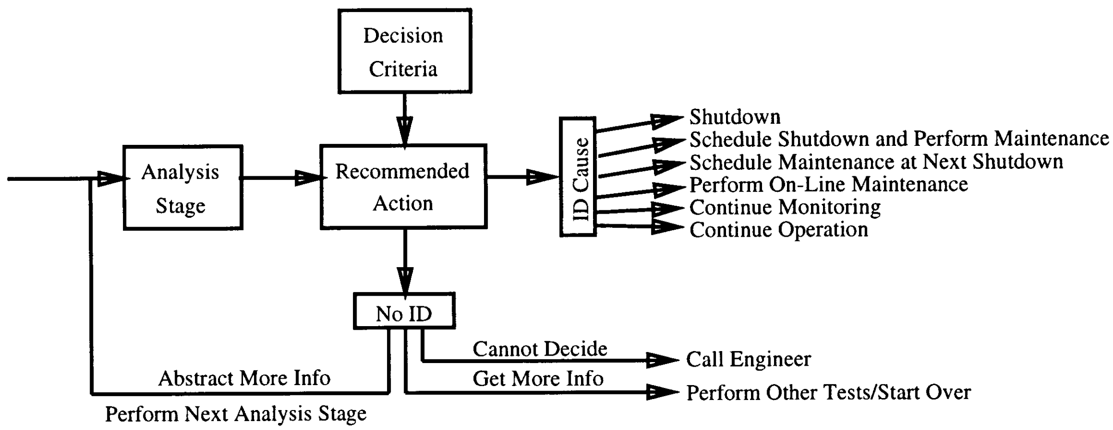


Figure 4-5: Overall Diagnostics System Block Diagram

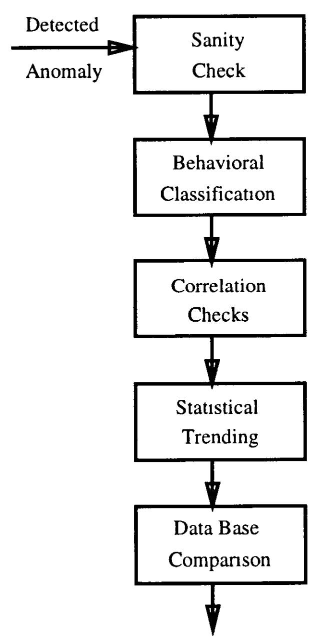


Figure 4-6: Stages of Analysis

based on original concepts and interpretations and may not truly reflect the final diagnostic system. At a future date, these examples will be reformulated to include any new methods of thinking.

4.3.1 Gas Module Diagnostic Example

The analysis in this example is developed to the level of being able to detect anomalies, perform sanity checks, and recommend actions. This analysis will be expanded in the future to include behavioral classification, correlation checks, statistical trending, and data base comparison.

0. Introduction to Example

In this example, the first event is the detection of an anomalous behavior in the transformer. This is followed by a series of steps that must be taken to diagnose the cause of the anomalous operation. These steps can be taken by a human, a machine, or a combination of both.

All transformers in service, including lightly loaded units known to be operating satisfactorily, evolve hydrogen and other simple hydrocarbon gases. By observing abnormal levels of gases, incipient failures may be detected [7, 8].

By the use of Syprotec's Hydran® 201R sensor, the level of hydrogen dissolved in the oil can be monitored almost continuously. For the MIT Pilot Test Transformer, the Hydran® 201R reading is taken every 10 minutes. In addition to hydrogen, the sensor is partially sensitive to three other gases, namely carbon monoxide, ethylene, and acetylene.

At the MIT Pilot Test Transformer, a high-intensity arcing event was simulated through a single long (tens to hundreds of seconds) spark; an incipient arcing failure was simulated with brief three-second arcs distributed over several days [6, p.111-114]. Figure 4-7 shows the load and excitation for the week beginning November 14, 1989. The results of the arcing events are shown in Figure 4-8. Figure 4-8 displays the residual response to the arc during steady-state. The diagnostic process developed here will apply to both the simulated anomaly in the example and the naturally occurring anomaly. The fact that a controlled example was used does not affect the diagnostic process. The procedure developed below used no prior knowledge of this event.

1. An anomaly is detected.

Based on the Hydran® 201R reading, an anomaly was detected on November 14 at 12:20 pm. The gas residual violated the set rate-of-change threshold for a set number of measurements. Here the level threshold was set to 18 ppm and the rate-of-change threshold was set to 5 ppm/measurement interval. As given above the measurement interval was ten minutes. The rapid 10-ppm rise ran contrary to experience. This indicates that the transformer oil contains a level of hydrogen that is increasing at a rate that is greater than normal. There were no anomaly indicating flags raised by the Thermal, Vibration, or Moisture Modules.

A definite step-like behavior was observed by examination of Figures 4-7 and 4-8. This observation will become more important as analysis involving behavioral classification is added to the diagnostic system in the future.

An entire range of gas-generating failure modes become viable diagnoses. These include cracked bushing, electrification, hot spot, arcing short, gas bubbles, contaminated oil, (possibly normal) aging, partial discharges, localized overheating, and sensor failure [6, p.95].

2. Determine anomaly time scale.

The flag raised in the detection system determines the time scale involved. This time scale reflects the triggering mechanism.

In this example, the changes have occurred quite rapidly. For this particular setup, the Hydran® 201R reading is taken every ten minutes. Therefore the time scale of the anomaly involved is minutes-to-hours.

3. Determine maximum reaction time.

Determine how much reaction time is available, based on the detected anomaly. The reaction time is defined as the maximum time allotted to the diagnostic system to respond to the detected anomaly. If the diagnostic system cannot recommend a course of action in the time allotted, a human must decide whether or not to shutdown the transformer. The two most critical items affecting reaction time are the severity of the anomaly and the time scale over which it occurred. The severity of the anomaly is determined by the amount by which a measurement, measurement residual, or a parameter residual violates its specified level or rate-of-change threshold and the particular characteristic or subsystem exhibiting the anomaly.

By examining the plot in Figure 4-8, the gas content residual changed 10 ppm in one measurement intervals. This was twice the 5 ppm rate-of-change threshold set for anomaly detection. This rapid rate-of-change supports the classification of "serious".

For this example, the available reaction time is minutes-to-hours. This behavior corresponds to the "large" anomaly case in the dissolved-gas characteristic of the transformer which is indicative of a potentially serious problem. The indication of a severe anomaly will generally require the fastest response to avoid a catastrophic failure of the transformer. Essentially, a quick decision must be made to determine if the transformer needs to be shutdown immediately or whether it can be left on line.

4. Determine related external events.

Determine any events that have occurred in the period of concern. Determine within an appropriate time scale if any maintenance was performed. Long term average load trends, influenced by basic load changes and operational decisions should be noted. Weather conditions may even produce anomalous effects.

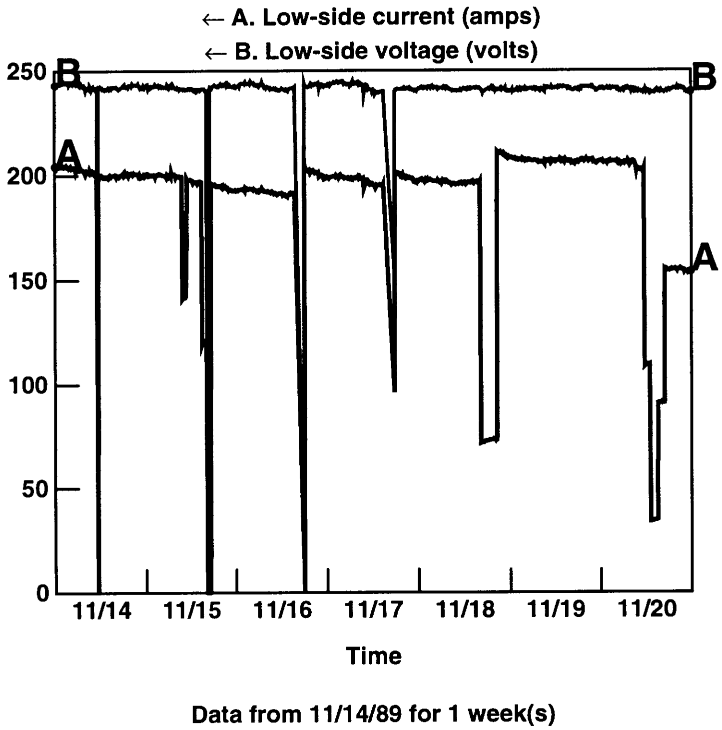


Figure 4-7: Load and Excitation During Steady-State

This transformer tends to be fairly heavily loaded and operates in a relatively high ambient temperature. This type of information will be available in a transformer specific database. If the information is unavailable, the diagnostic system will have the capability to query for additional input and make decisions and recommendations without it.

This transformer was shut down several times for maintenance and to draw oil samples for gas chromatography for comparison, as noted by the MIT Pilot Facility Log (1989). The load was restored to its previous level after each shutdown. Here, a maintenance shutdown occurred at 11:15 am, approximately three hours before the anomaly. This would initially tend to be very slight support for sensor failure.

5. Check Module that detected the anomaly.

Check the module that actually detected the anomaly. For this example, it was the Gas Module. Look for other indications, too small to have triggered the detection system, of

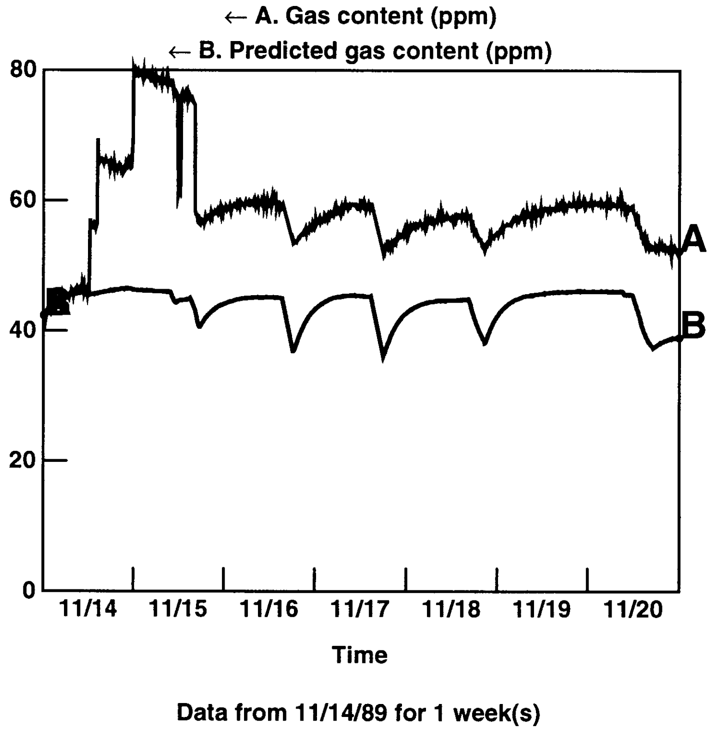


Figure 4-8: Hydran® 201R Response to Arc During Steady-State

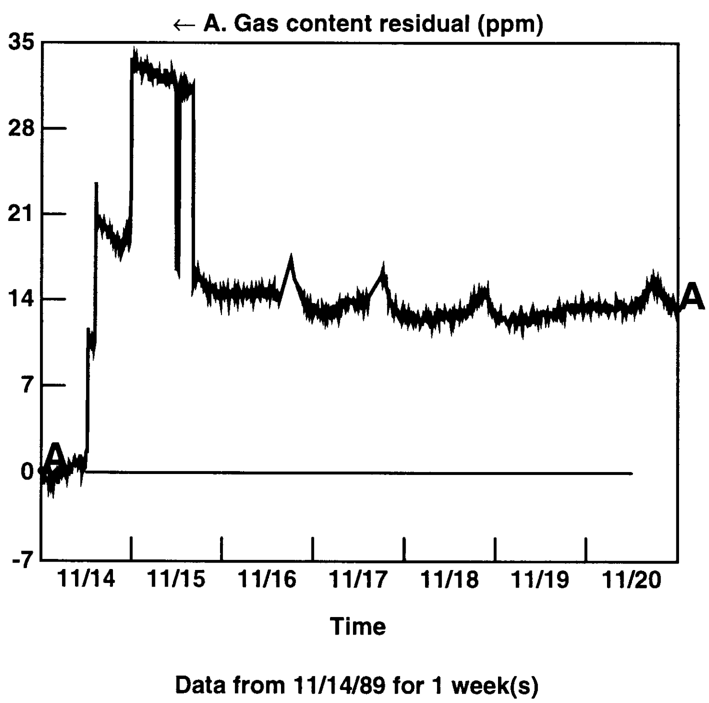


Figure 4-9: Residual Response to Arc During Steady-State

anomalous change (on short and long time scale) in the dissolved-gas characteristic.

Recent history of the gas residual reveals a possible precursor to the observed anomaly. A slight rise of approximately 1.5 ppm in the gas residual occurred at 11:50 am on November 14. This rise was too small to be detected, but can be seen in Figure 4-8. Other than this precursor, no additional information is revealed by examination of the gas module.

Could this behavior of the gas module be indicative of normal aging or potential failure? A gas concentration rise taking place over a number of years may be ignored, while the same rise occurring in a single year may be a cause for great concern. A trend (the rate of gassing) is used to distinguish between two conditions: normal aging and potential failure. Here, normal aging can be ruled out since normal aging does not occur on the time scale of minutes-to-hours observed here.

6. Check other Modules that could be affected by the candidate failure mode. Check these modules for measurement, measurement residual, estimated parameter, and parameter stability constant levels and rates-of-change. Analyze only those that might be affected in this case, which are the thermal and moisture modules. A series of relationships exist between failure modes and quantities observable by use of specific modules [6]. Here a failure mode detected by the Gas Module, may also be detected by the Thermal and/or the Moisture Module. By using information revealed by these modules working together, one failure mode may be distinguished from another. Steps A-C, as given below, may be performed in parallel.

A. Check Thermal Module.

Look for anomalous changes (on short and long time scale) in the thermal module. Determine measurement, measurement residual, estimated parameter, and parameter stability constant levels and rates-of-change of the thermal module. Has the top oil temperature gone up on the same time scale as the gas content?

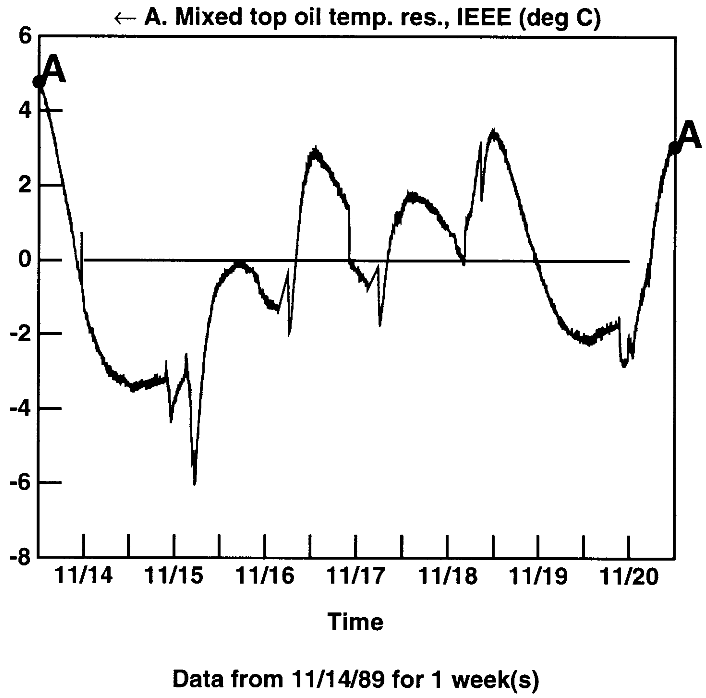


Figure 4-10: Residual Top Oil Temperature

In this case, the Thermal Module reveals no additional information. The top oil temperature did not experience any rise for the period of interest.

Since there was no effect on the thermal module, the diagnoses of electrification and hot spot may be eliminated. These problems would have affected both the gas module and the thermal module.

B. *Check Moisture Module.

Look for anomalous changes (on short and long time scale) in the dissolved-moisture content of oil. Has the moisture content gone up on the same time scale as the gas content? (*Sensor in development stage.)

During this experiment, measurements were being taken for dissolved-moisture by use of the Karl Fischer Titration Method [D 1533]. In this case, there was no significant increase in the dissolved moisture residual content. The moisture plots are unavailable at this time.

This would tend to rule out a hot spot next to the paper as a viable diagnosis because an increase in moisture content would be an indication of paper degradation due to excessive heating. There still might be a hot spot along a lead or at a connection to a bushing.

C. *Check acoustic sensor reading level.

Partial discharge activity could support a diagnosis of a hot spot. Partial discharges, which signify a partial breakdown of the insulation structure within a transformer, may cause localized overheating, known as a hot spot. In addition, any sort of arc would show up as severe partial discharge activity, because an arc is a complete breakdown between two surfaces at different potentials.

At the present time, we do not have a method for monitoring the partial discharge activity. Therefore we cannot use any indication of partial discharge activity in the diagnostic process. This is a piece of information that could prove valuable and is definitely needed. (*Sensor in development stage.)

7. Make initial diagnosis.

Based on these simple tests determine the cause if possible, or determine the possible causes. Eliminate failure modes no longer suspected.

In this case, the original candidate diagnoses were: cracked bushing, electrification, hot spot, arcing short, gas bubbles, contaminated oil, (possibly normal) aging, partial discharges, localized overheating, and sensor failure. Investigation of module operation has eliminated electrification, hot spot, cracked bushing, and aging as viable diagnoses. This leaves gas bubbles, arcing short, contaminated oil, partial discharges, localized overheating, and sensor failure.

8. Determine Recommended Mode of Action.

Actions recommended at this point are based on the initial diagnosis, reaction time, severity

criteria, decision criteria, etc. Prior to this step in the process, the diagnostic system has worked entirely with information developed from the on-line monitoring (detection) system and with information related to external events. At this stage however, the diagnostic system will start asking for additional input. This input includes tests that may be performed with the transformer energized and if necessary, tests that may be performed only with the transformer de-energized. The monitoring system will make every effort to determine a final diagnosis while the transformer is energized. De-energizing the transformer to acquire additional input is a last resort. In this case, recommended actions are:
Perform the following energized tests. The choice and order of tests are based on the initial diagnosis.

1. Perform External Visual Inspection – to ensure external auxiliary components are operating; This may reveal a potential problem in the early stages. Devices to check include pumps and fans, pressure relief devices, pressure relays, etc. [4, p.456].
2. Draw Oil Sample and Perform the Following Tests:

    a. Perform Visual Examination – to determine if deterioration is evident (to check for cloudiness, turbidity, metallic contaminants, particles of insulation, carbon, or other suspended materials). Cloudiness indicates moisture, carbon, and/or sludge. If the presence of carbon is indicated, the same arcing or partial discharge should be suspected. This visual examination may possibly detect contaminated oil or gas bubbles; strange odors should be noted as indicators of possible problems with electrical insulation or problems inside the transformer including hot spots or sustained partial discharge [4, p.276].
    b. Perform Dissolved Gas Analysis (DGA) – to back up gas module conclusions and provide more information about aging. DGA can distinguish between different types of failures because each type of failure tends to produce the various gases at different rates. The Rogers Ratio Method (and Key Gas Methods) can be then used to interpret the

results of the dissolved gas analysis. These methods may distinguish between partial discharges, different types of overheating, and some types of arcing.

Further separation of these diagnoses will require the performance of de-energized tests. These will be specified based on the results of the energized tests.

Make final diagnosis.

The system cannot arrive at a unique final diagnosis without information provided by the energized and de-energized tests. If this information is provided at a later date, the system will make a final diagnosis.

Additional monitoring reveals more serious anomalous behavior. Here two anomalies occur simultaneously at 2:20 pm. The gas residual steps up to 23 ppm with a 13 ppm rise/measurement interval. This anomaly violates the set 18 ppm level threshold as well as the 5 ppm/measurement interval rate-of-change threshold. This shows the need to update the maximum reaction time to reflect the current situation.

As a final note, the gas content data was observed for several days after the initial anomaly. This revealed a nearly constant nonzero residual. The residual stabilized around 14 ppm. This could indicate a possible sensor malfunction. Experience could suggest that the sensor might have an incorrect offset. These observations would not have initially been known when the first anomaly was detected. By continuing operation and monitoring, they would be revealed.

4.3.2 IEEE Thermal Module Diagnostic Example

This example is based on a real anomaly, although some hypothetical situations are combined in order to focus decision making. This allows some realistic recommended actions to be specified.

0. Introduction to Example

In this example, the first event is the detection of an anomalous behavior in the transformer. Here this is a long-term increase in the top oil temperature rise. This is followed by a series of steps that must be taken to diagnose the cause of the anomalous operation. These steps can be taken by a human, a machine, or a combination of both.

Figure 4-11 shows a plot of θ_{fl} for the MIT Pilot Test Transformer. θ_{fl}, a physical constant of the transformer, is the top oil temperature rise over ambient at full load. This test transformer was designed for a 65°C rise over ambient. When values for θ_{fl} violate the 65°C threshold, an anomaly is suspected.

1. An anomaly is detected.

Here an anomaly occurred when the 65°C threshold was violated for a set number of samples. In this example, θ_{fl} (calculated using estimated parameters K_1 and K_2 [35, p.107]) violated Level Threshold A. There is no apparent violation of any θ_{fl} Rate-of-Change Thresholds. This indicates that the transformer is running somewhat hotter than it is designed to run.

An entire range of thermally generated failure modes become viable diagnoses. These include cooling system sludging, cooling system component failure, winding structural damage, core structural damage, core insulation failure, hot spot, (possibly normal) aging, and sensor failure [6, p.95].

2. Determine anomaly time scale.

The flag raised in the detection system determines the time scale involved. This time scale reflects the triggering mechanism. In this example, the changes shown in Figure 4-11 have occurred quite slowly. Therefore the time scale of the anomaly is months.

3. Determine reaction time.

Determine how much reaction time is available, based on the detected anomaly. The reaction time is defined as the maximum time allotted to the diagnostic system to respond to the detected anomaly. If the diagnostic system cannot recommend a course of action in the time allotted, a human must decide whether or not to shutdown the transformer. The two most critical items affecting reaction time are the severity of the anomaly and the time scale over which it occurred. The severity of the anomaly is determined by the amount by which a measurement, measurement residual, or a parameter residual violates its specified level or rate-of-change threshold.

For this example, the available reaction time is weeks to months. This was determined by measuring the amount by which the 65°C threshold is exceeded. Examination of Figure 4-11 indicates this to be approximately 10% on average.

4. Determine related external events.

Determine any events that have occurred in the period of concern. Determine within an appropriate time scale if any maintenance was performed. Long term average load trends, influenced by basic load changes and operational decisions should be noted. Weather conditions may even produce anomalous effects.

This transformer tends to be fairly heavily loaded and operates in a relatively high ambient temperature. These load and weather patterns tend to support the cooling system sludging and (normal) aging diagnoses.

5. Check Module that detected the anomaly.

Check the module that actually detected the anomaly. For this example, it was the IEEE Thermal Module. Look for other indications, too small to have triggered the detection system, of anomalous change (on short and long time scale) in the thermal system, such as excessive heating. Could this behavior of the thermal module be indicative of normal

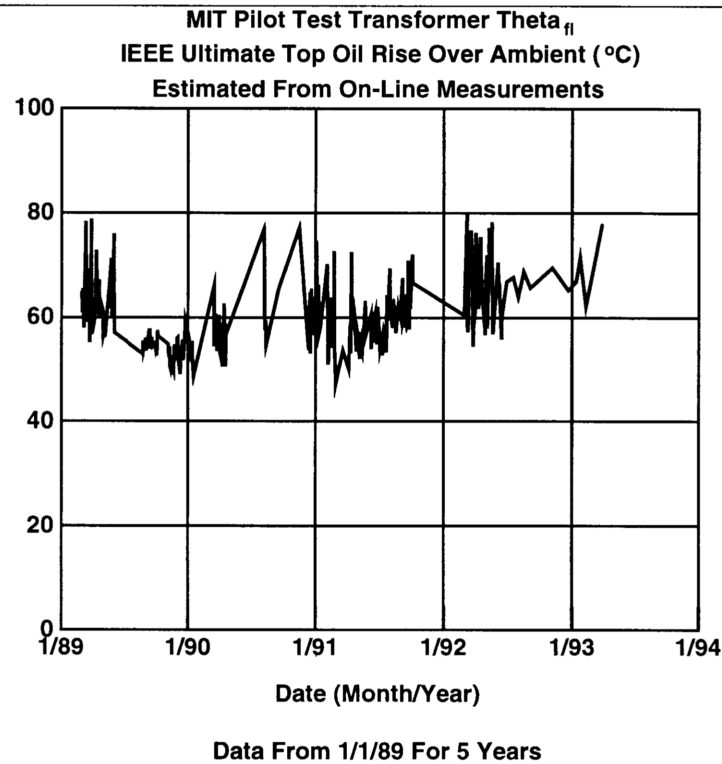


Figure 4-11: Top Oil Temperature Rise over Ambient at Full Load

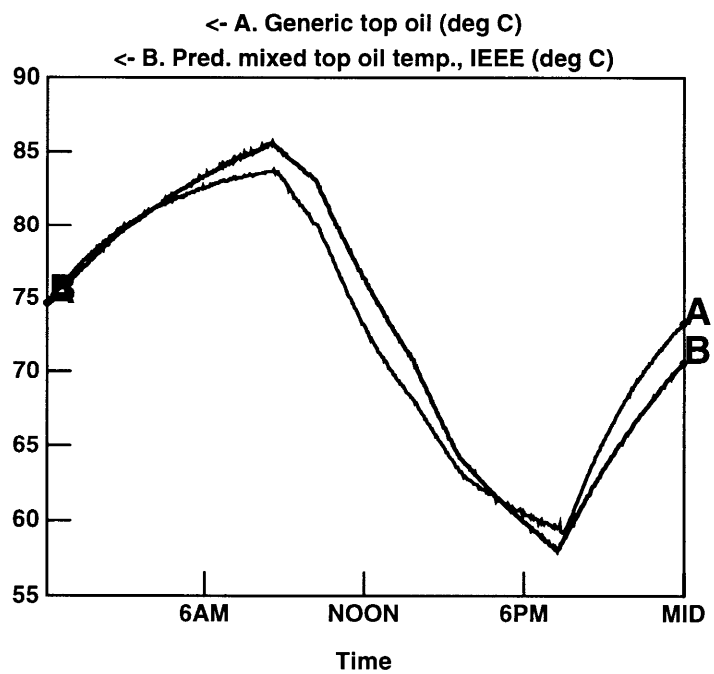


Figure 4-12: Generic and Predicted Top Oil Temperature (data for one day)

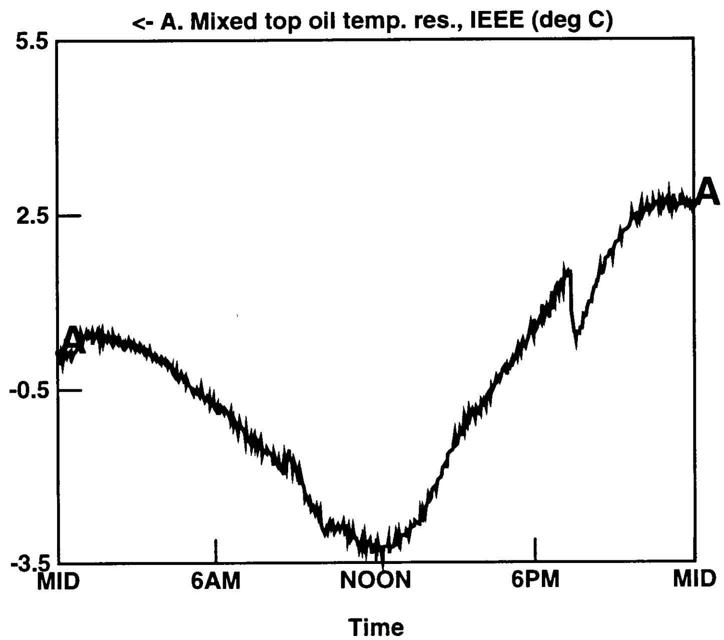


Figure 4-13: Residual Top Oil Temperature (data for one day)

aging or potential failure? Do the load and temperature rises make sense over the time scale of interest? Determine rate-of-change of additional outputs for the thermal module. These include measurement and measurement residuals. Figure 4-12 shows the plot of the Measured (Generic) and Predicted Top Oil Temperature while Figure 4-13 shows the plot of the Top Oil Temperature Residual. In this case, the Top Oil Temperature and the Top Oil Temperature Residual appear completely normal. This indicates that the thermal model structure is still valid and no drastic changes have occurred in the transformer's heat transfer system.

6. Check other Modules that could be affected by the candidate failure mode. Check these modules for measurement, measurement residual, estimated parameter, and parameter stability constant levels and rates-of-change. Analyze only those that might be affected in this case, which are the gas, vibration, and moisture modules. Steps A-D may be performed in parallel.

The behavior of the thermal measurements, measurement residuals, and estimated parameters do not support the diagnosis of sensor failure. The temperature rise for the load seen by the transformer also does not support the sensor failure diagnosis.

A. Check Gas Module.

Look for anomalous changes (on short and long time scale) in the gas module. Determine measurement, measurement residual, estimated parameter, and parameter stability constant levels and rates-of-change of the gas module. Has the gas content gone up on the same time scale as θ_{fl}?

In this case, the gas content has not gone up significantly. This tends to rule out a hot spot problem as there is no indication of the oil or paper degradation that would occur in the vicinity of a hot spot.

B. Check Vibration Module.

Look for anomalous changes (on short and long time scale) in the vibration module, in order to detect potentially dangerous changes in the physical structure of the winding.

In this case, the vibration module does not show any anomalies. This tends to rule out winding (or core) structural damage that might have resulted in constricted or blocked cooling passages.

C. *Check Moisture Module.

Look for anomalous changes (on short and long time scale) in the dissolved moisture content of oil. Has the moisture content gone up on the same time scale as θ_{fl}?

(*Sensor in development stage.)

In this case, no significant increase in dissolved moisture content would also tend to rule out a hot spot as a viable diagnosis because an increase in moisture content would be an indication of paper degradation due to excessive heating.

D. *Check acoustic sensor reading level.

Partial discharge activity could support a diagnosis of a hot spot. Lack of partial discharge activity supports the elimination of a hot spot as a viable diagnosis.
(*Sensor in development stage.)

7. Make initial diagnosis.

Based on these simple tests determine the cause if possible, or determine the possible causes. Eliminate failure modes no longer suspect.

In this case, the original candidate diagnoses were: cooling system component failure, cooling system sludging, winding structural damage, core structural damage, core insulation failure, hot spot, and (normal) aging. Investigation of module operation has eliminated winding structural damage, core structural damage, hot spot, and sensor failure as viable diagnoses. This leaves cooling system component failure, cooling system sludging, core insulation failure, and aging.

8. Determine Recommended Mode of Action.

Actions recommended at this point are based on the initial diagnosis, reaction time, severity criteria, decision criteria, etc. Prior to this step in the process, the diagnostic system has worked entirely with information developed from the on-line monitoring (detection) system. At this stage however, the diagnostic system will start asking for additional input. This input includes tests that may be performed with the transformer energized and if necessary, tests that may be performed only with the transformer de-energized. The monitoring system will make every effort to determine a final diagnosis while the transformer is energized. De-energizing the transformer to acquire additional input is a last resort. In this case, recommended actions are:
Perform the following energized tests. The choice and order of tests are based on the initial

diagnosis [6, p.23-27].

1. Perform External Visual Inspection – to ensure that external auxiliary components are operating
2. Draw Oil Sample and Perform the Following Tests:

    a. Perform Visual Examination – to determine if deterioration is evident, cloudiness indicates moisture, carbon, and/or sludge
    b. Perform Dissolved Gas Analysis – to back up gas module conclusions and provide more information about aging
    c. Perform Dissolved Moisture Measurement – to back up moisture module conclusions and provide more information about aging
    d. Perform Sediment Test – to determine the amount of sludging present in the oil
    e. Perform Interfacial Tension and Neutralization Number Tests – these tests are conducted in concert to provide more information about sludging

Visual inspection of cooling system component (pumps, coolers, piping) operation can be used to rule out cooling system component failure as a viable diagnosis. This reduces the list of viable diagnoses to cooling system sludging, core insulation failure, and aging. Dissolved gas and moisture analyses show no results of aging mechanisms–therefore aging is removed as a candidate diagnosis. Given the two remaining viable diagnoses, sludging and core insulation failure, cooling system sludging can be checked while the transformer is energized through a sediment test. This is performed next. Also, interfacial tension and neutralization number should give an indication of sludging.

In this case, the sediment, interfacial tension, and neutralization number tests, would indicate a large amount of sludging. At this point, the diagnostic system has eliminated as many viable diagnoses as it possibly can using the information available while the transformer is energized. Even though there is a high probability that the correct diagnosis is cooling system sludging, there are still two viable diagnoses: cooling system sludging and core insulation failure. Performance of the tests that are necessary to decide between these two diagnoses will require the transformer to be de-energized. Here, the diagnostic system would call an engineer and present the following information: there are two viable diagnoses, with the following probabilities:

Cooling System Sludging 0.6

Core Insulation Failure 0.4

Further separation of these diagnoses will require the performance of the following de-energized tests:

1. Perform Power Factor Test – to detect certain types of sludging
2. Perform Internal Visual Inspection – to check the clarity of the oil
3. Perform Core Ground Check – remove the core ground strap and check core insulation integrity with a megger

Since the reaction time has been determined to be weeks-to-months, these tests can be done during a scheduled outage, rather than requiring an immediate removal of the transformer from service. During the outage, a power factor test will provide information indicating whether or not certain types of sludging are occurring without requiring entry into the transformer. A visual inspection of the portion of the interior that can be seen from the top of the transformer would be performed. If the oil is clear, this fact would act against the cooling system sludging diagnosis. If the resistance between the core and ground is infinite this would eliminate core insulation failure as a viable diagnosis.

Make final diagnosis.

The system cannot arrive at a unique final diagnosis without information provided by the de-energized tests. If this information is provided at a later date the system will readjust the probabilities listed above.

The recommended action is: At the next scheduled outage, the engineer must decide between two possible recommended actions:

1. Reprocess oil and flush coolers, or
2. Perform de-energized tests specified above.

The reasons for the diagnosis are: the entire range of thermally generated failure modes (cooling system sludging, cooling system component failure, winding structural damage, core structural damage, core insulation failure, hot spot, (possible normal) aging, and sensor failure) was specified as initial diagnoses. By investigating other modules that could be affected by the thermal failure mode, some of the viable diagnoses were eliminated as candidates. The behavior of the thermal module eliminated the sensor failure diagnosis. The behavior of the gas and moisture modules as well as the acoustic sensor reading level ruled out the hot spot diagnosis. Winding (or core) structural damage was eliminated by the vibration module. Energized tests were next used to eliminate other candidates. External visual inspection eliminated cooling system component failure. Dissolved gas and moisture analyses removed aging as a candidate diagnosis. The sediment, interfacial tension, and neutralization number tests elevated sludging as a diagnosis, but did not eliminate core insulation failure. Arrival at a final diagnosis requires the performance of de-energized tests. This involves cost tradeoffs that are best made by an engineer. In this example it was not necessary to say that the cause cannot be determined and the reaction time has expired.

Chapter 5

Knowledge Acquisition and Structuring

A knowledge-based system (KBS) or knowledge-based expert system, is different from traditional procedural software in that its operation is guided by knowledge and data, not by a predetermined algorithm. This difference is a significant problem referred to as the knowledge acquisition bottleneck. This chapter examines the general structure of the KBS in Section 5.1. Section 5.2 examines the requirements of the interview method of knowledge acquisition. An example of this method is the focus of Section 5.3. Event reports proved to be a more practical method of knowledge acquisition and became a major research effort of this thesis. Section 5.4 outlines the format of these reports that efficiently capture the important steps and information that the expert uses. Section 5.5 contains abbreviated results of four sample event reports that emphasize the technical and cost tradeoffs in on-line transformer monitoring. Section 5.6 contains an overall diagnostic graph which was derived from selected results from the interviews and event reports.

5.1 General Structure of Knowledge-Based System

In general, the KBS is split into two distinct sections as shown in Figure 5-1. These sections are the *knowledge base* and the *diagnostic engine*. The knowledge base contains formalized

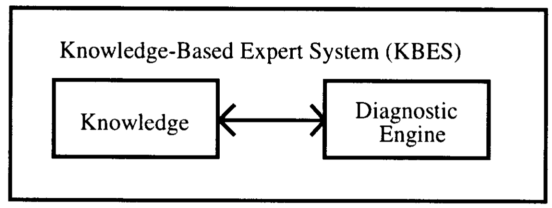


Figure 5-1: General Knowledge-Based Structure

expert experience in the area of transformer monitoring and diagnostics. The term formalized denotes that this experience/knowledge has been represented in a structured and useful manner to capture the intricacies of the diagnostic process. The knowledge base contains diverse forms of domain knowledge and can be simply thought of as facts and rules. The knowledge must be structured in a manner that allows it to be coded and utilized by the diagnostic/reasoning engine. There is no simple or general way to characterize the diagnostic engine, which in the generic case is termed the inference engine. Its structure depends on the nature of the problem domain and the way in which the knowledge is represented and organized. Obviously, an important issue is the derivation of the knowledge contained therein. This is termed *knowledge acquisition*, which is the process of gathering the relevant information that the KBS will utilize.

Figure 5-2 shows a very simplified example of the concepts discussed above. Here the diagnostic engine contains the tasks and methods that must be implemented in performing transformer diagnostics. The first task is to check the gas (Hydran® 201R) sensor reading against a set threshold. Prior knowledge indicates that if the reading is greater than the set threshold, then the transformer is to be switched off. The second task is to check if the Hydran® 201R oil temperature is within the range of 30-40°C. If it is within the range, prior knowledge indicates that Hydran® 201R sensor "starvation" is occurring. Sensor starvation occurs when the loop oil temperature comes close to the temperature of the Hydran® 201R unit and this consequently leads to unbelievable (too low) and useless readings.

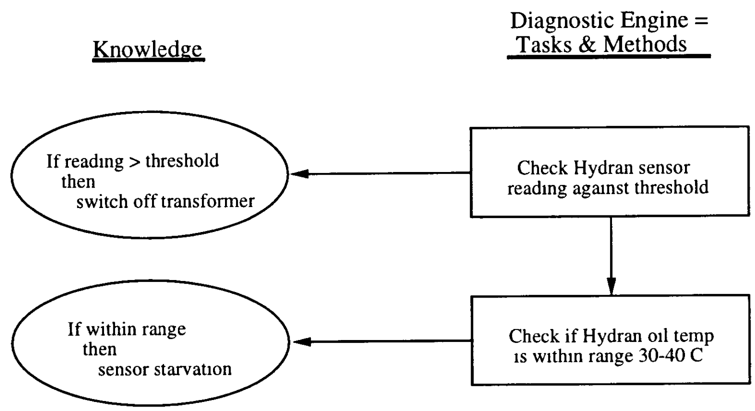


Figure 5-2: Simplified KBS Example

The eventual goal is to automate the diagnostic process as was discussed in Chapter 3. In order to develop an automatic diagnostic system, an on-line model-based transformer monitoring knowledge base must be developed. This allows the integration of on-line experience with general and specific transformer knowledge, sensor knowledge, and transformer anomaly knowledge. Within a KBS for transformer diagnostics, there are two main types of knowledge, namely classical and expert. Classical knowledge is the terminology used to denote the processes and techniques which can be obtained from literature regarding transformers. For example, this includes the use of the Rogers Ratio Method [7, 8] for interpreting the results of dissolved gas analysis tests. Expert knowledge covers the experimental diagnostic processes and heuristics elicited from transformer experts. Knowledge elicitation of this type is a very complex and tedious task and is accomplished either by direct interview sessions or from highly structured event reports generated by MIT personnel.

A Knowledge Acquisition Module, shown in Figure 5-3, captures these concepts. It shows the relationship between the knowledge engineer and the sensor, model-based, and classical domain experts. Knowledge is acquired from direct interview sessions with these experts in an a posteriori fashion. Knowledge is acquired from on-line monitoring experts

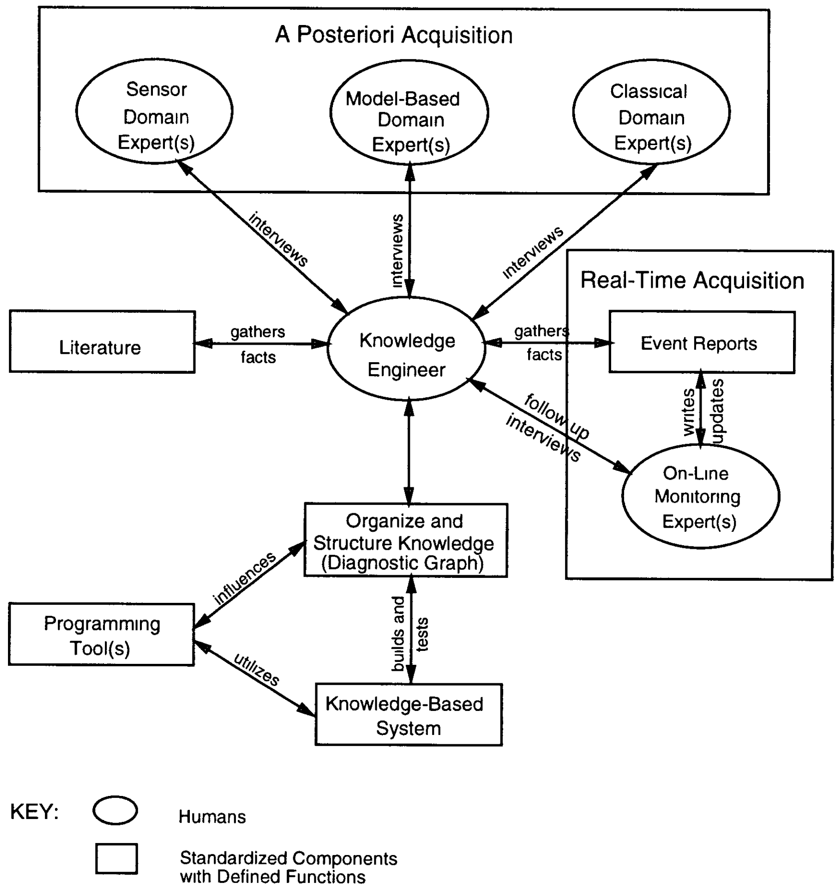


Figure 5-3: Knowledge Acquisition Module

through the use of event reports generated in real-time and through follow-up interviews. Classical knowledge is gathered from appropriate literature. The engineer's function is to organize and structure the knowledge from the literature, from interviews with the experts, and from the event reports generated by the experts. With the help of a programming tool, the engineer builds and tests the knowledge-based system.

The primary focus in this thesis is on obtaining on-line monitoring expert knowledge. The remainder of this chapter focuses on the interview method and the event report method of knowledge acquisition.

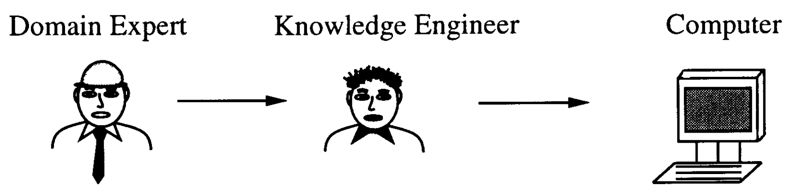


Figure 5-4: Knowledge Acquisition Mode

5.2 Traditional Knowledge Acquisition: Interview Method

Knowledge elicitation is the derivation of diagnostic processes and tasks from relevant transformer experts. An interview-based methodology has been adopted and is a commonly used manual technique. The type or mode of knowledge elicitation taking place is when a knowledge engineer extracts the knowledge from a domain expert and develops the KBS by utilizing this knowledge. This is represented graphically in Figure 5-4. The domain expert is a person who through years of experience and training has become extremely proficient at problem solving in a particular domain. The knowledge engineer is a person who will interview the expert, organize the knowledge, and eventually design and build the expert system.

Based on a series of sessions conducted at MIT, five main requirements emerged that are necessary for conducting an effective knowledge elicitation session. These are :

- Identification of Appropriate Expert(s)
- Agreed Agenda
- Suitable Setting
- Suitable Data and Material
- Audio Recording for Accurate Analysis

Identification of appropriate expert(s): Identifying people who really are experts and are willing to participate at their maximum capacity is critical. Through years of training and experience, experts are smooth and efficient in their procedures, strategies, and rules of thumb for problem solving.

Agreed agenda: Each session must have targeted items to discuss. These items may include anomalies which the experts have experienced and have knowledge of the outcomes. It may also include anomalies that have previously been analyzed (teachback). Each interview session was structured with specific goals and questions. It was also unstructured in the sense that spontaneous questions were necessary for clarifying and obtaining related information.

Suitable setting: A specific time and location must be chosen. The environment should be comfortable and free of interruptions in order to be conducive to knowledge elicitation.

Suitable data and material: Enough material must be available as to not restrict thinking or focus discussion on items that are irrelevant. Experts are good at plowing through irrelevant information to get at basic issues.

Audio recording for accurate analysis: A recording is made in order to preserve the session, to prepare written documents, and to create what is referred to in this thesis as diagnostic graphs. The diagnostic graphs are a readable and useful structure that contain formalized and transformed elicited knowledge.

There are three main tasks within the knowledge elicitation process :

- Guided expert analysis of transformer anomalies
- Formalization of the elicited knowledge
- Validation of the knowledge through teachback

Guided expert analysis of transformer anomalies: The analysis is guided by the researchers building the diagnostic KBS. This is to prevent the expert from making large, unexplained steps or psychological leaps during their analysis. This is often a result of

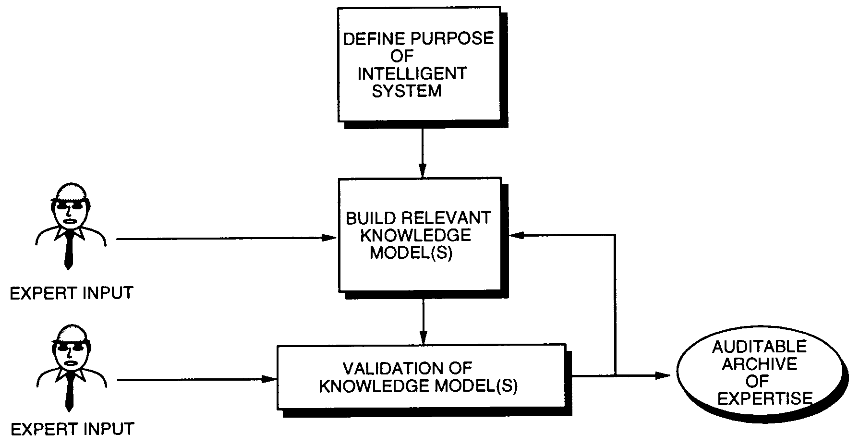


Figure 5-5: Iterative Knowledge Elicitation Process

their experience or prior knowledge of the anomaly. In essence, every possible direction of diagnosis and reasoning must be enumerated to produce a complete and accurate knowledge base. The interview is audio recorded to allow accurate analysis and interpretation by the researchers after the session. The recording also preserves the session for future research and training purposes.

Formalization of the elicited knowledge: Following the interview, the researchers transcribe the information recorded and noted. It is then transformed into some readable and useful formalized structure. This formalized structure for the purposes described here takes the form of diagnostic graphs.

Validation of the knowledge through teachback: After the knowledge has been formalized by the researchers, a further interview occurs with the expert. During this session, the knowledge engineer may describe the thoughts behind the diagnostic graph constructed from a previous session. At this point, the expert should indicate further useful information and highlight any erroneous aspects of the diagnostic processes, tasks, and decisions. This is termed *teachback*.

This three stage process is iterative, leading to an accurate representation of diagnostic knowledge. Two important deliverables are available at this stage. There is the diagnostic graph on paper as well as an audible archive of diagnostic expertise. This can be extremely useful for researchers or companies, as they may be used for training purposes, updating procedures, and understanding existing procedures. Figure 5-5 shows the iterative nature of this process in terms applicable in many different domains.

To emphasize these concepts, the next section gives an example of one knowledge elicitation session that took place at MIT. It includes a brief event description, the supporting plots, and the diagnostic graph that resulted from the session.

5.3 Detailed Analysis of One Interview Session

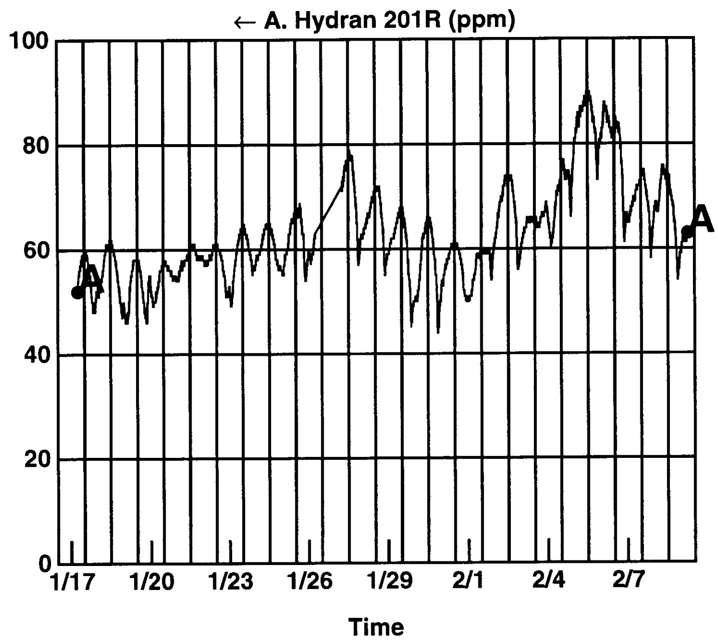
A series of knowledge elicitation sessions for transformer diagnostics were conducted. These allowed the acquisition of easily available expert knowledge relating to several anomalies experienced by researchers at MIT during the initial phases of the field installation. A focused discussion centered around supporting plots, measurements, and observations. After each session, a diagnostic graph or a piece of an overall diagnostic graph was constructed.

These sessions are on-going as previously undocumented anomalies are experienced. Although the focus of each session is on a particular anomaly, general diagnostic information is derived that is useful in other situations. A general solution space or overall diagnostic graph has emerged over time that contains all the results of these sessions intertwined, as shown in Section 5.6

A brief description of the very first session to take place at MIT follows. Teachback of this session is not documented here, although its results were taken into account in constructing the final diagnostic graph(s).

5.3.1 Increase of Hydran® 201R Gas Sensor Reading

The first interview session was studied in great detail as a number of conventions were established that are used throughout this entire thesis. As additional sessions were conducted, it became apparent that some of the steps or checks that had been implemented in series



Data from 1/17/95 for 24 day(s)

Figure 5-6: Composite Gas Content: 380 MVA Autotransformer

could have been implemented in parallel. For the purpose of this example, the analysis, steps, and conclusions are structured in the way the expert described them. Future sessions and versions of the diagnostic graph modified this approach.

In this case, the diagnostic system for transformers had two main subtasks which were the production of an initial hypothesis to explain the anomaly and the validation of the hypothesis. This concept is embodied in the example of formalized diagnostic knowledge which follows. If the initial hypothesis cannot be validated, then the diagnostic process must consider alternatives which are part of its knowledge base.

Triggering Event

At the knowledge elicitation session the following suspected anomaly was discussed. It was observed on a 345/115kV autotransformer, rated around 380 MVA, that the Hydran® 201R gas sensor reading showed an increase over a four day period starting on February 1 as shown in Figure 5-6. This was a cause of concern to the human monitoring the transformer as the increase looked as though it could be an increase in the overall gas content of the transformer. There had been a failure earlier in the year from this type of transformer where the dissolved gas showed a similar pattern just prior to failure. When analyzing the situation, the expert started the analysis by parsing the data into a format that allowed it to be plotted, since presently the primary diagnostic techniques resolve around observing plots of data.

Diagnostic Graphs

The expert interviewed started from this initial *triggering* event and worked through a number of plots of data to determine if there was any cause for concern. As a result of the knowledge elicitation, and ensuing teachback, a *diagnostic graph* was produced that formalized the diagnostic knowledge derived. It shows the diagnostic processes and data relationships exploited by the transformer expert. The diagnostic graph derived here is shown in two sections. An initial hypothesis is arrived at by using the first section shown in Figure 5-7. This also considers the immediate issues such as the requirement to de-energize the transformer for safety purposes. The second section of the diagnostic graph, shown in Figure 5-8, formalizes the expert's process of validating the initial hypothesis through supportive observations and data.

Diagnostic Graph Conventions

To clarify the results of the session and the plots used in the analysis, the diagnostic graph will be stepped through branch by branch. A number of conventions were adopted within the diagnostic graph shown in Figures 5-7 and 5-8. On the first graph, the box with the double dotted line is the triggering event for the diagnostic process. The second graph uses a dotted line to indicate items which appeared on the first section, but have an effect on the validation process. For both graphs a solid box is a diagnostic task, process, or decision. These tasks will eventually be automated. However, as the system is built in stages it will initially require human input. Ellipses denote outputs from the system. There are a number of diagnostic outputs envisioned for this system. These may include possible

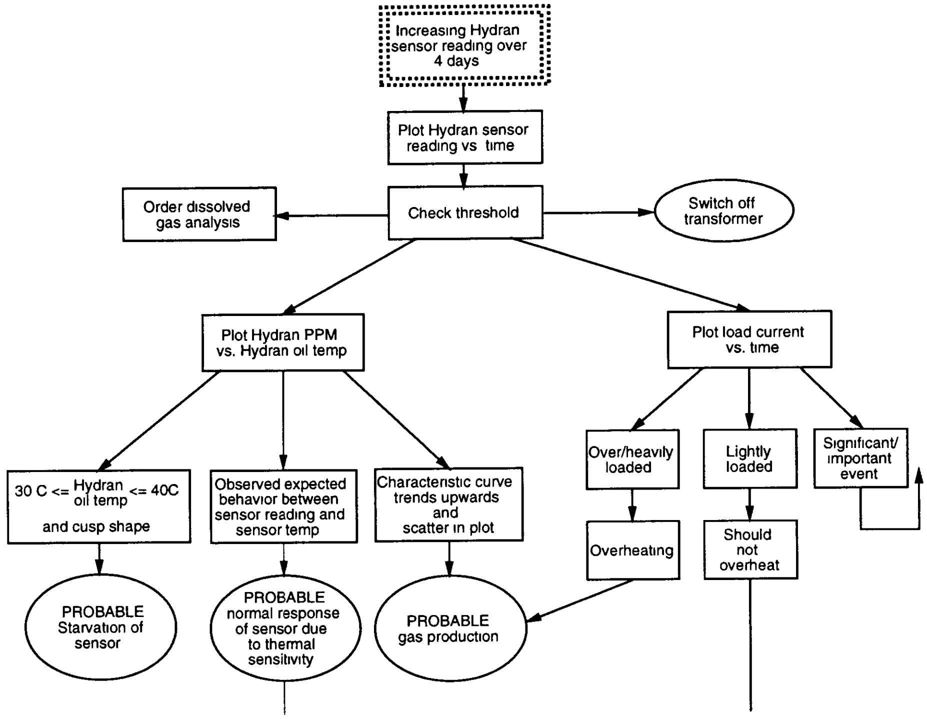


Figure 5-7: Diagnostic Graph for Increase of Hydran® 201R Reading

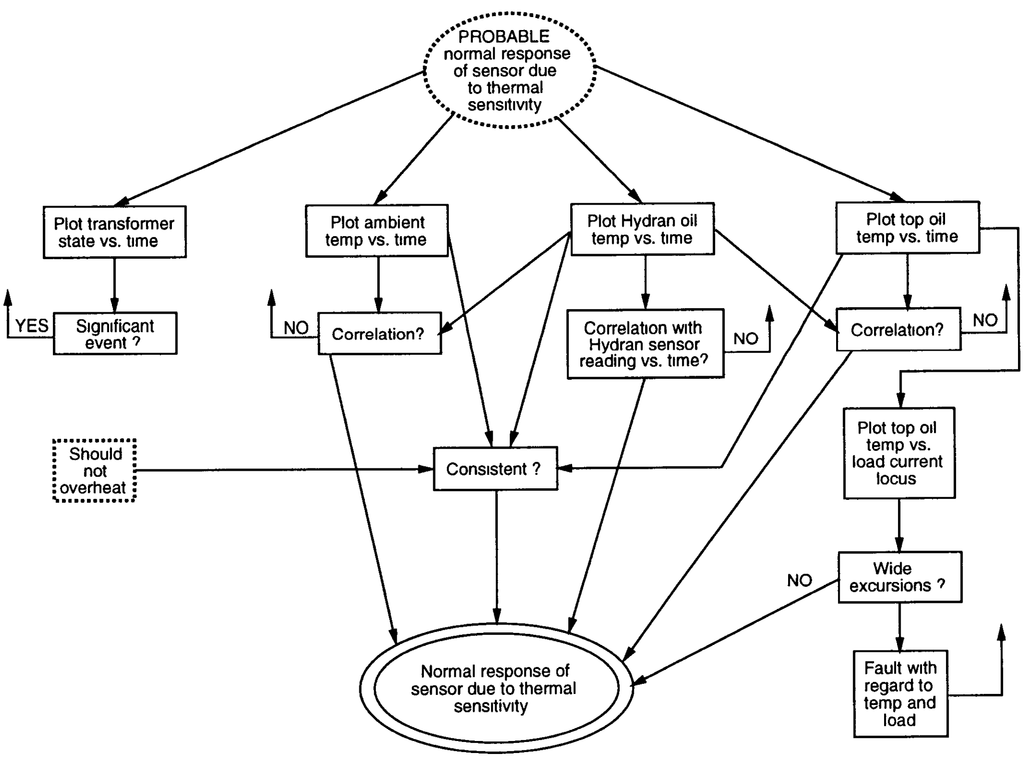


Figure 5-8: Continuation of Diagnostic Graph

conclusions or recommendations. The first of these shown is an immediate indication of when the transformer should be de-energized (switched off) for safety reasons. This always precedes any diagnosis of the nature of the anomaly observed.

Obviously, the system must output its indication of the actual anomaly which the transformer experienced or is experiencing. In addition, it is important that the system recognize expected behavior of the transformer and sensors. This allows engineers to be notified of dangerous increases in some monitored parameters. Moreover, the system should be able to suggest control actions to the engineers such as switching on the pumps and the fans when the transformer overheats.

Initial Hypothesis

In Figure 5-7, the triggering event was an increasing Hydran® 201R sensor reading over four days. The expert first plotted 24 days of Hydran® 201R data previously shown in Figure 5-6. The raw data was checked against a preset threshold in order to ascertain its severity. If the reading had been extremely high, the transformer would have immediately been switched off or shutdown. Otherwise, if the reading had been high and sufficient time were available, a dissolved gas analysis would have been ordered. Typically the measurement threshold checked is transformer dependent since some transformers have very low gas contents on the order of 10-20 ppm while others average 400 ppm for years and years. In this particular case, neither action was necessary.

The expert next plotted the Hydran® 201R data versus the Hydran® 201R oil temperature as shown in Figure 5-9 for the same period. This was done to determine if the sensor reading varies with temperature as expected, if the sensor was "starved", or if there was an increase in gas content. In this case, the sensor had an almost linear response to temperature as the plot shows the Hydran® 201R reading going from about 90 ppm at -5°C to about 45 ppm at 30°C. The relationship between sensor reading and temperature is quite well behaved which indicates a normal response of the sensor due to thermal sensitivity, as shown as being a "probable" conclusion in Figure 5-7. For this sensor configuration, the Hydran® 201R oil temperature did not fall within the suspect starvation range of 30 to

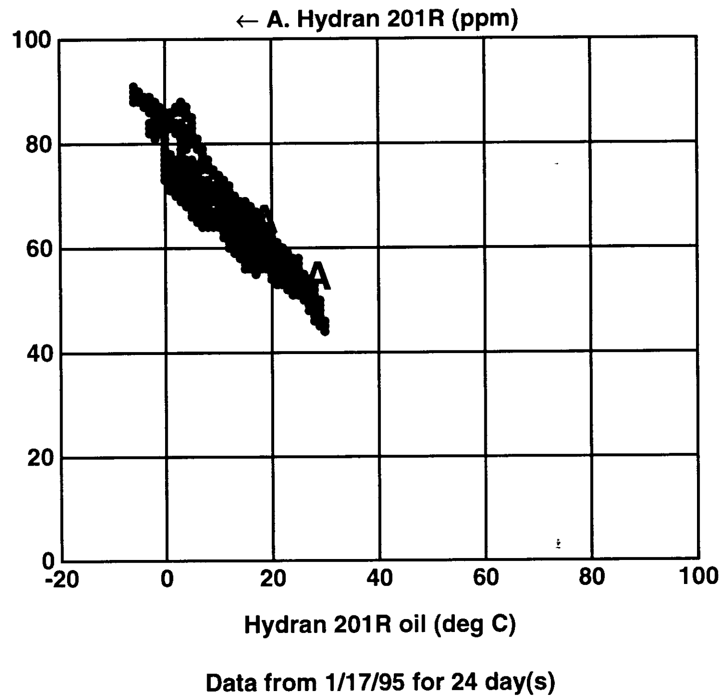


Figure 5-9: Hydran® 201R vs. Oil Temperature: 380 MVA Autotransformer

40°C and the curve plotted did not have a cusp shape. Therefore the conclusion of probable starvation of the sensor was eliminated. There was no scatter in the data and the characteristic curve did not trend upward. Therefore the probable gas production conclusion was also ruled out. The probable conclusion of normal response of the sensor due to thermal sensitivity will be expanded in Figure 5-8.

Another measurement the expert checked early in the analysis was the primary or load current shown in Figure 5-10. For this transformer, 0 to 800 Amps represents the full load range. The load is checked since it gives an indication of how heavily or lightly loaded the transformer was during the period of interest. Since this transformer was lightly loaded, around 50%, it is improbable that it would overheat. Over or heavily loading a transformer tends to cause overheating which might result in gas production. No significant or important events occurred with the loading during the period of interest. If there had been an event, its status would have fed to an appropriate point in the graph. It can be noted that a fairly repetitive loading pattern occurs that depends on the time of day and the day of the week.

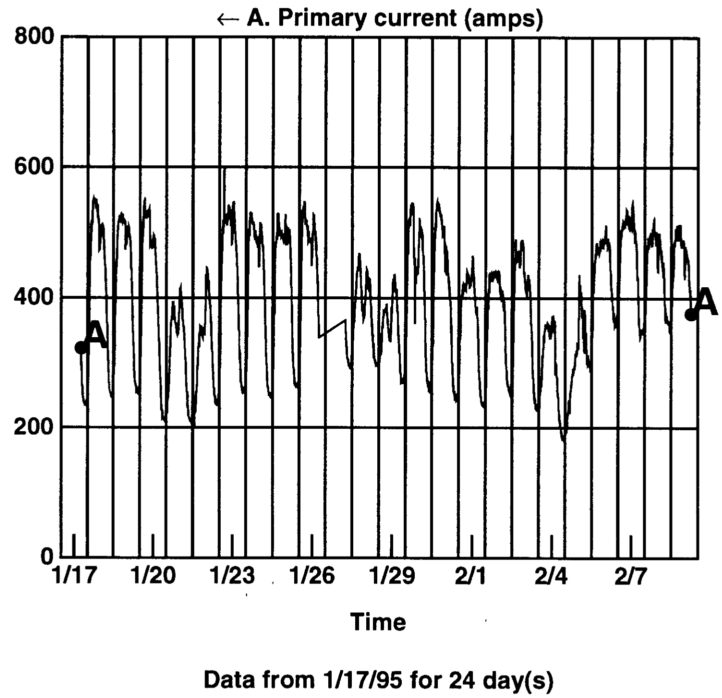


Figure 5-10: Primary Current: 380 MVA Autotransformer

Validation of Hypothesis

So far, a "gut" reaction level of analysis has been performed. The initial hypothesis of normal response of the Hydran® 201R sensor due to thermal sensitivity is expanded in Figure 5-8. This piece of the diagnostic graph formalizes the expert's validation of the initial hypothesis through additional supporting observations and data.

At this point in the analysis, the cooling state of the transformer was plotted to make sure there was no abnormal behavior in the cooling system. The plot is not shown since it only reveals that during the 24 day period, the transformer had been in State 0 which is the OA (oil air) state or natural convection mode. No significant events were detected.

The next item checked was the Hydran® 201R oil temperature which was plotted strictly versus time as shown in Figure 5-11. This was done to make sure there was nothing abnormal occurring with the temperature of the Hydran® 201R sensor and to verify the relationship between the sensor temperature and sensor reading. As expected, when the temperature goes down, the sensor reading goes up, and vice versa. This correlation tends

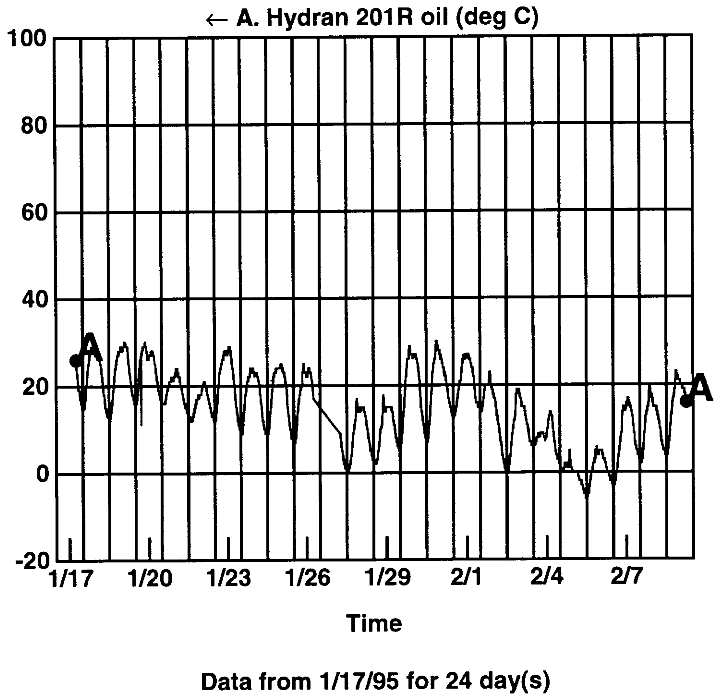


Figure 5-11: Hydran® 201R Oil: 380 MVA Autotransformer

to support the hypothesis of normal response of the Hydran® 201R sensor due to thermal sensitivity.

Another measurement checked was the ambient temperature as shown in Figure 5-12. The ambient temperature also shows a fairly repetitive pattern like that of the load current. At this point, a positive correlation was seen between the ambient temperature and the Hydran® 201R oil temperature, once again supporting the hypothesis of normal response of the Hydran® 201R sensor due to thermal sensitivity.

Figure 5-13 shows the Top Oil Temperature plotted for 24 days. It was examined for any anomalous changes in the thermal system of the transformer. The top oil temperature is a function of the loading on the transformer and the ambient temperature. This plot shows that the temperature is consistent with the load and the ambient temperature. A strong positive correlation between the Hydran® 201R oil and the top oil temperatures were observed as expected, which supports the conclusion of normal response of the Hydran® 201R sensor due to the thermal sensitivity. As a final check of the thermal system, Figure 5-14 shows the top oil temperature plotted on the y axis and the primary current plotted on

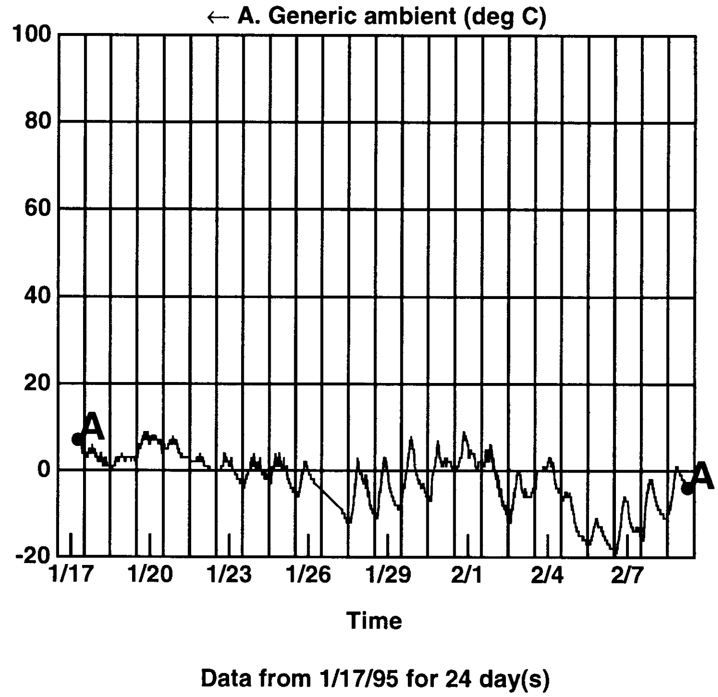


Figure 5-12: Ambient Temperature: 380 MVA Autotransformer

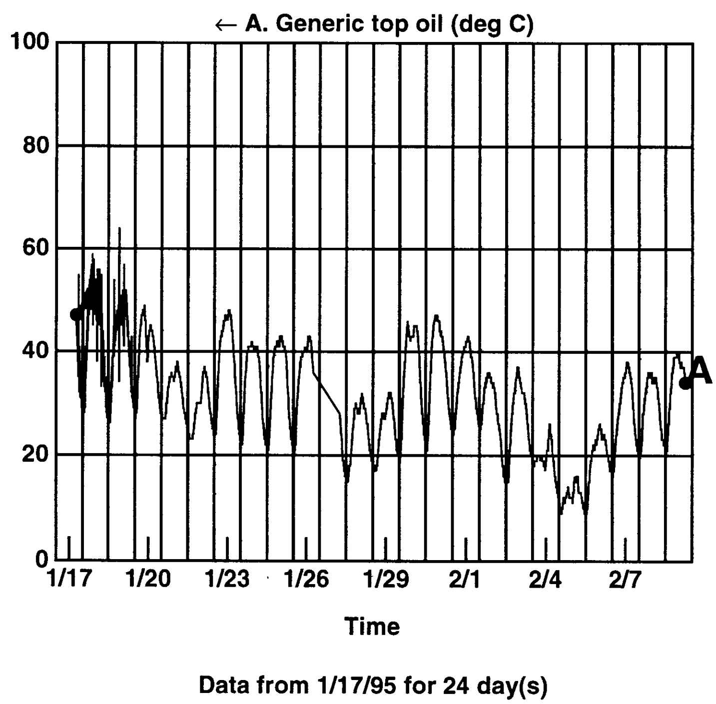


Figure 5-13: Top Oil Temperature: 380 MVA Autotransformer

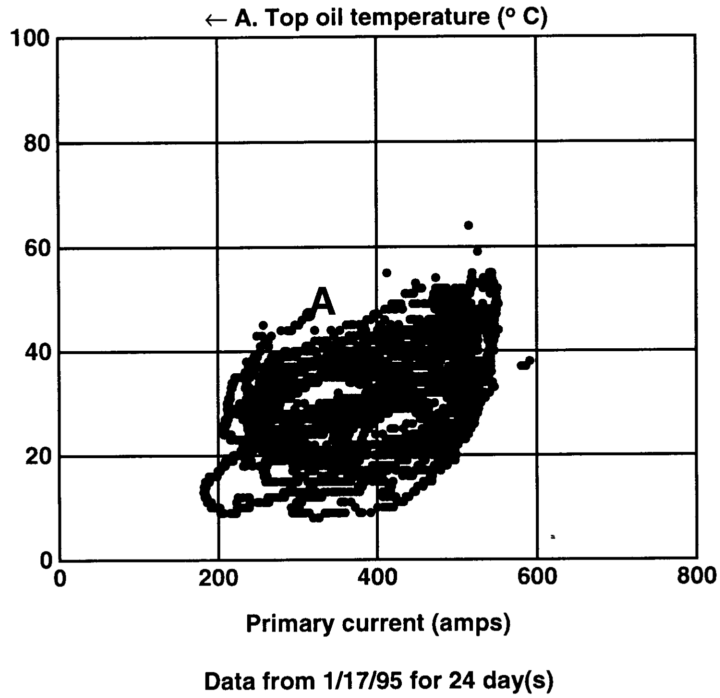


Figure 5-14: Top Oil Temp vs. Primary Current: 380 MVA Autotransformer

the x axis. There is a fairly well defined locus of points that is due to the dynamics of the transformer. The oil temperature changes slowly with time as the load current goes up and down. Wide excursions would have indicated a fault with regard to the top oil temperature and the load.

A final consistency check, Figure 5-15 shows a plot of the top oil, Hydran® 201R oil, and ambient temperatures. All three temperatures were consistent in that they had the same shape and perfectly tracked each other. This also indicates that the transformer is behaving normally in regards to the thermal system, which supports the conclusion of normal response of the Hydran® 201R sensor due to the thermal sensitivity.

Conclusions

All of the analysis supports the initial diagnosis that the observed behavior of the Hydran® 201R is just its normal response due to thermal sensitivity and that transformer is not generating any gas. The main conclusion is that there is nothing wrong inside the transformer

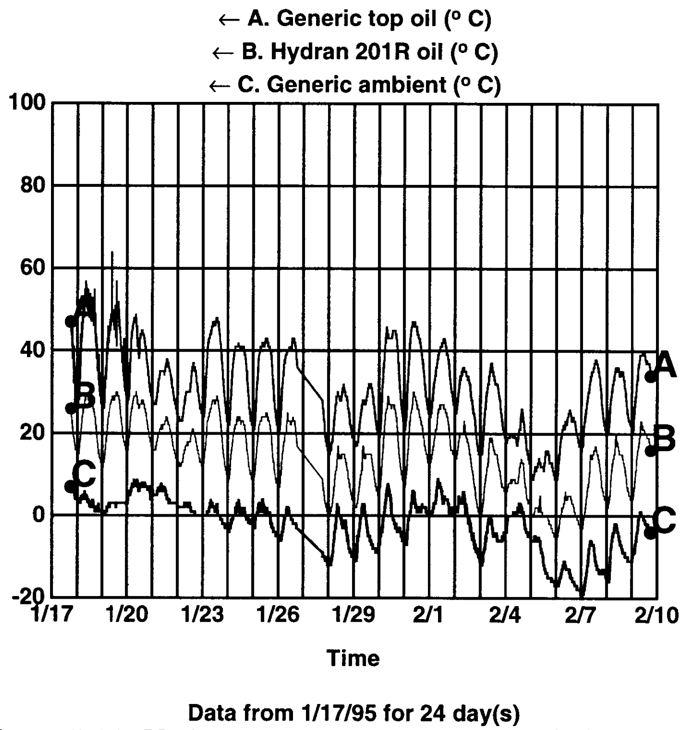


Figure 5-15: Various Temperatures: 380 MVA Autotransformer

that would cause gas generation. The secondary conclusion is that the Hydran® 201R sensor reading is believable. It is not experiencing starvation and the relationship of sensor reading to sensor temperature follows the expected pattern. During this analysis, a sensor validation procedure first took place and then a transformer diagnosis. The utility backed up this diagnosis with the results of dissolved gas measurements they had been taking once per week.

As a final note, all of this analysis was done with on-line raw data. No residuals were used in the analysis, as this particular transformer was not being monitored by the MIT on-line monitoring system. If a system had been in operation, no flags or alarms would have been raised, therefore no cause for human concern.

This example points out that the knowledge elicitation process when done solely in an interview fashion is extremely difficult, tedious, and time-consuming. It requires that the domain expert and the knowledge engineer have sufficient time to discuss diagnostic steps, procedures, processes, and tasks. For on-line transformer monitoring, there are no existing experts with years of experience. The MIT Transformer Monitoring Group members are the domain experts as well as the knowledge engineers. This is a unique situation that if properly managed will eliminate some of the steps of the interview process. Part of the research of this thesis led to a written event report. This is a reporting method in which knowledge can be immediately captured and then structured at a future date. This is the focus of the next section.

5.4 Practical Knowledge Acquisition: Event Reports

Based on a series of lengthy interview sessions as well as many anomalous events that occurred during the middle of the night, it became apparent that timing is critical in capturing the diagnostic steps the expert uses in problem solving. Experience showed that human expertise can quickly fade and that significant periods of disuse can seriously result in reduced proficiency of certain types of skills. Therefore, it became critical that a permanent written record must be made soon after anomalous transformer events occur and are subsequently analyzed. This is similar to the protocol analysis method of knowledge acquisition in which the domain expert generates reports of how he solves a particular set of problems [43]. A practical method for knowledge elicitation is described below.

5.4.1 Event Report Format

Over a period of several months, a format for the written reporting of transformer events emerged. The format has been refined through a series of iterations in an attempt to capture the important steps and information while providing a useful document for the utility and for researchers. The written reports generated as part of this research have become a permanent record or repository for the knowledge of several experts.

Reports were developed from the perspective that flags are being generated by the monitoring system that are subsequently being transmitted to the pagers and then analyzed. The format is based on the assumption that both MIT (researchers) and the utility (customers) would be using the information in some fashion. The event report format records information in a form that will eventually become the format for the knowledge database.

A suitable event report format should be adopted for other monitoring system setups (modules, sensors, alarms, etc.) and configurations of researchers and utilities or customers. The written report format is described below.

Heading

A report heading must be specified and should include the words "MIT Adaptive Transformer Monitoring System". The Electric Utility, Station name or number, and Transformer identifier or number, as well as the date(s) of the event must be listed. The author(s) of the report and any other personnel monitoring the transformer during the event should be listed along with the address and phone number for contact purposes. The date of the last revision of the report should be included as updates are often made when additional information becomes available.

Title

An effective title contains three parts identified as Flag Synopsis, Symptom(s), and Root Cause(s). The flag synopsis should give an indication of the signalling event. The symptom(s) should give an indication of the source of the problem, whether it is in the monitoring system, the sensors, or the transformer. The author of the event report should provide as much detail as can be indicated with a fair degree of certainty. This is normally done after logging into the monitoring computer. The root cause(s) should be an explanation for the entire event that is as specific as possible. The title should be short, but contain enough information that is critical in classification purposes. It is anticipated that these reports will eventually become an on-line resource. The three part title is illustrated with two examples.

Example 1:
No New Data Messages
Loss of Communication with DAS
DC Power Supply Filter Board Failures

Example 2:
Gas Residual Out of Range (Lower Threshold A)
Hydran® 201R Sensor Starvation
Hydran® 201R Oil and Ambient Temperatures too close in FOA Cooling State

Abstract

The abstract contains a brief event description and conclusion. It should concisely state what the event or problem was, only what information was used for the final diagnosis, and the bottom line conclusions. The abstract benefits both MIT and the utility. It is primarily used as a synopsis such that only those parties interested in the details have to read the entire report.

Recommendations

Only realistic and easily implementable recommendations for both MIT and the utility are described here. Recommendations for the utility include any operational or maintenance procedures. These could include directives such as lower the load, manually turn on the pumps and fans, or perform dissolved gas analysis. For MIT, recommendations could include items related to the monitoring system, such as change the bin structure or reset the flag generation limits.

Flags Generated

The flags generated by the monitoring system during the event should be listed here. A listing of flags is important for understanding what happened, what order information was conveyed, and at what time the event occurred. If feasible, all flags should be specified. Otherwise, a few at the beginning, middle, and end of the event or those flags containing the most information should be documented. Oftentimes, flags containing data with the largest or smallest magnitude during the event convey most of the information.

Time Scale of Event

It is important to give some indication as to how fast the event took place. For example, the Hydran® 201R reading had been steadily climbing at 25 ppm per hour for the last 10 hours or the load (primary current) just dropped to 0 amps during the last 5 minutes.

Reaction Time

The reaction time refers to how quickly a human responded to the flags and decided that something needed to be checked or done. For example, if the Hydran® 201R reading went to 2000, that would probably be an immediate reaction (minutes) because something needs to be checked right now. On the other hand, if the top oil residual went to -8.5 and stayed there, thus generating numerous identical flags, a human would wait much longer (hours) before determining why this happened or before changing an alarm setting. The nuisance factor of the pagers or the time of the day should not be included in the reaction time.

Event Classification

All events should be classified as serious, moderate, or minor after the standard set of plots, flags, and other information are examined. Event classification should take into account the type of problem and whether it appears to be a transformer failing, sensor malfunction or failure, bad model parameters, etc. An explanation of how the severity of the anomaly was determined should be indicated.

Event Log

The event log is a chronological listing (date and time) of important flags, calls to or from the utility, input from other experts, etc. This is very important in reporting problems, doing follow up, and having a permanent record in case of serious consequences.

Analysis

The analysis section should contain not only analysis, but also diagnosis and an explanation. This is the "meat" of the event report, as it contains a detailed analysis of the event from start to finish with references to supporting plots and other information.

Detailed Conclusion

The detailed conclusion should specifically state the conclusion(s) reached. All conclusions must be justified with explanations.

Unanswered Questions

Oftentimes questions remain unanswered and problems unsolved. Were things observed that the human did not understand or cannot explain? If so, what are these things and what is needed in order to be able to answer them?

Actions Taken

Any specific actions taken either by MIT or the utility should be listed here. For instance, MIT adjusted the gas residual thresholds at 3 a.m. so that the human could go back to sleep. The utility replaced the top oil sensor that was malfunctioning.

Future Recommendations

Recommendations cannot always be immediately or cost effectively carried out. Recommendations listed here should be of the "wish list" type and include items such as install a weather station or install a moisture sensor and accompanying model.

Plots Used

Any plots used in the analysis and diagnosis should be attached at the back of the report with the figures labelled. A prepared check list of the standard plots is available so one can easily indicate which plots were used and in what order. The number of days for the plots should be specified along with an indication of any customized ones that were used in the analysis. The standard plots for one, two, four, and eight day periods include:

Primary Current
Hydran® 201R Reading, Predicted Gas, and Gas Residual
Hydran® 201R Reading vs. Hydran® 201R Oil Temperature
Cooling State
Top Oil, Hydran® 201R Oil, Ambient, and Predicted Internal Winding Temperatures
Top Oil Rise over Ambient Temperature (Top Oil - Ambient) vs. Primary Current
Top Oil Reading, Predicted, and Residual; Predicted Internal Winding Temperature

Other standard plots for 13, 26, and 52 weeks include:

Composite Gas Content for the different Cooling States

IEEE θ_{fl} (max top oil rise over ambient) for the different Cooling States
Thermal Time Constant for the different Cooling States

5.5 Sample Event Report Results

To date, more than 35 separate on-line transformer monitoring cases have been documented. The event reports are in varying stages and levels of analysis. Four abbreviated sample event report results are given below.

5.5.1 Hydran® 201R Sensor Calibration Procedure

Title

Gas Out of Range (Upper threshold B), Changed Too Fast, Module Unable to Predict
Series of Large Step Changes, Gradual Decreases, and Oscillations of Hydran® 201R
Hydran® 201R Sensor Calibration Procedure

Abstract

On March 26 at 8:13, the gas module became unable to generate a prediction of the gas content of the oil when the Hydran® 201R reading went from 61 ppm to 997 ppm in 5 minutes generating a threshold B violation and a changed too fast flag. This event raised concern since a reading of 997 is indicative of a transformer that has already failed.

Initial analysis showed that the transformer was normal in every respect that could be measured or checked. The transformer was on-line which indicated that a failure had not occurred as the primary current was 280 Amps. Thermally the transformer was normal as the top oil temperature was approximately 25°C. The transformer had been and was in natural convention (OA). Experimental acoustic energy sensors showed nothing. The Hydran® 201R temperature response curve showed no scatter in the data prior to the event, which indicated gassing had not been occurring.

MIT notified the utility which immediately became alarmed and ordered an emergency dissolved gas analysis and dispatched an operator to the station. MIT continued real-time monitoring which within an hour revealed a very predictable pattern for a Hydran® 201R calibration sequence indicated by an initial large step change in the Hydran® 201R reading, then a decay, then several more step changes over a ninety minute period. This was confirmed by the operator sent to the station who caught the technician on the site.

Recommendations

For the Utility: Inform MIT of maintenance procedures in advance.

For MIT: Develop and maintain a maintenance log as well as a paging procedure for communication with the utility.

Flags Generated

The first three flags generated, an intermediate one, and the last one are listed below.

gasmod(3/26 8:13): gas is out of range, threshold B! (997)
gasmod(3/26 8:13): gas has changed too fast! (61 → 997)
gasmod(3/26 8:13): Unable to predict (values out of range)
gasmod(3/26 8:23): gas has changed too fast! (997 → 65)
gasmod(3/26 9:38): gas has changed too fast! (0 → 53)

5.5.2 Loss of Station Control (Auxiliary) Power

Title

Gas Out of Range (Lower Threshold B), Changed Too Fast, Module Unable to Predict
Loss of Hydran® 201R Signal (gas=-500)
Loss of Station Control (Auxiliary) Power

Abstract

On July 24 at 17:58, the gas module indicated that the gas residual had exceeded threshold B and that the module was no longer able to generate a prediction. A Hydran® 201R reading of -500 does not fall within the believable range of 0 to 2000 ppm. The Hydran® 201R readings for the day prior to the event, all fell within the normal operating range and showed no unusual behavior.

At the time of the flags, the transformer appeared to be normal in every aspect initially checked. It was a hot summer day as the ambient temperature hovered around 25°C. The top oil temperature had been fluctuating around 50°C. The primary current had been near

550 Amps during mid afternoon, which was near the full load capacity of 600 Amps. It had been dropping off prior to the event and was approximately 470 Amps at 17:58.

What was abnormal was the transformer cooling state switching from State 3 FOA 1-2 (Both Cooling Groups On) to State 1 FOA 1 (Cooling Group 1 On) at the same time the Hydran® 201R reading went to -500. There was a direct correlation between the two events. For the currently measured top oil temperature, half of the cooling should not have suddenly gone off. With the high load coupled with the hot summer day, severe overheating could result. The utility was immediately notified of this situation.

After speaking to the utility and J. W. Harley concerning the DAS, it was learned the the -500 reading represents an open circuit in the 4-20 mA communication loop between the Hydran® 201R sensor and the DAS. Possible causes are auxiliary power failure, Hydran® 201R failure, or Hydran® 201R electronics package failure.

Recommendations

For the Utility: Provide MIT information concerning how the Hydran® 201R, the other sensors, and the cooling are powered or wired.

For MIT: Notify the utility of an Auxiliary Power Failure. Provide immediate operational control recommendations that include the estimated time until overheating as well as directives to reduce or sustain the load current.

Flags Generated

The first three flags generated during the event are listed below.

gasmod(7/24 17:58): gas is out of range, threshold B! (-500)
gasmod(7/24 17:58): gas has changed too fast! (55 → -500)
gasmod(7/24 17:58): Unable to predict (values out of range)

5.5.3 Rain Squalls on Transformer and Sensors

Title

Gas Residual Out of Range (Upper threshold A)

Hydran® 201R Reading Rising while Prediction Remained Steady
Rain Cooling Hydran Sensor and Enclosure

Abstract

On July 25 at 4:33 a.m., the gas module indicated that the gas residual had exceeded threshold A. The gas residual was 8.4663 ppm, which exceeded the preset limit of 7.9 ppm which had been set statistically at 3 standard deviations from the mean. The limit was exceeded when the Hydran® 201R reading rose from 119 ppm to 127 ppm in 49 minutes. During the same period, the gas prediction changed from 117.1 ppm to 118.5 ppm. This anomalous behavior seems to have been caused by rain squalls at the utility station which cooled the Hydran® 201R sensor, but not the loop oil (Hydran® 201R oil) sensor.

The top oil temperature exhibited an impulse-like drop of 8°C at the same time the Hydran® 201R showed an impulse-like increase of 8 ppm. This is the "classic" signature of rain cooling the top oil sensor. The load was essentially stable at 240 Amps during this period, while the ambient and loop oil temperatures showed no corresponding impulses. The gas model parameters had been stable in the preceding five weeks.

In conclusion, the rain squall cooled the Hydran® 201R sensor rapidly while not affecting the loop oil temperature. The resulting temperature gradient across the sensor caused the sensor reading to increase 8 ppm quite rapidly without a corresponding increase in the predicted gas reading, thus generating flags. Once the rain stopped, the Hydran® 201R reading dropped back down towards the prediction and the residual correspondingly fell within the acceptable range. Experience shows that the gas residual should statistically be set at a minimum of 4 standard deviations from the mean value.

Recommendations

For the Utility: Install covers over all sensors affected by weather conditions.

For MIT: Change the gas residual threshold A to 10.5 since the limits were previously set too tight.

Flags Generated

The first three flags generated during the event are listed below. The threshold A limit was temporarily adjusted to suppress flag generation until the Hydran® 201R reading started to more closely match the predictions.

gasmod(7/25 4:33): rgas is out of range, threshold A! (8.4663)
gasmod(7/25 4:33): rgas is out of range, threshold A! (9.4663)
gasmod(7/25 4:33): rgas is out of range, threshold A! (9.4663)

5.5.4 Poor Thermal Model Performance

Title

Topoil Residual Out of Range (Upper threshold A)
Top Oil Prediction Rapidly Decreasing while Measurement Remained Steady
Poor Thermal Model in face of Rapidly Falling Ambient Temperature

Abstract

On June 8 at 22:48, the IEEE thermal module generated a flag indicating that the top oil temperature residual of 20.8454°C had violated threshold A which was set at 20.5°C. A positive residual of this type would tend to indicate that the top oil temperature is hotter than it should be for the operating and ambient conditions.

Analysis of the situation revealed that the measured top oil temperature had been steady at 40°C for several hours while the prediction fell rapidly throughout the day, resulting in a large positive residual. The falling prediction correlated directly with a rapidly falling ambient temperature, as often happens in the springtime. There was no correlation with the load, the cooling state, or the gas module, although the Hydran® 201R was experiencing severe starvation.

The thermal model includes no dynamics for the effect of ambient temperature on top oil temperature, so the top oil temperature prediction fell rapidly with ambient while the actual top oil temperature fell more slowly due to thermal inertia. Slight violations of this type that do not increase in severity should not be reported.

Recommendations

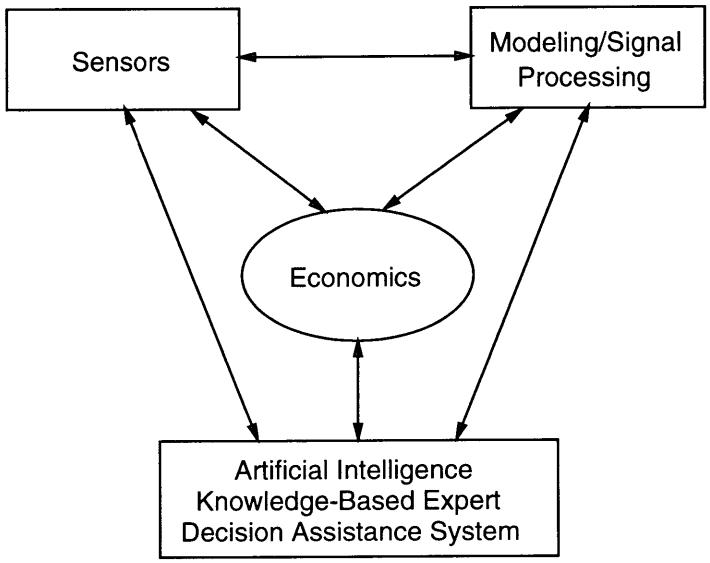


Figure 5-16: Tradeoffs in On-Line Monitoring

For the Utility: None.

For MIT: Develop a better thermal model that includes dynamics for the effect of ambient temperature on the top oil temperature.

Flags Generated

The first three flags generated during the event are listed below. The threshold A limit was temporarily adjusted to suppress flag generation until the thermal model recovered.

ie3mod(6/8 22:48): rgtoil is out of range, threshold A! (20.8454)
ie3mod(6/8 22:53): rgtoil is out of range, threshold A! (20.82)
ie3mod(6/8 22:58): rgtoil is out of range, threshold A! (20.7935)

5.5.5 Efficient On-line Monitoring Tradeoffs

Overall, the event reports revealed that there are economic and technical tradeoffs in on-line transformer performance monitoring. This is graphically depicted in Figure 5-16.

The first event report, Hydran® 201R Sensor Calibration Procedure, described the effects of a calibration procedure on the monitoring system and on the recommendations MIT makes when no advance warning is given of maintenance procedures. The calibration procedure produces a very recognizable pattern in the Hydran® 201R readings and the best economical solution for dealing with this is to recognize the calibration pattern with artificial intelligence based techniques.

The second event report, Loss of Station Control (Auxiliary) Power, described the effects on the Hydran® 201R sensor when the utility loses control power. It represents a serious situation that can result in overheating if not attended to properly. This type of problem is most economically detected with artificial intelligence based techniques.

The third event report, Rain Squalls on Transformer and Sensors, described the affect of rain on several sensors at the utility station. This produced anomalous behavior that resulted in a positive gas residual that exceeded the preset threshold limit. Economically, the best solution for this problem is to cover all sensors affected by the weather.

The fourth event report, Poor Thermal Model Performance, described the affects of a rapidly falling ambient temperature on the thermal model. This resulted in a positive top oil residual that exceeded the preset threshold limit. Economically, the best solution for this problem is to develop a better thermal model.

5.6 Overall Diagnostic Graph

An overall *diagnostic graph* was produced that formalizes the diagnostic knowledge derived from the interview sessions and the event reports. It shows the diagnostic processes and data relationships exploited by the transformer expert. The graph is continuously updated as new anomalies or events are experienced and diagnosed. The interactions between measurements, residuals, or on an even higher level between modules, becomes apparent. The graph shows that several diagnostic outputs may result when the effects of an anomaly are "traced" through the graph by hand.

Figures 5-17, 5-18, and 5-19 show the most current version of the graph split into three sections. It contains mainly knowledge from the interview sessions, with limited knowledge from the on-line cases. It is currently in a state of revision based on some of the above sessions, but it allows observation of actual transformer diagnostic research in progress. It primarily focuses on the measurements and what diagnostic information they provide.

The overall diagnostic graph follows the conventions adopted in Section 5.3. Since the graph is in three figures, diagnostic processes and outputs that are shared between the figures are shaded gray. This version is at the level a human can read and understand, although it must be converted to a more specific level before being useful as part of an automated diagnostic system. The goal was to provide a standard structure that is easily expandable to incorporate new knowledge (diagnostic processes and data relationships) as it is acquired. It was critical that a basic structure be adopted since acquiring knowledge and updating the graph is a very tedious and difficult task.

In the general case, the triggering event is a detected anomaly. In the field-deployed system, the "flag" method of detection generates a large number of nuisance flags that result from harmless change in external conditions not related to the health of the transformer. Therefore, the focus of this thesis actually changed from strictly doing diagnostics to developing an intelligent detection scheme that validates the "flags", which is the focus of Chapter 6. Here it is assumed that an intelligent detection scheme was utilized to detect anomalies.

After an anomaly is detected, the human would typically plot the individual measurements and residuals for a time period of interest which could be on the order of hours, days, weeks, or longer. Based on the type of anomaly, the human may have reason to suspect either sensor, transformer, or model problems and may strategically enter the graph at any point and bypass unnecessary steps. But, in order to best understand the graphs, a brief explanation is provided as each piece of the graph is analyzed in succession from left to right.

In Figure 5-17, the primary current and cooling state information are analyzed. If the primary current is 0 amps, then the transformer is off-line which means that it either tripped (manually or automatically) or that it failed. Typically the utility is contacted for additional information. If the primary current is greater than 0 amps, then the transformer is still on-line. An important check at this point is to make an assessment of the loading. If the transformer is over or heavily loaded this could lead to overheating which could result in gas production. If the transformer is lightly loaded then it should not overheat. At this point other significant or important events, such as a large step change in the current, should be noted. The cooling state of the transformer is determined along with information concerning recent state changes. If there was no recent state change, then the cooling state probably has no effect on the gas reading. If there was a cooling state change from OA to FOA, then this could possibly result in gas bubble generation which should be tested for in order to find out the cause. If there was a cooling state change from FOA to OA and the Hydran® 201R oil temperature is between 30 and 40°C, then there is the possibility of sensor starvation.

In Figure 5-18, the acoustic sensor readings, the ambient temperature, and the top oil temperature are analyzed. The acoustic sensors are not currently being used in the field installations, but an abnormal noise level could indicate a loss of dielectric strength of the insulation or an increase in electric stress. Here, a normal noise level indicates that the transformer is probably behaving normally. The ambient and top oil temperatures are examined to see if they are appropriately correlated with the Hydran® 201R oil temperature. If they are, then the transformer is probably behaving normally. At this point, the top oil temperature is plotted versus the primary current or load. The locus is examined and if wide excursions are evident, then there could be a fault with regard to the top oil temperature and the load. Otherwise, it is additional evidence that the transformer is behaving normally. An overall consistency check is performed between the loading, ambient temperature, cooling state, top oil temperature, and the Hydran® 201R oil temperature as given in the middle of the graph. Consistency indicates probable normal transformer behavior.

In Figure 5-19, the Hydran® 201R oil temperature and sensor readings are analyzed. If the two measurements are correlated, then there is probably no malfunction of the sensor and a possible malfunction of the transformer. If the measurements are not correlated, then there is a possible malfunction of either the sensor or transformer. The sensor readings are checked for believability and if they are not believable, then there is the possibility of a

Hydran® 201R sensor failure and most likely the transformer is behaving normally. At this point, the sensor reading is compared with known patterns and readings that have specific meanings. For instance, an unexplained erratic reading could be possibly be caused by bubble generation, or by a possible problem with the fuel cell in the Hydran® 201R sensor, or by sensor starvation. Believable readings that are continuously high could be due to possible arcing. On the other hand, believable readings that are not high indicate normal sensor behavior. If the two measurements are not correlated, then they should be plotted against each other and then the locus examined. For instance, if the characteristic curve tends up and scatter is evident in the plot, then this possibly could be caused by gas production.

Much research effort in the future is necessary for completing the documentation for the 35 cases and for incorporating the knowledge into the overall diagnostic graph. The next critical step is to incorporate residuals and their relationships and information vital to the diagnostic process. This will be left for future research efforts.

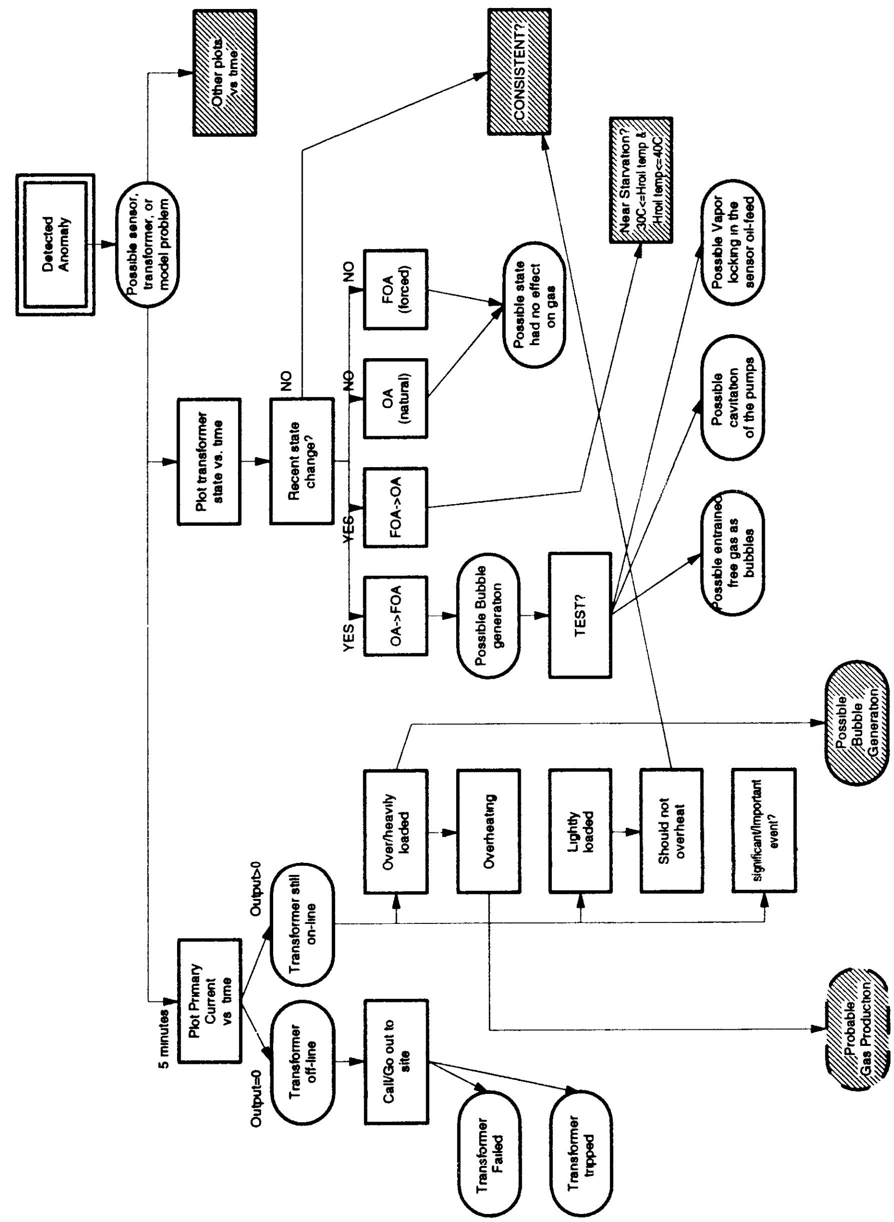


Figure 5-17: Overall Diagnostic Graph: Section 1

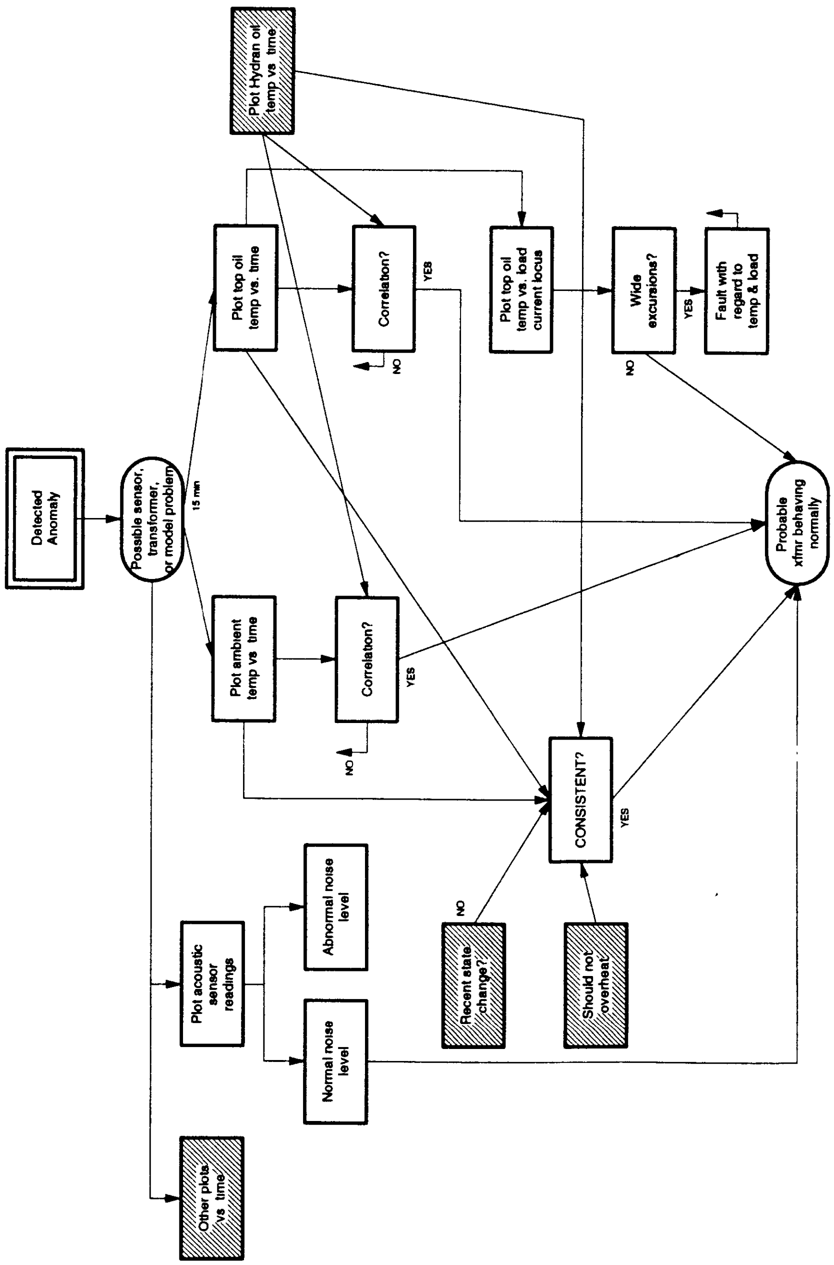


Figure 5-18: Overall Diagnostic Graph: Section 2

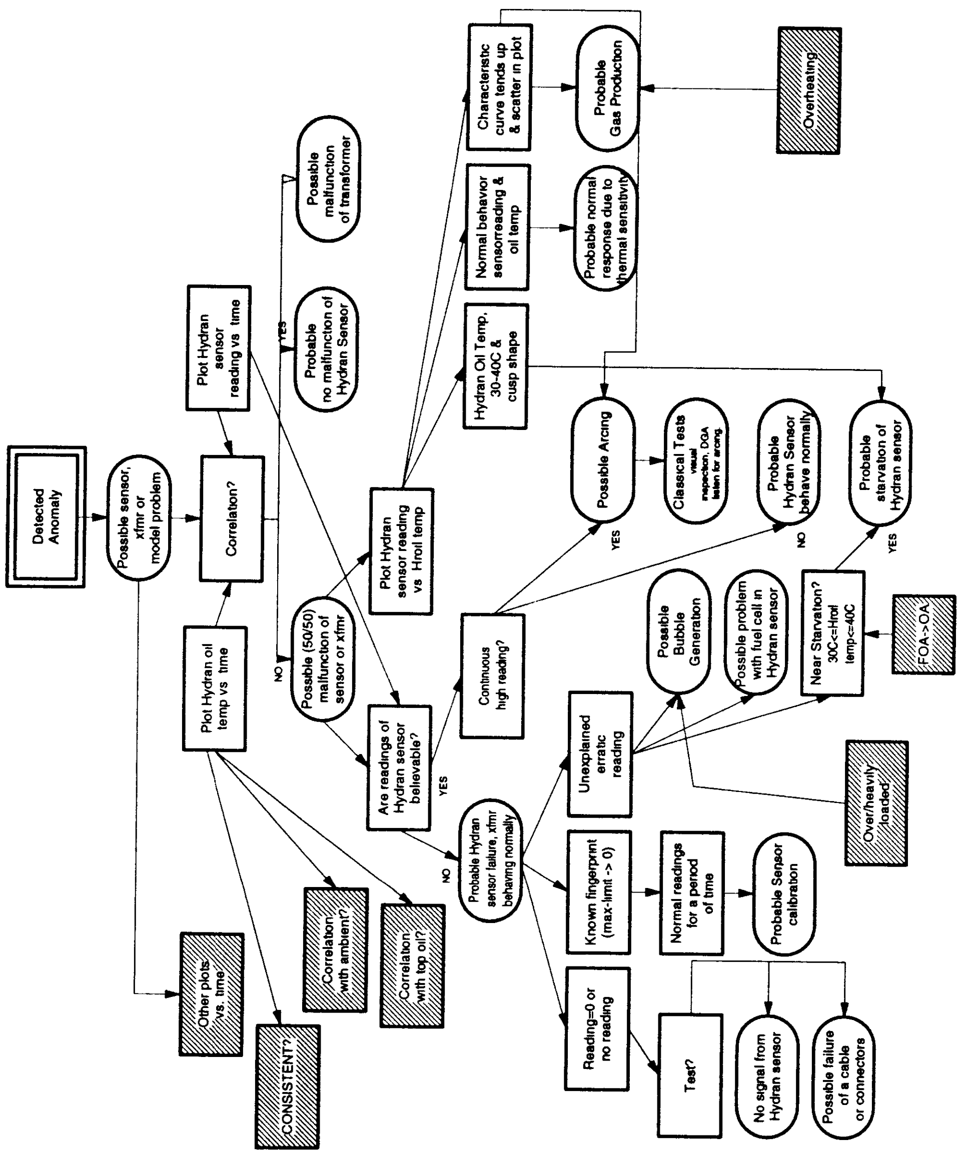


Figure 5-19: Overall Diagnostic Graph: Section 3

Chapter 6

Intelligent Anomaly Detection

The anomaly detection scheme that is currently implemented in the field-deployed monitoring system is simple, but experience shows that it creates a large number of nuisance flags that result from harmless changes in external conditions not related to the health of the transformer. A better anomaly detection scheme is needed in order to eliminate the need for virtually all of the short term diagnostics that have been necessary to explain the nuisance flags generated by the field-deployed system. The scheme must also maintain the necessary sensitivity to detect anomalous changes in the transformer's internal condition. This chapter proposes and examines an anomaly detection scheme that is based on both spatial and temporal information and ultimately integrates more intelligence into the anomaly detection process.

Section 6.1, Anomaly Detection, describes the background and the general methodology for the proposed detection scheme. A thorough discussion at a general and detailed level is presented along with corresponding terminology and notation. Section 6.2, Detection Examples, illustrates the use of the detection scheme from Section 6.1. It presents three examples of magnitude detection and one example of rate of change (ROC) detection which illustrate the potential usefulness of the detection scheme. In order to verify its general capability, Section 6.3, General Detection Runs, evaluates the scheme on several criteria for a six month period of data from two different transformers presently under surveillance.

6.1 Anomaly Detection

Anomaly detection is the process of sensing and affirming the occurrence of abnormal or anomalous changes in the transformer's internal condition. Two types of anomalies are magnitude violations and abnormal rates of change. The approach taken in the present field-deployed system is that the detection function is rather simple and is based on straight limit checking of fixed thresholds of magnitude and rate of change. Exceeding a magnitude threshold or rate of change limit raises a "flag" that may indicate the presence of an incipient failure situation, although most often this has not been the case. Flags are often generated by fast (a few minutes) transient conditions, particularly cooling state changes, which are not accurately modeled.

In creating the knowledge base and by carrying the pagers, we have concluded that a better anomaly detection scheme is required before a diagnostic system can be implemented. The "flag" scheme is simple but experience shows that a point-wise determination of the transformer condition creates a large number of nuisance flags that result from harmless changes in external conditions not related to the health of the transformer. A better anomaly detection scheme should eliminate the need for virtually all of the short term diagnostics that have been necessary to explain the nuisance alarms generated by the field-deployed system, while still maintaining the necessary sensitivity to detect anomalous changes in the transformer's internal condition.

An intelligent detection scheme used for monitoring transformers must deal with real-time data, operate continuously, detect abnormal changes in the system, eliminate nuisance alarms, and only activate further levels of diagnostics and alert the operator in cases that need immediate attention. A novel detection scheme has been developed that is a (brute-force) method for integrating "how much" a signal stream has exceeded normal limits (spatial) and for "how long" (temporal). It takes into account both spatial and temporal information as provided by the data and model outputs, thereby providing a continuous indication of the condition of the transformer.

In the context of anomaly detection, the word *spatial* is used to represent the location of a value (measurement, residual, processed data) along a one-dimensional continuous

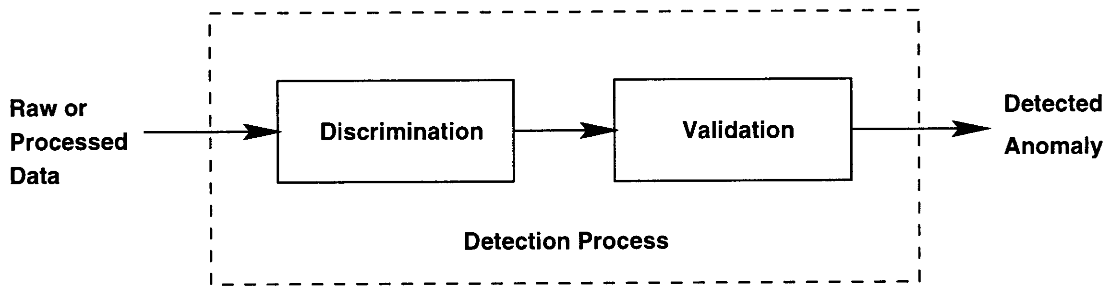


Figure 6-1: General Magnitude and ROC Detection Scheme

expanse of all possibilities (-∞ to +∞). The point-wise location is further classified as normal or abnormal with varying degrees of possibilities based upon overlapping fuzzy sets defining the normal and abnormal ranges of transformer operation for the particular value. This classification can occur at any point in time, although it does not take into account any aspect of time in its definition or classification mechanism. The word *temporal* is being used to introduce a finite interval of time over which to determine if any present or prior abnormal spatial classification during the finite time interval warrants an alarm.

This section presents this novel magnitude and rate of change (ROC) detection scheme in both a general and detailed version. Examples of this scheme are presented in Section 6.2.

6.1.1 Detection Scheme: Overview

Figure 6-1 shows the proposed Magnitude and Rate of Change (ROC) Detection Scheme, which consists of Discrimination and Validation. Very simply, discrimination is the act of identifying whether raw or processed data is normal or abnormal. This is presently accomplished in the field-deployed system by checking if any data value and/or residual exceeds a preset threshold and/or if its rate of change between successive measurements changes too fast. Section 3.2 described the use of multiple thresholds in the field deployed system. The generalized detection scheme improves this system by defining both upper and lower thresholds (LC, LB, LA, UA, UB, UC, etc.). These are used to partition the abnormality into ranges of seriousness that indicate the critical nature of the violation on a one-point basis. For example, UB is more critical than UA, and LB is more critical than UA. In addition, this classification indicates if the raw or processed data is either too low (LC, LB, LA, etc.) or too high (UA, UB, UC, etc.) based on expected transformer behavior. The use of multiple upper and lower thresholds provides more information about the anomaly than has been previously available.

Therefore, discrimination further classifies the abnormal behavior by indicating which threshold has been exceeded. Based on the field experience, an alarm should not be raised at this instant since a one-point determination of any aspect of the transformer's condition is not an accurate representation of the present situation. It is not accurate due to the previously described fast transient conditions, short term effects of the environment, model inaccuracies, uncertainty in the measurements, spurious readings, etc. Since cooling state dependent transformer time constants vary from about 100 to 600 minutes, one tends to classify transformer related "parameters" as being normal or abnormal over a period of time rather that at one point in time.

For this reason, a validation step is necessary. In this thesis, validation is defined as the process by which a reasonably certain determination can be made that a specified threshold or value has been exceeded long enough to be a cause for concern. This step substantiates the seriousness of the violation by gathering additional observations or evidence of the same type before raising an alarm. This also takes into account "How long has it been bad?" and "How bad is it?". The number of data points needed for validation is signal dependent. If validation is confirmed, an anomaly is said to be detected.

6.1.2 Detection Scheme: Details

Figure 6-2 shows the steps comprising the proposed Magnitude and ROC Detection Scheme. Magnitude and ROC detection differ in exactly "what" measure is being spatially and temporally classified and just how frequently this occurs. A basic description of each of the blocks is given below. Additional details will be provided as necessary in Section 6.2 which

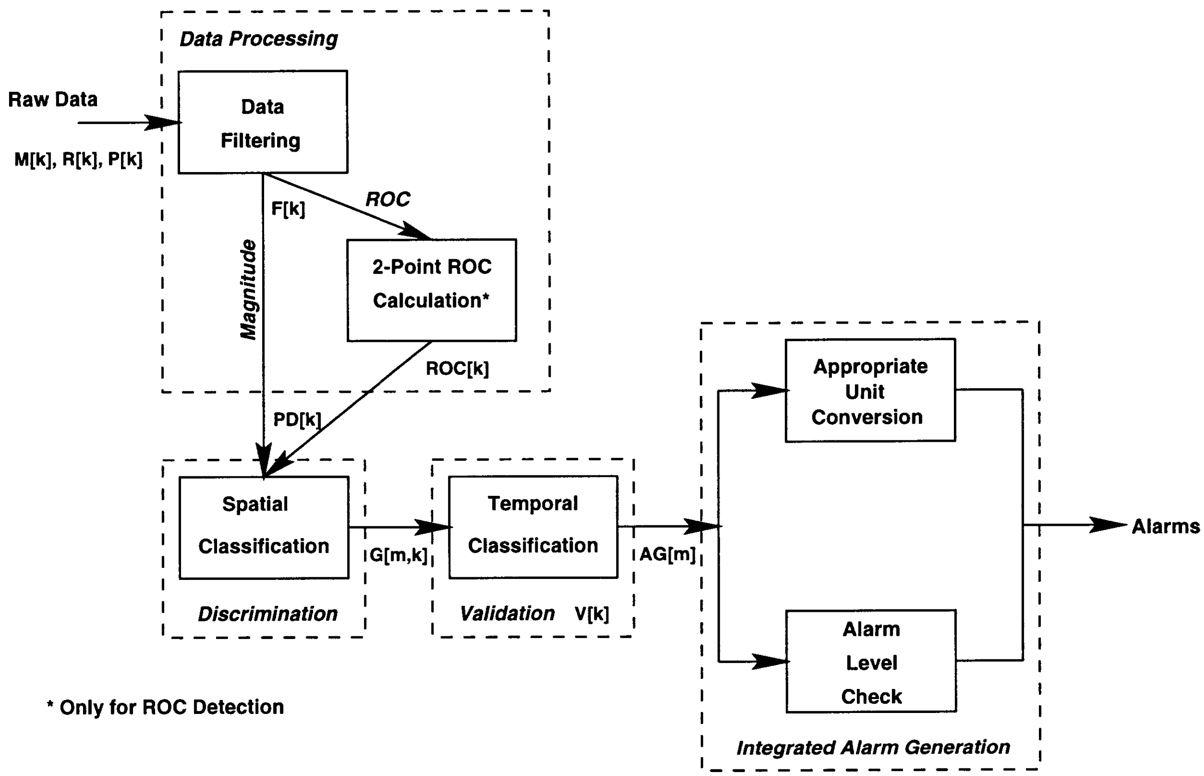


Figure 6-2: Details of Magnitude and ROC Detection Scheme

contains the examples.

Data Processing

Data Processing consists of Data Filtering and a Two-Point Rate of Change Calculation which is used only for ROC detection and not for magnitude detection. A discussion of each follows.

The transformer monitoring system contains raw data (signals) which consists of measurements from the DAS and of residuals and model parameters calculated and derived from these measurements. Adapting the notation from Chapter 3, measurements are represented as $M[k]$, residuals as $R[k]$, and parameters as $P[k]$. Here k is the time step index and it ranges from 0 to $-L$, where L is the number of previous time steps required and differs according to the value of interest. Depending on the time scale of interest, certain signals require some type of **Data Filtering** or smoothing in order to be useful. Filtering could include eliminating the undesired frequency components from the signal or just the simple weighting of the various frequency components of the signal.

Smoothing techniques for transformer data must be chosen carefully based on the time scale of interest, the actual dynamics of the underlying signal, and exactly what is to be removed from the signal. Depending on the signal, it has been useful to perform smoothing in order to remove noise and to remove the short term effects of the environment (wind, clouds, sun, rain, etc.) on temperature measurements. System modeling is required on some signals in order to remove the daily transformer load and temperature cycle, and even the weekly cycle of load. The field-deployed system is currently monitoring transmission system transformers which see load variations every weekday and a different pattern of load on weekends.

In this step, an appropriate filter must be specified along with the data sampling interval to use. For example, a moving average filter of length two-hours could be used with data sampled every 5 minutes. A filter of this length is necessary to remove the short term noise and the short term effects of the environment. It uses the same data sampling interval as the modules/models described in Chapter 3. In order to remove the long-term effects such as the seasonal variation, appropriate data processing techniques must be carefully chosen depending on the signal. For certain signals when magnitude detection on a very short time scale (minutes to hours) is desired, the raw data will not be filtered. Magnitude and ROC detection on longer time scales relies heavily on appropriately filtered data to provide useful results. It should be noted that parameter estimation for the adaptive gas and thermal models is also a "filtering process" in that it removes the effects of exogenous inputs from the data.

The **Two-Point Rate of Change Calculation** step in the Data Processing block is used only for ROC detection. The computation of a two-point ROC is extremely simple, but the difficult part is in deciding exactly what two processed data points should be used and the interval of time between them. For the purpose of this work, the ROC calculation is given by Equation (6.1). $F[k]$ and $F[k-l]$ represent the two processed data points. Here l is the number of time steps between the two points, T is the sampling period, and lT represents the true time separation between the two points. The ROC may be scaled to meaningful units as desired by use of a scaling factor C. For example, if $ClT = 7days$, then an average ROC per day sustained for 7 days is determined.

$$ROC[k] = \frac{F[k] - F[k-l]}{ClT} \tag{6.1}$$

Improper ROC detection can result in numerous false alarms. Calculating a ROC on a time scale of minutes picks up noise in the signals, spurious readings, short term environmental effects, fluctuations in the signals caused by cooling state changes, etc. Changes caused by these types of sources should not be reported and certainly not alarmed since they do not indicate anomalous changes in the transformer's internal condition. The current field-deployed version of the monitoring system detects these unwanted changes since a two-point ROC calculation is performed every 5 minutes. This type of ROC calculation has provided insight into how the various signals behave and how they are related on a very short time scale, but has provided no meaningful and useful information concerning the transformer condition.

Intelligent ROC detection is accomplished on a longer time scale defined by hours, days, weeks, months, or even greater periods of time. The appropriate choice of time scale is determined by the dynamics of the signal under consideration, the critical nature of the signal or transformer, what is computationally practical, and what measure is really useful. Several ROC schemes were proposed and tested. Most revolved around obtaining a meaningful point derivative [47] and then combining a chosen number in some fashion in order to obtain the overall trend or inertia of the signal. These approaches provided insight into the problem of ROC detection on the minutes to hours time scale and led to the necessity of a longer term ROC calculation.

It must be emphasized again that a meaningful measure of change is the most critical step at this point. In calculating a two-point ROC, the interval of time between the two points must be specified along with how often the ROC is calculated. For example, assume that in the data filtering step, that a gas residual mean is computed every 3 hours based on the previous 24 hours of gas residuals sampled once every 5 minutes. One applicable ROC calculation would be the ROC of this mean over an interval of 7 days, computed every 3 hours. The first ROC value requires 8 days of start up time (1 day for the first 24 hour mean and 7 days for the interval). Eight of these ROC values are calculated in any 24 hour period. During normal transformer operation and behavior, these mean values are expected to be zero.

The output of the overall data processing block is defined as $PD[k]$. As previously described, this is raw data that has been transformed by a filtering step and an optional ROC calculation into a processed data point, $PD[k]$. Hence, either $PD[k] = F[k]$ or $PD[k] = ROC[k]$. This is the input to the Discrimination stage as shown in Figure 6-2.

Discrimination

Spatial Classification is being used as a method of discrimination. For all measurements, residuals, and processed data, the continuous expanse of all possibilities, ($-\infty$ to $+\infty$) is partitioned into a finite number of categories or sets. Spatial classification determines in which set(s) in space a measurement, residual, or processed data value lies. This step may even further classify the anomalous behavior as either transformer, sensor, or perhaps model related. By intelligent choices for spatial threshold settings, an idea of the believability of the data can be obtained.

The first step in spatial classification is fuzzification which converts the point-wise (crisp) values of all measurements, residuals, and appropriately processed data into fuzzy sets. This reduces the inaccuracy that occurs at crisp traditional set boundaries by substituting fuzzy sets consisting of a collection of elements that can be a member of the set with a partial degree of membership between zero and one. This differs from binary sets that restrict the value of the set element to either zero or one. The grade of membership in a fuzzy set is expressed by a membership function. The choice of membership functions and their underlying fuzzy sets is based on (1) the historical setup of binary thresholds for "flag" generation from the monitoring systems in the field, (2) experience with these thresholds, (3) uncertainty in the specific measurements, residuals, and parameters and (4) the linguistic notions that are meaning dependent based upon the physical domain. Therefore, sensor measurement error and mistuning of the new system are not as critical as in the old binary threshold system [51].

In Discrimination, each processed data point, $PD[k]$, is assigned a membership grade for each fuzzy set defining its continuous expanse of possibilities. The grades representing each point are defined as $G[m, k]$ where $m = 0, 1, ...(s - 1)$ and s is the number of fuzzy sets. As before, $k = 0, -1, ... - L$. From the theory of fuzzy sets and appropriate choice of membership functions, Equation (6.2) holds for all m and k, while Equation (6.3) holds for all k.

$$0 \leq G[m, k] \leq 1 \tag{6.2}$$

$$\sum_{m=0}^{s-1} G[m, k] = 1 \tag{6.3}$$

Based on field experience, for short term magnitude detection, measurements require seven fuzzy sets ($s = 7$) for classification as shown in Figure 6-3. The corresponding labels are 'sensor low', 'very low', 'low', 'normal', 'high', 'very high', 'sensor high'. These

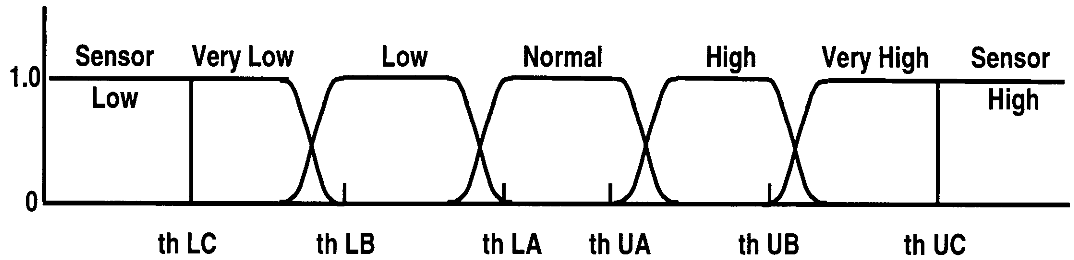


Figure 6-3: Membership Function for Measurements

labels correspond to $m = 0, 1, 2...6$ respectively. The Normal region, defined by the lower and upper thresholds (th) LA and UA, is representative of normal transformer operation. Thresholds LB and UB, indicating a (possibly) more serious problem, are set based on human experience. Thresholds LC and UC are set at the sensor measurement limits provided by the manufacturer. For example, the Hydran® 201R sensor limits are given by its performance range of 0 to 2000 ppm. Therefore LC and UC are set at 0 and 2000 ppm respectively. For long term magnitude detection of measurements, only five regions are used and are labelled 'very low', 'low', 'normal', 'high', and 'very high'. The membership function is similar to that of the measurements and residuals. It should be emphasized that labels across different time scales and signals may be the same, but the interpretation of the information varies.

Five fuzzy sets ($s = 5$) are required for short term magnitude detection of residuals as shown in Figure 6-4. A residual is the error representing the difference between the measured and the predicted value. The corresponding labels are 'very low', 'low', 'normal', 'high', and 'very high'. These labels correspond to $m = 0, 1, 2, 3, 4$ respectively. The High region is used to indicate that the transformer's health is not in danger at this moment, but could be approaching a dangerous situation. Very High indicates that the transformer's health is presently in danger. Likewise, the Low and Very Low regions are a source of concern. For long term magnitude detection of residuals, only three regions are used and labelled as 'low', 'normal', and 'high'. The membership function is similar to that of the

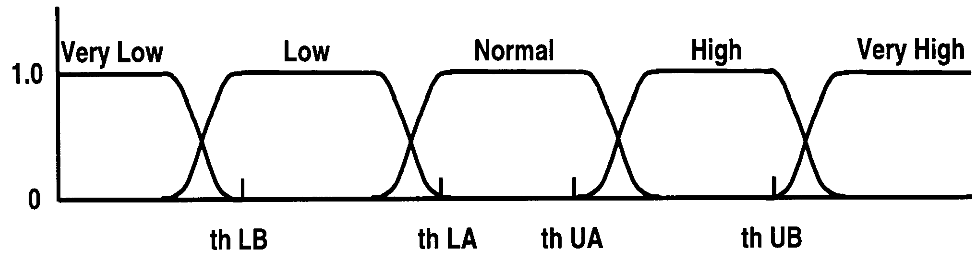


Figure 6-4: Membership Function for Residuals

measurements and residuals and is not shown.

Three fuzzy sets ($s = 3$) are required for long term ROC detection. ROC detection on shorter time scales employs five fuzzy sets to quickly distinguish between different levels of increases and decreases. For example, increasing slowly has a different implication than increasing rapidly, and decreasing rapidly has a different implication than increasing rapidly on a short time scale. However, for ROC detection on longer time scales, a tremendous amount of smoothing and delay has already been incorporated in calculating the ROC value. Based on experimentation with field data, any increase or decrease on a long time scale is unacceptable and partitioning the abnormality into additional classifications provides no useful information since any increase or decrease is quite serious and should be addressed immediately.

For long term ROC detection, the membership function is similar to that of the measurements and residuals and is not shown. The corresponding labels for the three fuzzy sets are 'abnormal decrease', 'normal', and 'abnormal increase'. These labels correspond to $m = 0, 1, 2$ respectively. The Normal region is used to indicate acceptable rates of change over a specified time period. The Abnormal Increase indicates an unacceptable upward (positive) ROC which could indicate that the transformer's health is in danger. The Abnormal Decrease indicates an unacceptable downward (negative) ROC which could possibly indicate model or sensor problems or abnormal transformer operation.

The detection scheme can be extended for very long term magnitude and ROC detection

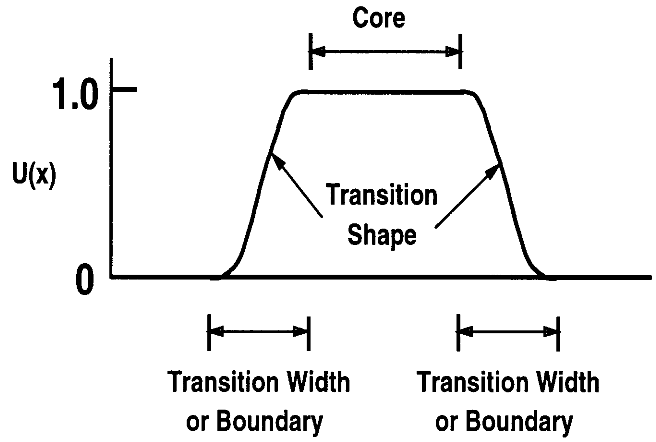


Figure 6-5: Features of Each Fuzzy Set

by the use of the model parameters. This is accomplished by appropriate selection of fuzzy sets, spatial thresholds, and alarm levels. Tracking the parameters gives a sense of subtle changes that possibly would have been undetected by the shorter term magnitude and ROC detection schemes. These changes could be indicative of slowly developing failures, abnormal operation, the transformer aging process, etc. It must be emphasized that sufficient time and operating conditions are necessary in order to obtain a statistically significant number of parameters for each of the cooling states. Each cooling state requires a separate set of parameters as described in [6, 35].

Figure 6-5 shows the features that must be chosen for the fuzzy sets making up each membership function. The transition region shape shown is the sigmoid function. The logistic function, one particular type of sigmoid function, is used here. It is a strictly increasing function that exhibits smoothness and asymptotic properties [54]. Equation (6.4) shows its general form, where a is the slope parameter which was chosen arbitrarily to be 0.5 in order to retain symmetry. The transition widths or boundaries between categories were chosen to reflect the noise in the signal and the variance in estimating the specific thresholds.

$$\phi(x) = \frac{1}{1 + e^{-ax}} \tag{6.4}$$

Spatial thresholds for measurements are based on gross expectations of transformer behavior, much the same as standard utility alarm levels. The measurement thresholds are very traditional and are obtained directly from the transformer's nameplate or from the ANSI operating guidelines. These static measurement thresholds do not take full advantage of the range of data and experience with the signals. Abnormalities do not necessarily result in measurement threshold violations, but are often detectable by significant residuals that may indicate that the transformer is behaving abnormally based on external factors such as load and ambient temperature. The model-based (residual analysis) approach provides a large increase in sensitivity and noise margin over traditional measurement threshold detection.

Residual and ROC spatial thresholds are based on statistical analysis of model and transformer behavior. Much field experience led to the belief that the distribution of the residuals was approximately normal or Gaussian. In order to rigorously test the normality assumption or hypothesis, the Kolmogorov-Smirnov (K-S) test, extensively discussed in [47], was performed. A six month sample of gas and top oil temperature residuals was gathered from Boston Edison Company's (BECo) Station 211, Transformer 345A, from January 1 until June 30, 1997. The test yields a K-S statistic D, which is defined as the maximum value of the absolute difference between two cumulative distribution functions. This can be represented by:

$$D = \max_{-\infty<x<\infty} |S_N(x) - P(x)|, \tag{6.5}$$

where $S_N(x)$ represents the cumulative distribution function of the residuals and $P(x)$ represents the cumulative distribution function for the theoretical normal distribution. Application of the K-S test to the gas residuals yielded a K-S statistic $D = 0.05$ with a significance level, calculated by Equation 14.3.9 in [47], of 6x10^{-128} of disproof that the residuals are normally distributed. Figure 6-6 shows the histogram of the 52091 gas residual values from the selected period. For the gas residual, the mean was 0.0197 ppm with a standard deviation of 1.91 ppm. Application of the K-S test to the top oil temperature residual yielded $D = 0.016$ with a significance level of 5x10^{-12} of disproof that the residuals are normally distributed. Figure 6-7 shows the histogram of the 52091 top oil temperature residual values from the selected period. For the top oil temperature residual, the mean

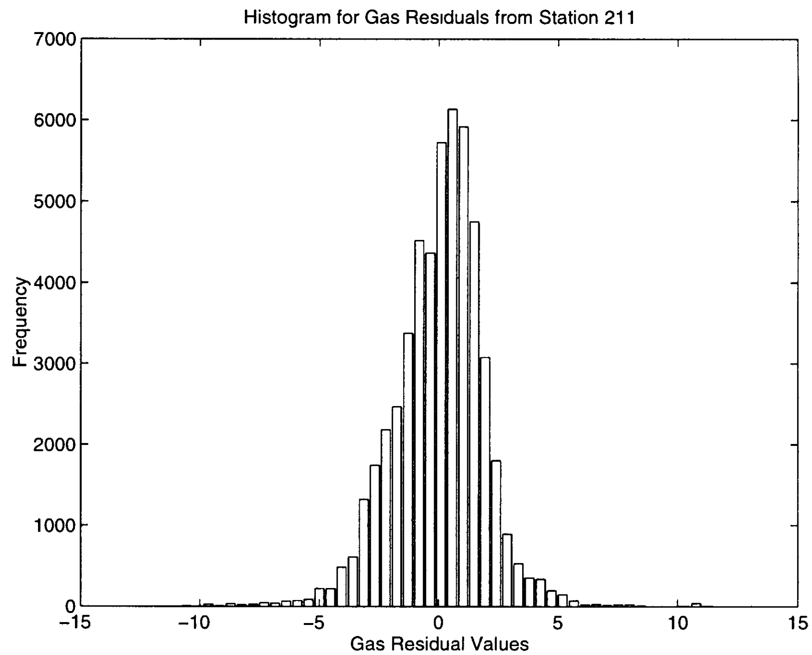


Figure 6-6: Station 211, Transformer 345A, Gas Residuals 1/1-6/30/97

was 0.0197°C with a standard deviation of 1.91°C. Therefore, based on this analysis, the hypothesis that both the gas and the top oil temperature residuals from fault-free periods are normally distributed can be accepted (although not proven) with greater than 99.9% certainty.

Based on the normality of the distribution of residuals, the "Normal" region, strictly between th LA and th UA in Figure 6-4, was defined as anything falling within four standard deviations ($\pm 4\sigma$) of the mean. Statistically for the normal distribution, the probability of obtaining a deviation greater than $\pm 4\sigma$ from the mean is approximately 0.006% [57]. This high level of confidence was selected in order to avoid frequent false alarms that occurred within $\pm 3\sigma$. Since these spatial thresholds are chosen statistically, they are therefore transformer independent. Currently, it is impossible to accurately set spatial thresholds from first principles since the transformer must be exercised to learn its limits. Large power transformers are individually designed to meet a utility's specifications. Therefore, the classification of a measurement, residual, or ROC as normal or anomalous is dependent on experience with the signal.

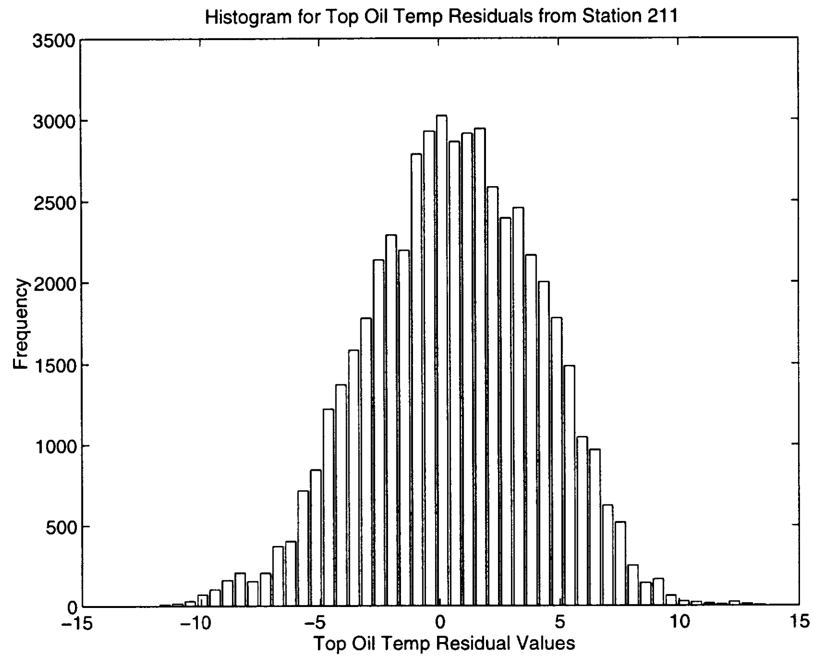


Figure 6-7: Station 211, Transformer 345A, Top Oil Temp Residuals 1/1-6/30/97

Spatial classification of measurements and residuals gives only a snap shot view of the state of the whole system at one point in time. Based on experience this is not an acceptable method of classifying the present condition of the system. This is due to the occurrence of spurious readings, slight threshold violations for a very short period of time, model inaccuracies, etc. In addition, since cooling state dependent transformer time constants vary from about 100 to 600 minutes, one tends to think of transformer related "parameters" as being low, normal, or high over a period of time. A better representation of the condition of the transformer includes a temporal dimension as described below.

Validation

The unique aspect of this detection scheme is that it combines a temporal dimension that is simple, easily constructed and maintained, and useful in significantly reducing the number of nuisance alarms. The temporal dimension is performing the validation step in which a determination is made that a specified spatial threshold has been exceeded long enough and is serious enough to raise an alarm. Prior attempts to filter bad data and then decide when an alarm should be raised required a large number of rules that were difficult to implement and were unmanageable.

This **Temporal Classification** piece of the detection scheme uses a "fuzzy" like approach. It uses previously calculated membership grades from the spatial classification. Region by region, a normalized validation window, $V[k]$, of a specified length, L, is applied. The scaling of the weighting factors of the validation window is multiplied by the membership grade at each point in time for the length of the validation window. The resulting sum is referred to as the accumulated membership grade, $AG[m]$. Mathematically this is shown in Equation (6.6). Due to normalization of $V[k]$ and the definition of $G[m, k]$ from Equation (6.2), $AG[m]$ is strictly between 0 and 1 for all m as shown in Equation (6.7). It additionally sums to 1 over all values of m as shown in Equation (6.8). Alarm levels are then set region by region for each accumulated membership grade.

$$AG[m] = \sum_{k=0}^{-L} G[m, k]V[k] \tag{6.6}$$

$$0 \leq AG[m] \leq 1 \tag{6.7}$$

$$\sum_{m=0}^{s-1} AG[m] = 1 \tag{6.8}$$

For short term magnitude detection, the length of the normalized validation window is chosen to remove noise and do some amount of smoothing without losing transformer dynamics. For longer term magnitude and ROC detection, the length of the validation window is much shorter than for short term detection. This is driven by the fact that the steps prior to temporal classification (data smoothing and spatial classification) have already incorporated a large amount of temporal information into the resulting membership grades.

A normalized sigmoid function is chosen as the validation window. By definition, it assumes a continuous range of values from 0 to 1 and is differentiable. This nonlinear

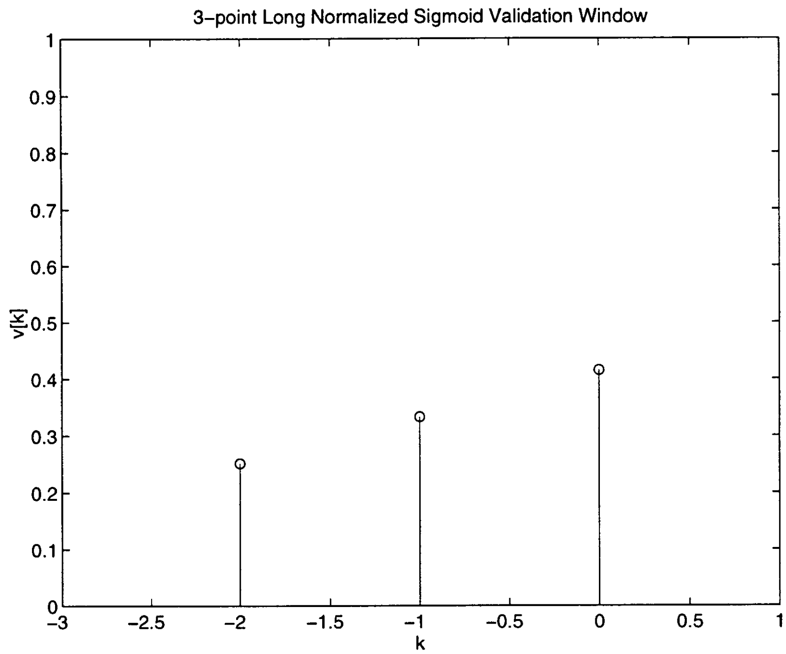


Figure 6-8: Example: A 3-point Normalized Sigmoid Validation Window

weighting allows recent data to be weighted more heavily than past data, which is often desirable in order to introduce a "forgetting factor". For example, a 3-point normalized sigmoid validation window, shown in Figure 6-8, has the following coefficients:

$$[\, 0.2517 \quad 0.3333 \quad 0.4150 \,] \tag{6.9}$$

A 3-point normalized linear filter that does straight averaging, shown in Figure 6-9, has the following coefficients:

$$[\, 0.3333 \quad 0.3333 \quad 0.3333 \,] \tag{6.10}$$

Other linear and nonlinear validation windows can be used as appropriate.

In summary, the upper and lower spatial thresholds defining the regions, the width of the transition regions, and the transition region shapes are parameters that are spatially related and used for discrimination. The length of validation window, the type of validation window, and the alarm levels for the accumulated membership grades are parameters

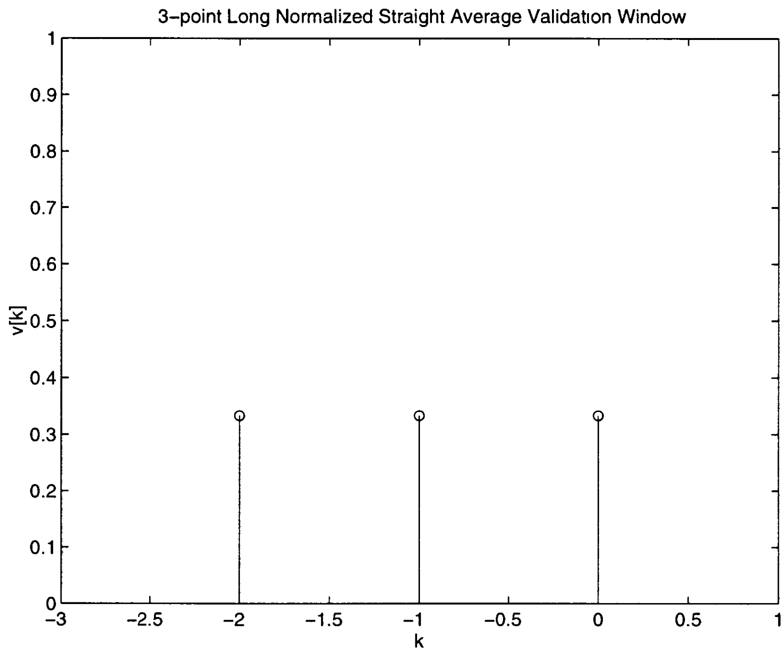


Figure 6-9: Example: A 3-point Normalized Straight Average Validation Window

that are temporally related and used for validation. Separating the detection process into spatial and temporal components enhances the system's ability to reject false positives while maintaining excellent sensitivity and providing a structure that is easy to setup and maintain.

Integrated Alarm Generation

Integrated Alarm Generation consists of an Alarm Level Check and an Appropriate Unit Conversion. A discussion of each follows.

The alarm levels are chosen based on the type of detection (magnitude or ROC) under consideration, the type of signal being analyzed, the particular region, and the amount of time it would take before an alarm condition is reached based on various scenarios. Essentially a trade-off curve is established. In this way, a signal in the Very High region for short periods of time rings an alarm much sooner than a signal just on the edge of the High region for long periods of time. The alarm levels are directly applied to the

Measurement Alarm Level	*Region*
LC	Sensor Low
LB	Very Low
LA	Low
UA	High
UB	Very High
UC	Sensor High
Residual Alarm Level	*Region*
LB	Very Low
LA	Low
UA	High
UB	Very High
ROC Alarm Level	*Region*
LA	Abnormal Decrease
UA	Abnormal Increase

Table 6.1: Relationship between Alarm Levels and Spatial Regions

accumulated membership grades, which due to normalization, are strictly between 0 and 1. The activation and deactivation points for the alarm levels are then set region by region for each accumulated membership grade. When the Validation process makes a definitely certain determination that a specified spatial threshold has been exceeded long enough to be a cause for concern, a corresponding alarm is generated. For example, Alarm UA indicates a validated violation of $th\ UA$, Alarm UB indicates a validated violation of $th\ UB$, etc. Hence, there is a one-to-one correspondence between the spatial thresholds and the alarms. The labels for the various regions used for Discrimination are related to the alarms as shown in Table 6.1 for simple measurement, residual, and ROC detection. Hysteresis is included in order to prevent alarm oscillations. For example, an alarm could be activated at an accumulated membership grade or level of 0.8 for the High region of the gas reading, but then only deactivated at an accumulated membership grade or level of 0.4.

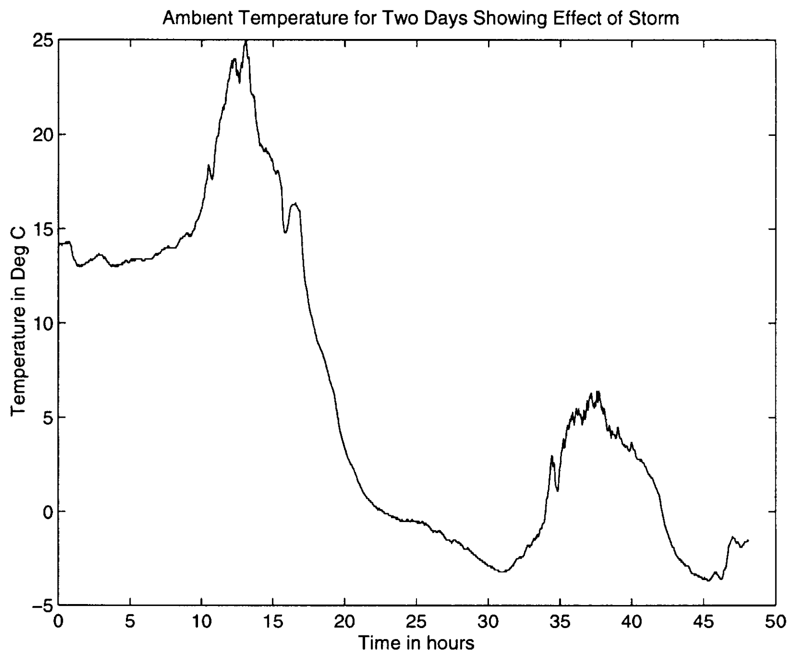


Figure 6-10: Ambient Temperature during Storm (deg C)

Appropriate Unit Conversion

As was evident in the detailed magnitude and ROC detection scheme, the raw data may be manipulated by several independent techniques before an alarm condition is reached. The direct calculations and results are meaningless to the monitoring system users. Therefore, a conversion routine is necessary to generate appropriate reporting units for use in the alarms. For example, a gas ROC might be reported to the user as an average number of ppm per day sustained for a given number of days. Specifically, the user would be informed that the gas or Hydran® 201R reading increased on average 5 ppm per day for 7 days.

6.2 Detection Examples

This section is designed to illustrate the detection scheme previously described in Section 6.1. Three examples of Magnitude Detection and one example of ROC Detection are presented. These examples are based on real transformer data and reveal the power and usefulness of the detection scheme.

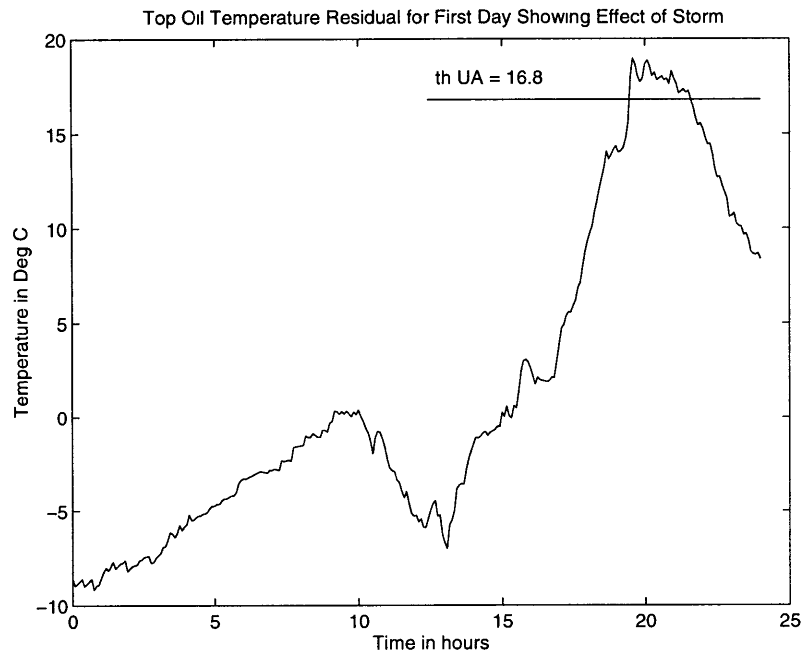


Figure 6-11: True Top Oil Temperature Residual (deg C)

6.2.1 Short Term Magnitude Detection: Top Oil Temperature Residual

Application of the proposed two-dimensional spatial/temporal detection scheme to the Top Oil Temperature Residual is as follows. One evening, with the present field-deployed single-point detection scheme, MIT, the current operator of the monitoring system, was paged every 5 minutes for over 2 hours from a 345/115kV autotransformer rated greater than 280 MVA with messages indicating that the top oil temperature residual was above the allowable 16.8°C binary threshold limit for "flag" generation. For this transformer, statistical analysis of 19 days of State 0 (OA) top oil temperature residuals, when combined with the method of setting up the residual spatial thresholds previously described, yielded $th\ UA = 16.8$ and $th\ UB = 26.8$.

Analysis by MIT revealed this was caused by a storm in which the ambient temperature (measurement) fell quite rapidly. Figure 6-10 shows a two day plot of the Ambient Temperature and Figure 6-11 shows the True Top Oil Temperature Residual for the first 24 hours of the given ambient temperature. The thermal model includes no dynamics for the effect of ambient temperature on the top oil temperature, so the top oil temperature prediction fell rapidly with ambient while the true top oil temperature fell more slowly due to thermal inertia. This problem with the IEEE Thermal Model specified in IEEE C.57.115 (1991) is thoroughly discussed in [32]. Slight violations of this type that do not increase in severity should not be reported.

In describing this example, the steps of the spatial/temporal detection scheme are followed as outlined in Section 6.1. For short term magnitude detection, the raw residuals calculated by the MIT Monitoring System are being directly used. Therefore, no Data Processing is necessary. In the Discrimination step, spatial threshold values and transition widths must be chosen for the applicable fuzzy sets shown in Figure 6-4. As previously discussed, statistical analysis yielded $th\ UA = 16.8$ and $th\ UB = 26.8$. To incorporate fuzziness as described by the proposed detection scheme, a transition width, as shown in Figure 6-5, of 3°C was chosen based on analysis of the noise in the data and the uncertainty in the measurements. For the Validation Step, a 65 minute long validation window was chosen. Alarms UA and UB are activated at levels of 0.8 and 0.4 and deactivated at a level of 0.2 for the High and Very High regions respectively.

The accumulated grade, $AG[m]$, was calculated for each region by use of Equation (6.6). Figure 6-12, Cumulative Membership Grades for the True Top Oil Temperature Residual, shows the High region for the period of interest. In this case, no alarm condition is ever reached.

In a hypothetical situation, if the top oil temperature residual had continued rising at the same rate this would have become a cause for concern. Figure 6-13 shows this hypothetical situation. With the same validation window, spatial thresholds, and transition region widths as before, the Cumulative Membership Grades are calculated and the High and Very High regions are shown in Figure 6-14.

Comparing the cumulative membership grades for the hypothetical case shown in Figure 6-14 with the true case shown in Figure 6-12, an Alarm UA activation level of 0.8 generates an alarm in the hypothetical case where the situation continues to get worse, but does not generate an alarm in the true case where there is no real problem. An Alarm UB level of

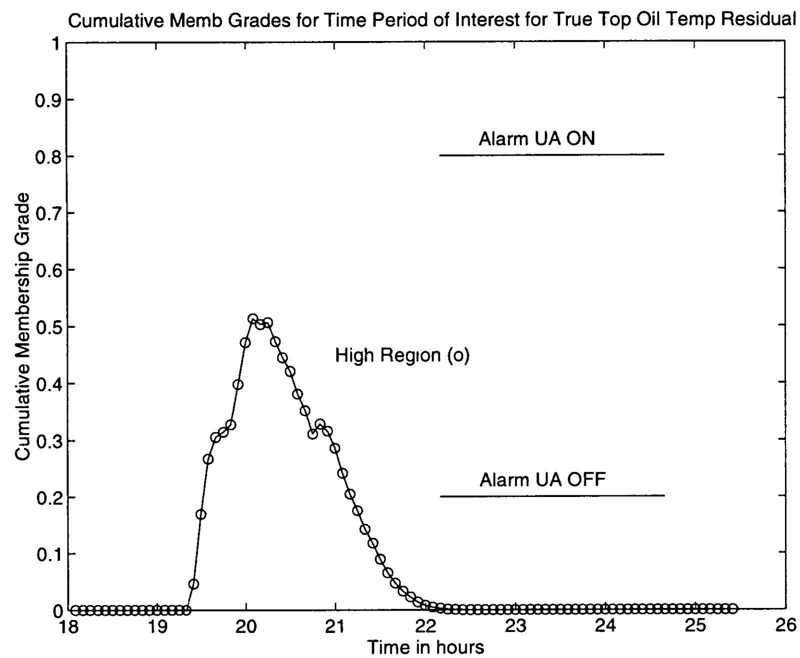


Figure 6-12: Cumulative Membership Grades for True Top Oil Temperature Residual

0.4 for the Very High region activates an even more serious "Alarm UB" an additional 75 minutes after "Alarm UA" in Figure 6-14. Eventually, Alarm UA turns OFF at a level of 0.2, while Alarm UB remains ON, signifying this situation requires attention.

The two-dimensional spatial/temporal detection scheme is a significant improvement in the intelligent performance of the current field-deployed system. It "filters" out the slight violations of the spatial threshold, while preserving sensitivity to violations that increase in severity or last for long periods of time. Based on field experience, even in situations that are increasing in severity, an intelligent delay in reporting anomalous behavior is required and actually beneficial. Oftentimes, anomalous behavior in the earliest stages cannot be analyzed due to a lack of data (information) directly related to the situation. Building in a delay allows more data to be collected by the monitoring system which makes the analysis and decision making quicker, more effective, and more accurate.

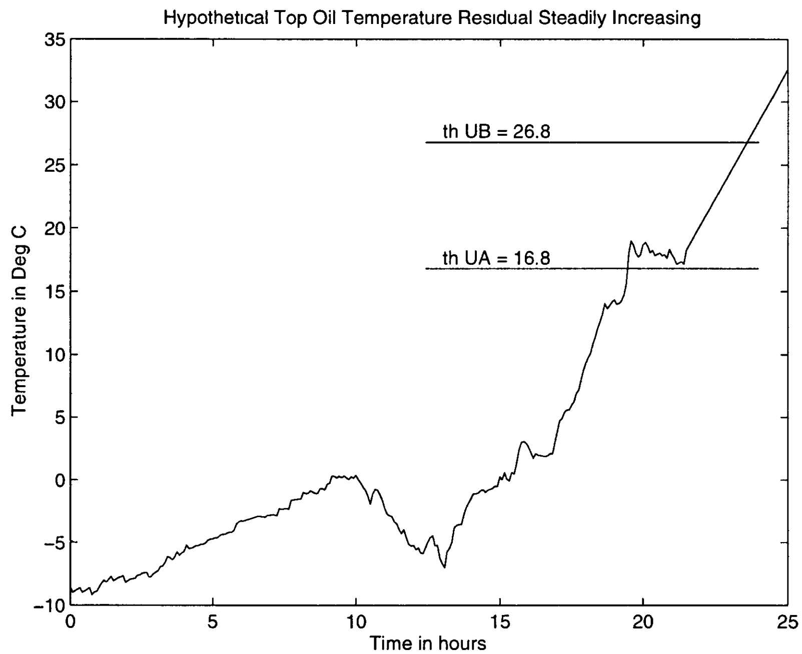


Figure 6-13: Hypothetical Top Oil Temperature Residual (deg C)

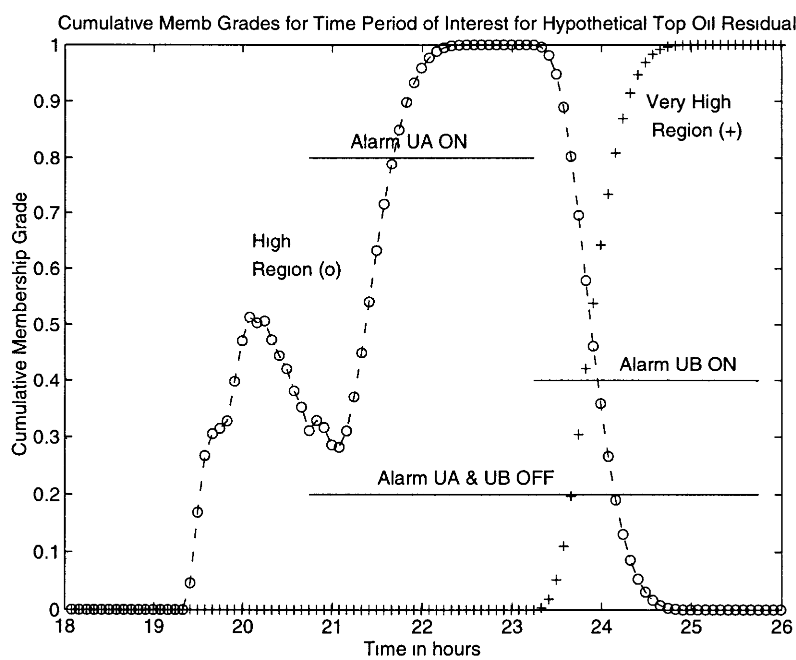


Figure 6-14: Cumulative Membership Grades for Hypothetical Top Oil Temperature Residual

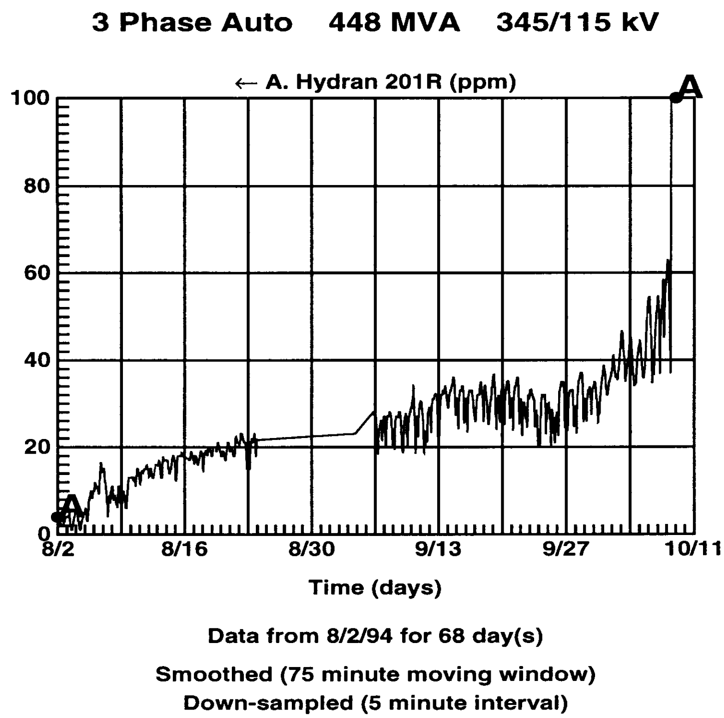


Figure 6-15: Dissolved Gas Content for Failed Transformer

6.2.2 Short Term Magnitude Detection: Gas Residual

This example and the following two examples use data recorded from a transformer that failed. Some background information is included as part of this example in order to provide a clear picture of the situation.

The raw data were recorded from a three-phase 345/115kV, 450 MVA shell-form auto-transformer with a tertiary that was not externally loaded. This transformer was energized on August 2, 1994 and operated until October 8, at which point it failed due to an arc from the center of the high side of Phase B to the bottom of the tank [5]. This transformer was fitted with a TPAS^{TM} since a similar transformer had failed just previous to the installation of this one. The TPAS^{TM} was simply taking measurements and recording the data. MIT performed a model-based analysis after the transformer failed using the TPAS^{TM} data. Figures 6-15 and 6-16 show the Dissolved Gas Content and the Composite Gas Residual, calculated from the model-based analysis, for the Failed Transformer.

The actual data collected had several problems. The data prior to August 2 were

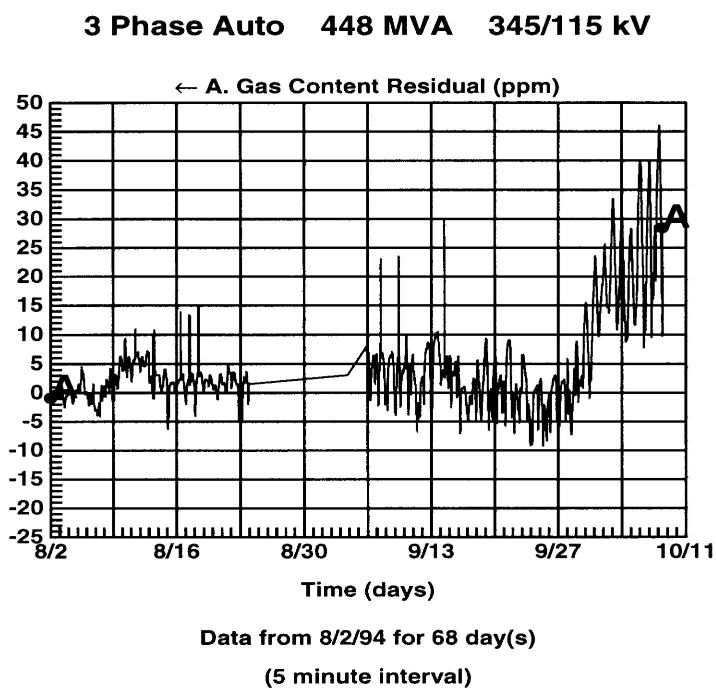


Figure 6-16: Composite Gas Residual for Failed Transformer

unusable and were discarded. For simplicity, the analysis and plots shown here start on August 2. Overall, the data were quite noisy. A start up transient is present roughly during the first 10 days. After that, the TPAS^{TM} failed to take data for about two weeks from August 24 until September 6. Once the TPAS^{TM} began collecting data again, the Hydran® 201R experienced periodic "starvation", described in Chapter 5, which was evident until the failure. A through-fault had occurred in mid-September and it is hypothesized that the through-fault caused a distortion of the winding and a disruption of its insulation. The resulting tracking caused both production of combustible gases and the eventual failure a few weeks later. The overall Hydran® 201R reading and gas residual began drifting upward almost two weeks prior to the failure as evidenced by the data.

In this case, the combustible gas content as measured by the Hydran® 201R sensor, did not reach very high levels prior to the actual failure. As seen in Chapter 2, for this particular utility, when monthly transformer surveys reveal Hydran® 201R readings less than 100 ppm, there is no follow-up procedure. Even for readings between 100 and 200 ppm the normal procedure is to monitor the Hydran® 201R with two surveys per month rather than the normal monthly survey. Only for readings over 200 ppm, is an oil sample typically requested. Typically utility personnel would not be concerned about the 60 ppm readings that occurred immediately prior to the failure. Since a similar unit in the same location had just failed, it was felt that this one should be watched more carefully than prescribed by these normal procedures. Periodic Dissolved-Gas Analysis (DGA) results were being studied for possible gas generation. The utility consulted the manufacturer who deemed the transformer fine the afternoon before the failure. Therefore, a reasonable conclusion here is that traditional testing techniques are unable to pick up this sort of incipient failure [5].

The gas residual is useful in detecting anomalous changes in the dissolved gas content of the oil that might not necessarily be detected by the Hydran® 201R reading alone. As discussed in Chapter 3, a positive residual indicates that the gas content of the oil is "too high" based on the present ambient and operating conditions.

Following the steps in the spatial/temporal detection scheme, the setup parameters are now defined. For this transformer, statistical analysis using every gas residual from September 4 through the 18th yielded $th\ UA = 15.0$ [5]. For simplicity of illustration purposes, no value was set for $th\ UB$, although in practice one could be implemented. The data used in the calculation contains points from the period after the initial asymptotic rise in the gas content, but before the evolution of the incipient failure. A transition width of an additional standard deviation, approximately 3.75 ppm, was chosen. This was based on uncertainty in the measurements, noise in the data, and what seemed practical. For short term magnitude detection, a 65 minute long validation window was used. Alarm UA is activated at a level of 0.8 and deactivated at a level of 0.2 for the High region. Since no value was set for $th\ UB$, no Alarm UB is implemented.

Close observation of Figure 6-16 shows three spikes in early September that violate $th\ UA$. These were associated with cooling state changes as shown in Figure 6-17. Figure 6-18 shows the Gas Residual for days 58 to 63 after energization. This is the first period in which the spatial threshold ($th\ UA$) was violated for more than one point. The accumulated membership grades for the High region are calculated and shown in Figure 6-19. The one

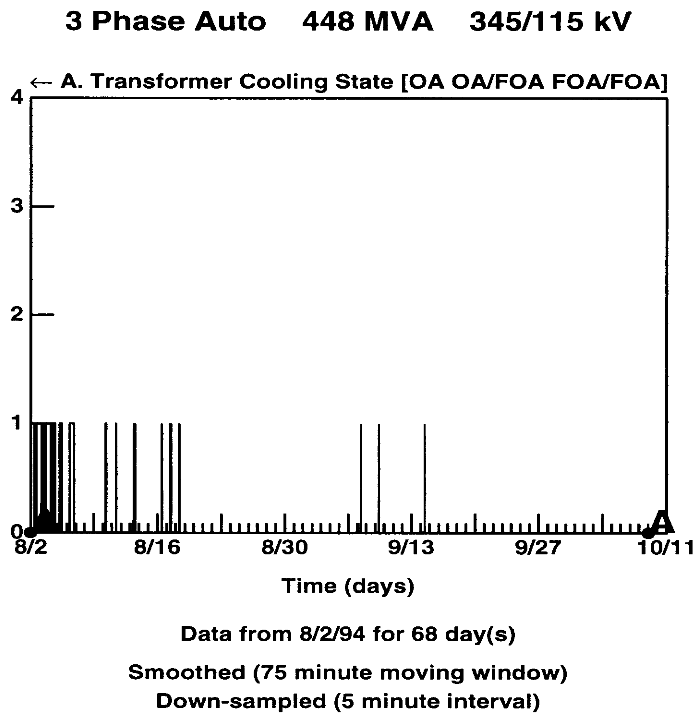


Figure 6-17: Cooling State for Failed Transformer

point spikes in early September barely affect the cumulative membership grade for the High region and certainly do not trigger an alarm. Even the minor gas residual violation that occurs on the 59th day has very little effect on the cumulative membership grades and does not activate an alarm. Field experience with the pagers shows that even at this point, there is not enough information from which a conclusion can be drawn.

An Alarm UA level of 0.8 generates the first alarm on the 60th day. The gas residual stays in the alarm condition for approximately 8 hours before dropping out of alarm at a level of 0.2 as shown in Figure 6-19. On the 60th day, the operator would be alerted and then would likely proceed with an off-line analysis of the event. This alarm occurs 8 days prior to the actual failure. From the 60th day until the 68th day, the alarm toggles between the ON and OFF state due to the thermal sensitivity of the Hydran® 201R sensor and oil flow starvation. This causes the magnitude of the gas residual to cycle periodically on a daily basis, which ultimately affects the accumulated membership grades in a similar manner.

This short-term magnitude detection should be considered an early warning mechanism.

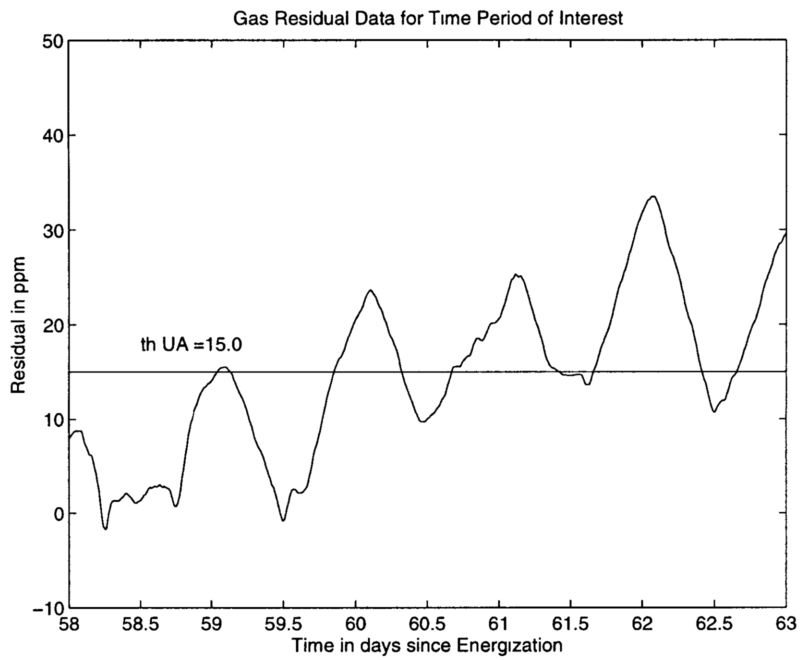


Figure 6-18: Gas Residual for 5 Days: Failed Transformer

Due to the periodic nature of the signals, a short term magnitude alarm may clear, although a critical situation exists or is developing. All alarms of this type must be investigated and then correlated with any additional alarms and information derived from off-line analysis.

6.2.3 Long Term Magnitude Detection: Gas Residual

In this example, the gas residual from the failure data is being used for longer term magnitude detection than in the previous example. Longer term magnitude detection avoids the problems associated with the daily load and temperature cycle of transmission system transformers tied closely to the distribution system, noise in the data, and the actual spatial threshold settings. It also eliminates the situation in which "Alarms" are going ON and OFF which can be annoying and give a false sense of security. In certain instances, the situation appears to be getting better or is again "Normal" when the alarm goes OFF, although overall, this is not the case.

Within reasonable interpretation, most transmission system transformers tied closely to

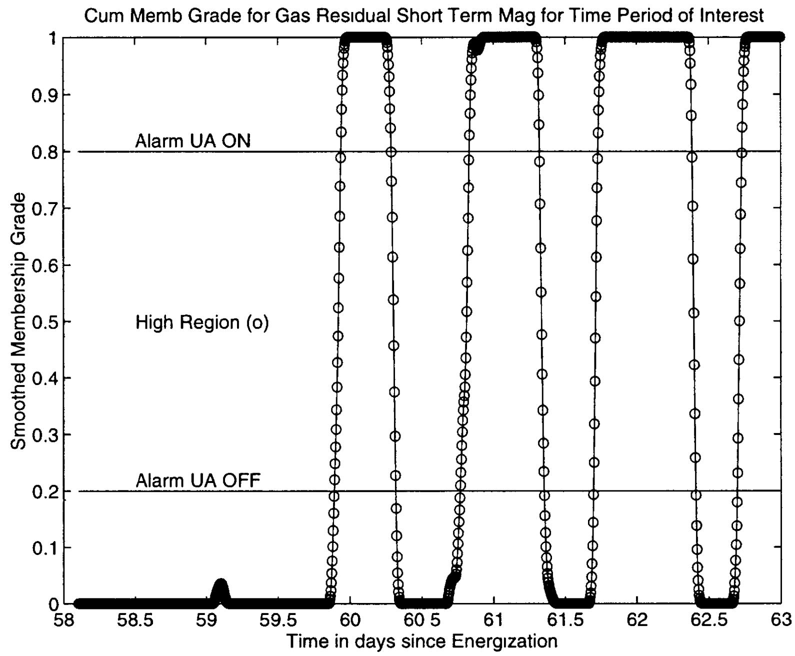


Figure 6-19: Short Term Cum. Memb Grades for Gas Residual Magnitude: Failed Transformer

the distribution system have signals, exclusive of cooling state, that are periodic in nature. This includes the transformer and model inputs, namely the primary current and ambient temperature, as well as the outputs, namely the top oil temperature and residual, the Hydran® 201R reading and gas residual, and the Hydran® 201R oil temperature.

Therefore, for these transmission system transformers, the overall change in a periodic transformer related signal in any 24 hour period has a central tendency or an expected value of 0. In other words, the mean takes on a constant value that should not exhibit statistically significant changes on a daily basis. Slight variations can be explained by weather conditions, cooling state changes, estimation and installation of new sets of model parameters, etc. A more noticeable variation, termed weekend effect, occurs on Saturdays, Sundays, and holidays. Typically on these days, a lower load results in lower mean temperature and gas measurements than normally occurs on weekdays. Re-occurring abnormal changes could be indicative of a serious problem and warrants further analysis and investigation.

Due to the daily variation in the gas residual, a 24 hour mean gas residual value is

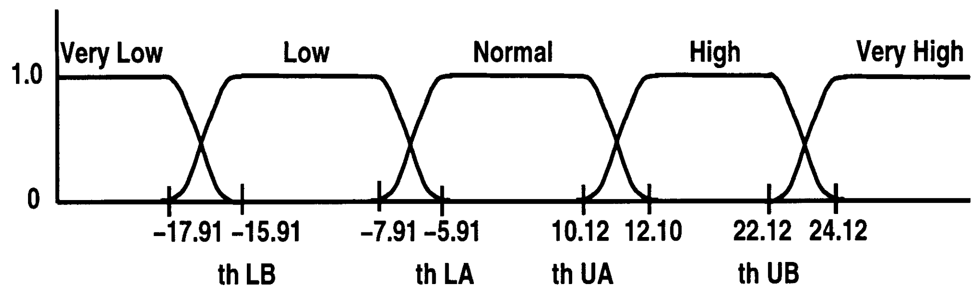


Figure 6-20: Membership Function for Long Term Magnitude

computed and used. This value is calculated every 3 hours based on the previous 24 hours of gas residuals sampled every 5 minutes. Any 24 hour period removes the daily cycle. Therefore, the expected value of any 24 hour gas residual mean is zero. Sampling every 3 hours generates eight 24 hour mean gas residual values per day.

Figure 6-21 shows the Gas Residual 24 hour mean estimated every 3 hours. The "one day start up" and the "no data" periods are appropriately labelled. From the data available and estimating every 3 hours, there were a total of two hundred twenty nine 24 hour means prior to the 60th day after energization. Statistical analysis yielded the mean value of these points to be 2.1032 and the standard deviation was 2.0038. Here $th\ UA = 10.12$ which was set at the mean value plus four standard deviations (2.1032 + 4∗2.0038) and $th\ UB = 20.12$ was set 10 ppm higher as shown in the plot. A transition width of 2.0 ppm was chosen since it represented approximately one additional standard deviation. By relating these numbers to the membership function for long term magnitude detection, the fuzzy sets take on a form shown in Figure 6-20. Here the Normal region extends all the way to 12.12 while the High region starts at 10.12, with a resulting overlap of approximately 2.0, as given by the transition region. The High region extends from 10.12 to 22.12 while the Very High region starts at 20.12 and goes until infinity.

A 25-point (72 hour) long normalized sigmoid validation window was used and is shown in Figure 6-22. Figure 6-23 shows the Cumulative Membership Grades for the Normal, High, and Very High regions. An Alarm UA level is set at 0.8 and is reached on the 61st

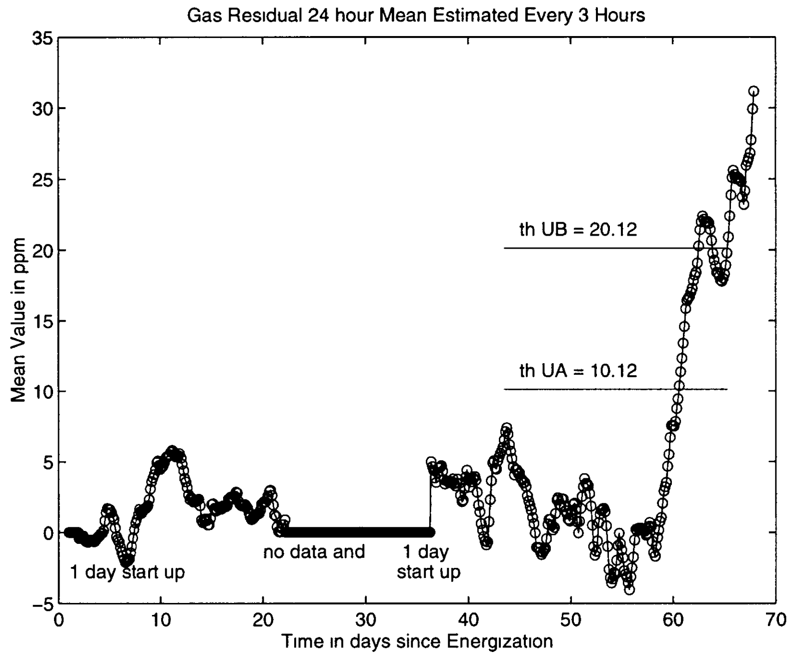


Figure 6-21: 24 Hour Gas Residual Average Magnitude: Failed Transformer

day. An Alarm UB level for the Very High region is set at 0.3. Both Alarms UA and UB clear at a level of 0.2. These Alarm levels were chosen based on experience with magnitude detection, the particular region, and the amount of delay desired before an alarm condition is reached.

It is interesting to note the effect of the two weekend days, September 24 and 25th, occurring on day 62 and 63 after energization. The magnitude of the mean values corresponding to the weekend are noticeably reduced as shown in Figure 6-21. This in turn drastically affects the cumulative membership grade for the High and Very High regions. Alarm UB occurs during day 62, indicating the situation is getting worse. But due to the weekend having a huge effect, Alarm UB turns OFF at the start of the 64th day, while Alarm UA has remained ON since the 61st day and never reaches a condition to be turned OFF.

This longer term magnitude detection can be adjusted accordingly to minimize the effect of the typical weekend loading patterns. A longer smoothing window can be used, although this puts more delay into the system in reaching certain alarm conditions. This longer term

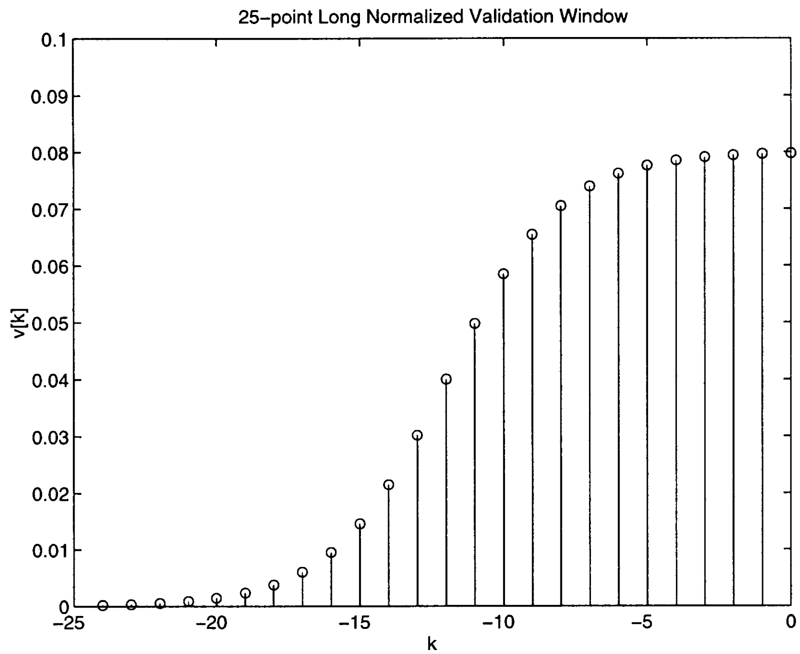


Figure 6-22: 25-point Normalized Validation Window

magnitude detection does eliminate the need for "peak" detection caused by the very short term magnitude detection which results in alarms going ON and OFF.

6.2.4 ROC Detection: Gas Residual

In this example, the ROC of the gas residual is useful in detecting anomalous changes in the gas content of the oil. A positive ROC of this residual signifies an increasing gas content, which can be indicative of especially serious problems. This example uses the gas residual data computed from the failed transformer previously discussed.

Setting up the parameters in the detection scheme for ROC detection is the most critical step in this example. Close observation of the gas residuals shows a quite noticeable daily cycle due to the thermal effects of the Hydran® 201R sensor and oil flow starvation. Based on experience with ROC detection, the short term noise and daily periodic variation must be removed from the data. This was accomplished in the data filtering step of the detection process by averaging data collected every 5 minutes over a 24 hour period, in order to

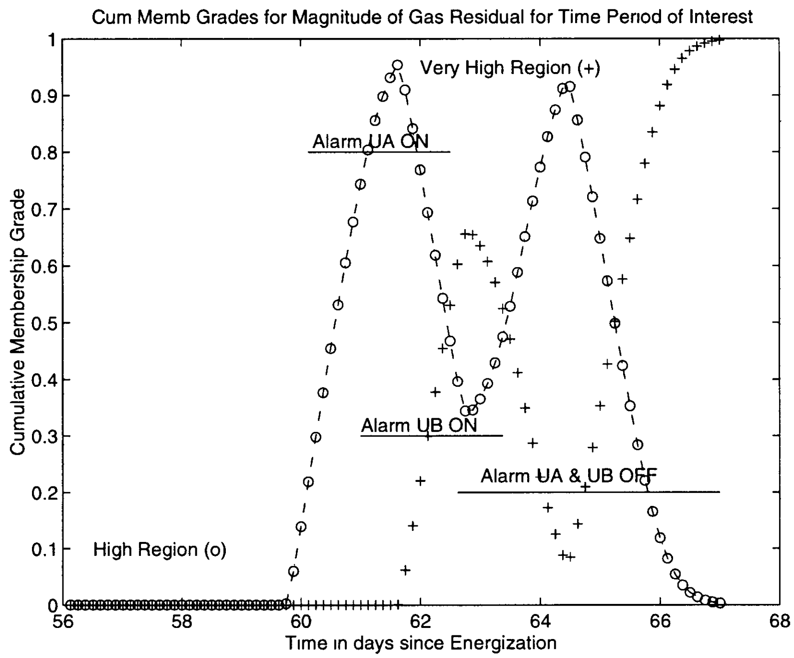


Figure 6-23: Cum. Memb grades for Gas Residual Magnitude: Failed Transformer

calculate the mean value for that 24 hours. A mean is computed every 3 hours based on the previous 24 hours of gas residuals. In essence, a moving average calculation is taking place.

At this point, a two-point ROC was calculated using Equation (6.1). This became the trickiest part in obtaining a meaningful ROC. In addition to the predominant daily variation, there is also a more subtle weekly variation that is not as strong as the daily one. This is evident in the gas residual plot as well as from off-line spectral analysis. If this is not handled correctly, the resulting ROC can be misleading. The optimal decision was to effectively, yet indirectly, remove the weekly cycle. Careful analysis proved that "like" days must be compared, or in other words, ROC must be calculated on multiples of 7 days. Otherwise, holidays and weekends cause a skewing of the data.

For example, the gas residual mean value calculated at noon 7 days ago, $F[k-l] = F[-56]$, is subtracted from the mean value calculated at noon today, $F[k] = F[0]$, and then divided by $ClT = 7$, to obtain the sustained ROC per day for one week as given by Equation (6.1). These 7 day ROC of the mean values are calculated every 3 hours, yielding

8 points per day. An eight day start up period is needed to produce the first ROC point, after which a new ROC value is calculated every 3 hours.

Figure 6-24 shows the 7 Day ROC of the Gas Residual Mean sustained for 7 days. For example, at 60 days after energization, the value is 3.5 ppm. This means that on average, a 3.5 ppm change per day has been sustained for the past 7 days. It is interesting to note the sudden increase from -0.8 to 3.7 in the ROC between day 58 and 62. The "eight day start up" and "no data" periods are appropriately labelled. The large swings in the magnitude are attributed to starvation.

Spatial thresholds were selected for the Abnormal Decrease, Normal, and Abnormal Increase regions for the ROC based on statistics using all of the available data up until eight days prior to the failure. There were 244 ROC of the daily mean values that met this criteria. The mean of the ROC values was calculated to be -0.0466 and the standard deviation was 0.4606. The Normal region was defined to be between -1.8 and 1.8. Figure 6-24 shows the upper threshold labeled as $th\ UA = 1.8$. A transition width of 0.46 ppm, or one additional standard deviation was chosen. From this Figure, only 2 points fall within the transition region. For this particular data set, the Hydran® 201R heater was on for the entire period. This resulted in the very small standard deviation. In reality, the limits cannot be set this tight since they would have to be updated every time the Hydran® 201R heater was turned off or on.

Figure 6-25 shows the Cumulative Membership Grades for the Gas Residual ROC for the Normal and Abnormal Increase regions. This is based on a 3-point sigmoid validation window. Three points were chosen since a tremendous amount of smoothing and delay was incorporated in the Individual Membership Grades, spaced three hours apart, that it would be unwise to build in much more delay. The Alarm UA activation and deactivation levels are set at 0.8 and 0.2 respectively as shown in the Figure. This can be achieved by several different scenarios or avoided for slight spatial threshold violations that immediately decrease.

The important consequence is that on the 60th day after energization (October 1), an Alarm UA for the ROC on the gas residual would have been raised. This is approximately 8

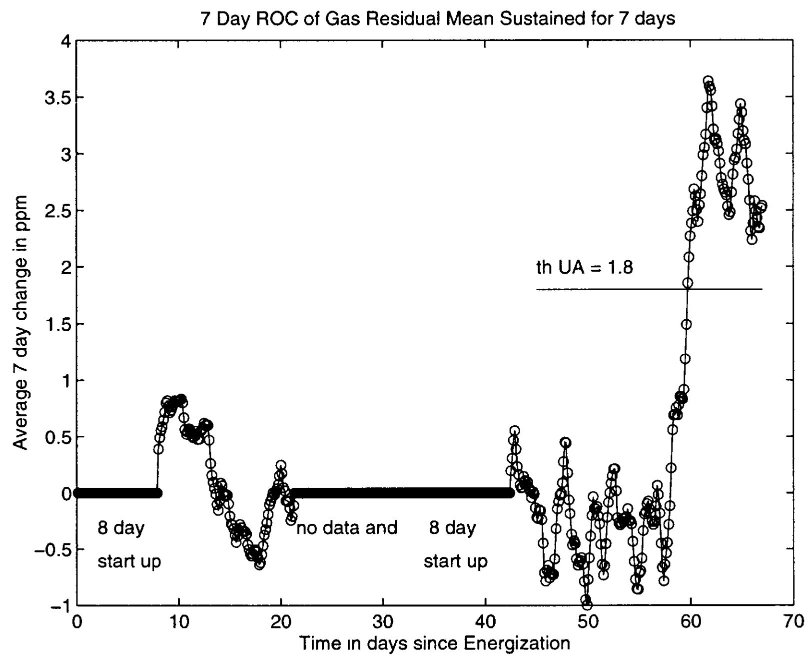


Figure 6-24: Sustained Gas Residual ROC for 7 Days: Failed Transformer

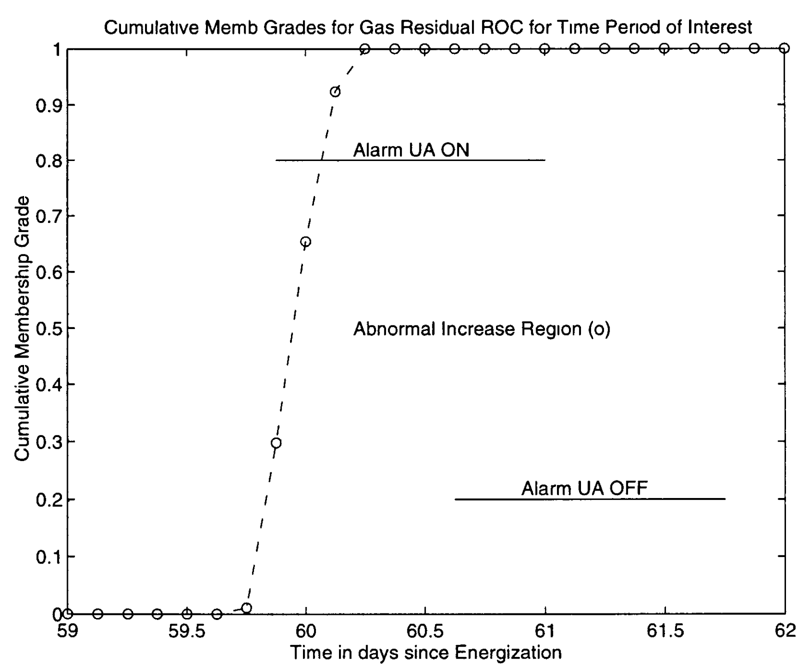


Figure 6-25: Cum. Memb. Grades for Gas Residual ROC: Failed Transformer

days prior to the actual failure (October 8). The alarm message would have indicated that the gas residual (ROC) had been increasing on average 2.5 ppm per day for the previous 7 days. This represents an overall change in the gas residual of 17.5 ppm during the previous week. Once the alarm condition is reached, it never clears prior to the failure. The gas residual ROC reaches a maximum value of 3.7 ppm per day for 7 days on the 62nd (October 3) and then oscillates between 2.5 and 3.5 ppm until the failure. The magnitude and frequency of this oscillatory behavior is similar to that experienced during the first 60 days. Therefore, one should not assume that the situation is improving at any point. As evidenced by Figure 6-25, the Cumulative Membership Grade for the Abnormal Increase region rises quickly to the maximum value of 1.0, on the 60th day (October 1) and remains there until the failure occurs.

Close observation of the Dissolved Gas Content (Hydran® 201R readings) does not reveal anything abnormal on the 60th day after energization, although a definite upward trend is visible after that day. An expert's examination of this data might have led to some concern, although it is costly and not an automatic method for generation of alarms. At no time did the Dissolved Gas Content reach even remotely high levels by either typical transformer or utility standards. Since this transformer had not been in service very long, it is hard to specify exactly what the average gas content value should have been. The gas residual provides a level of sensitivity that is not possible with the "raw" Hydran® 201R readings. When a well thought out ROC for the gas residual is implemented, a level of sensitivity, even in the face of very noisy data as well as daily and weekly transformer cycles, is obtained that is not possible with the "raw" Hydran® 201R readings.

This eight day early warning for the utility would have provided sufficient time for additional off-line tests and procedures. The ROC alarm then could be correlated with the alarms raised from the short and long term magnitude detection methods. Appropriate utility action could have avoided irreversible and severe damage to the transformer and surrounding environment. It must be emphasized that the utility did not have this type of on-line information from which to make decisions. They were relying only on periodic Dissolved Gas Analysis (DGA) results and raw data from the TPAS^{TM}.

6.3 General Detection Runs

Section 6.2 illustrated the potential power and usefulness of the proposed detection scheme for specific examples. In order to verify its general capability and usefulness, this section describes evaluations of the proposed scheme based on several criteria for two different transformers presently under surveillance. First, the two schemes are compared based on the number and types of events that are detected. Second, the sensitivity of the two schemes for residual magnitude and ROC detection is examined by tightening the spatial thresholds based on statistical analysis of the underlying data and then by determining and comparing the total number of events detected for different threshold settings.

6.3.1 General Detection Run Setup

Two transformers from different manufacturers were chosen for the general detection run. The test run data consisted of a 6-month period of data from each transformer. The transformers and data sets chosen represented the "best" and "worst" possible scenarios for the monitoring and detection system. The initial data was validated in the sense that no significant amount of data was missing from each of the 6-month periods and that the transformers were not taken out of service during the selected periods. This ensured that the detection scheme would not need to be reinitialized or reset during each test run.

Only the two residuals (gas and top oil temperature) were individually and independently evaluated for magnitude and ROC detection. In practice, the five measurements (top oil temperature, Hydran® 201R oil temperature, Hydran® 201R reading, primary current, and ambient temperature) will consist of a magnitude and a ROC calculation for use in detection and in other stages of the diagnostic process. The measurements are not being evaluated here since there are relatively few flags generated by them and the proposed detection scheme has been shown to eliminate all flags generated by spurious readings, while detecting gross sensor failures and other events that require attention. Therefore, there is no benefit in setting up and evaluating the detection scheme for the test data runs involving the measurements.

Detection of an "event" occurs if any flag or sets of flags result from the point-wise detection scheme or if any alarm or sets of alarms result from the proposed detection scheme. A separate count of events is made for each residual for magnitude and ROC detection as they are evaluated by the two detection schemes. Individual flags and alarms are not counted, but what is counted is the number of events the flags and alarms correspond as long as the occurrences are clearly separated in time, which is defined to be approximately 30 minutes for counting purposes. Therefore oscillations about a threshold or level will not result in an overestimation of the number of events. Although if the same event occurs several times per day, each occurrence will be counted as a separate event, as long as the occurrences are clearly separated in time. In the ideal monitoring system, an alarm (or flag) processor will be included to filter continuously reoccurring alarms. The human will be able to acknowledge the alarms and to adjust how often they are notified of alarms that continue or worsen.

Any resulting flags or alarms signifying events can be traced back to or related to an underlying cause(s). Presently this capability requires human interaction with the monitoring system. The underlying cause may be a transformer failing, sensor malfunction or failure, bad model parameters, weather, cooling state changes, etc. One underlying cause may result in event detection by more than one method (magnitude or ROC) and by more than one measurement (top oil temperature, Hydran® 201R oil temperature, Hydran® 201R reading, primary current, and ambient temperature) or residual (gas and top oil temperature). Therefore a separate count of events is made for each combination of method and residual.

Section 6.1 described the use of multiple threshold settings and alarm levels for providing varying degrees of information concerning the seriousness of the anomaly. For the general residual magnitude and ROC detection runs in this section, only thresholds LA and UA for point-wise detection and Alarms LA and UA for proposed detection are specified. Specification of additional levels (LC, LB, UB, UC, etc.) results in no change in the number of detected events. Additional levels only indicate the degree of seriousness and perhaps source of the event. For simplicity of the test routines, the Alarm ON and OFF levels are identically set. Oscillations of alarms (rarely encountered in the test runs) about these levels

Sensors	*Type/Description*	*Station 211* *Tr. 345A*	*Station 509* *Tr. 345A*
Primary Current	Auxiliary CT	√	√
Ambient Temp	RTD	√	√
Top Oil Temp	External RTD	√	√
Loop Oil Temp	RTD	√	√
Winding Temp	Luxtron Fiberoptic Probes		√
Dissolved Gas	Hydran® 201R	√	√
Cooling State	Breaker Closure Contacts	√	√
Tertiary Breaker Closure	Breaker Closure Contacts		√

Table 6.2: Sensors Installed for Transformer 345A, Stations 211 and 509

is manually examined to aid in the event count. In practice, hysteresis will be included in order to prevent alarm oscillations.

The point-wise detection scheme of the present field-deployed system should presumably detect all events requiring attention due to the extreme sensitivity of the technique. Therefore point-wise detection provides virtually 100% (although this cannot be verified) detection of events, but also results in numerous false positives, as evidenced by the field installations. Detection of positives (events) is far from definitive in regard to establishing that the detected event warrants further attention. In fact, based on experience, the event most likely requires no further analysis or human intervention. The detection of false positives is a severe nuisance and "crying wolf" too often can ultimately result in a monitoring system that will be completely ignored. The proposed detection scheme will retain an almost identical level of sensitivity to that of the point-wise detection scheme while cutting down on the number of false positives, although it may also result in a small number of undetected positives (false-negatives). A thorough discussion of general detection issues in high voltage engineering can be found in [13].

6.3.2 Transformer #1 (BECo Station 211, Transformer 345A)

The first transformer, a 3-phase 345/115 kV core-form autotransformer, is in a critical location in Boston Edison Company's (BECo) transmission system. It is triple rated,

Data Processing	*Value*	*Descriptor(s)*
Sampling Period (T)	5	min
Data Filtering	–	none
ROC Calculation	–	none
Spatial Classification	*Value*	*Descriptor(s)*
Fuzzy Sets (s)	3	low, normal, high
Mean ($\overline{R}_{gas}$)	0.02	ppm
Standard Deviation ($\sigma_{R_{gas}}$)	1.91	ppm
Transition Region (width)	$\sigma_{R_{gas}}$	ppm
Transition Region (shape)	S	sigmoid
Temporal Classification	*Value*	*Descriptor(s)*
Validation Window (V[k]) (length)	25	25 points (120 min)
Validation Window (V[k]) (shape)	S	sigmoid
Alarm Generation	*Value*	*Descriptor(s)*
Alarm Level LA	0.8	low
Alarm Level UA	0.8	high

Table 6.3: Station 211 Detection Setup Parameters: Gas Residual Magnitude

270/360/450 MVA, OA/FOA/FOA, for 65°C rise over ambient. It has a 13.8 kV tertiary winding that is used for circulating current control, although the winding is not accessible from the outside. The transformer was manufactured by Asea Brown Boveri (ABB) and put into service on December 29, 1995. It has been continuously monitored by the MIT monitoring system since this time.

The transformer is just over two years old and is typically operated near its maximum OA rating. Therefore, the cooling rarely comes on even in the summer months. The adaptive mathematical models work as well as can be expected while the J. W. Harley^{TM} DAS and accompanying sensors, shown in Table 6.2, rarely experience problems. Overall, this transformer and monitoring system are well behaved. The result is that relatively few "flags" or error messages are generated by the monitoring system.

The data to be analyzed was taken from the period of January 1 until June 30, 1997. Typically the fewest problems occur during that time of the year due to the loading patterns and accompanying cooling states. Before setting up the general run for the proposed detection scheme, the "errors" file, described in Chapter 3, for this transformer was manually

th UA and th LA	*Gas Residual Magnitude*	*Point-Wise (number)*	*Proposed (number)*	*Reduction (%)*
$\overline{R}_{gas} \pm 4\sigma_{R_{gas}}$	Positives (Events)	14	3	78.6
	False Positives	0	0	0
	Undetected Positives	0	0	0
$\overline{R}_{gas} \pm 3\sigma_{R_{gas}}$	Positives (Events)	37	9	75.7
	False Positives	–	–	–
	Undetected Positives	–	–	–
$\overline{R}_{gas} \pm 2\sigma_{R_{gas}}$	Positives (Events)	219	70	68.0
	False Positives	–	–	–
	Undetected Positives	–	–	–

Table 6.4: Station 211 Comparison and Sensitivity of Methods: Gas Residual Magnitude

examined in order to get an idea of the number of and types of problems that occurred during the 6 month period. This was also done in order to ensure that the data from the chosen period was valid, meaning that no significant amount of data was missing.

Observation of the "errors" file revealed several important messages. On April 6, during the daylight savings time change, no data was or could be recorded during the hour in which the clocks were set ahead. "No New Data" messages were recorded in the file, followed immediately by "New Data" messages. Therefore one hour of data starting at 2 a.m. appears to be missing, although in reality data was still being recorded. On May 14, the monitoring system was shutdown for maintenance for one hour and fifty five minutes, resulting in no data being received or recorded during this time. In total, there was approximately 3 hours of missing data from the 6 month period. This did not appear to be a significant problem in setting up and evaluating the detection schemes. On June 12, the Hydran® 201R heater was turned off due to continuing starvation of the sensor.

All five measurements were within normal ranges during the period. The top oil temperature, Hydran® 201R oil temperature, primary current, and ambient temperature did not exceed their respective preset thresholds used by the monitoring system to detect abnormal levels. Only the Hydran® 201R reading exceeded its believable range (0 to 2000 ppm) once, with a reading of 2138 ppm on May 12, which was due to an operator testing and replacing the Hydran® 201R display.

The two residuals were also within the somewhat arbitrarily set normal ranges during the period and did not exceed their respective preset magnitude thresholds. The residual thresholds in the monitoring system were intentionally set wide enough to avoid numerous "flags" from being generated. There were a few gas residual ROC "flags" that resulted from cooling state changes.

The proposed detection scheme is most useful for residual magnitude and ROC detection. Since there were no real problems with the measurements for magnitude and ROC detection, no analysis was done. To better evaluate the proposed scheme, basic statistics (mean and standard deviation) for the top oil and gas residuals were computed using all residuals from the 6 month period in order to systematically re-set the spatial thresholds that were somewhat arbitrarily set in the field-deployed system. Since it is difficult to compare the weekly ROC with the point wise rate of change method presently implemented in the field-deployed system, no direct comparison will be made here.

Choices for the proposed detection scheme parameters were discussed extensively in Sections 6.1 and 6.2. Therefore the actual choices will not be justified, but will be explained in detail when necessary.

Figures 6-26, 6-27, and 6-28 show the gas residual for the period of interest separated into two month periods. Table 6.3, Station 211 Detection Setup Parameters: Gas Residual Magnitude, shows the values either calculated or chosen for the four major detection scheme steps shown in Figure 6-2. This Table lists the four steps as Data Processing, Spatial Classification, Temporal Classification, and Alarm Generation and should be self-explanatory. Analysis of the gas residual for the entire data set, yielded a mean value, denoted by $\overline{R}_{gas}$, of 0.02 ppm and a standard deviation, denoted by $\sigma_{R_{gas}}$, of 1.91 ppm. This residual or error term is zero centered as expected and has relatively little variation about the mean. Therefore the raw gas data and the model prediction were always very closely matched for the six month period. Since the Hydran® 201R heater was on for all but eighteen days of the period, the data was very good and more stable than for other periods in which the Hydran® 201R heater is off. This resulted in the small standard deviation noted above.

Table 6.4, Station 211 Comparison and Sensitivity of Methods: Gas Residual Magnitude,

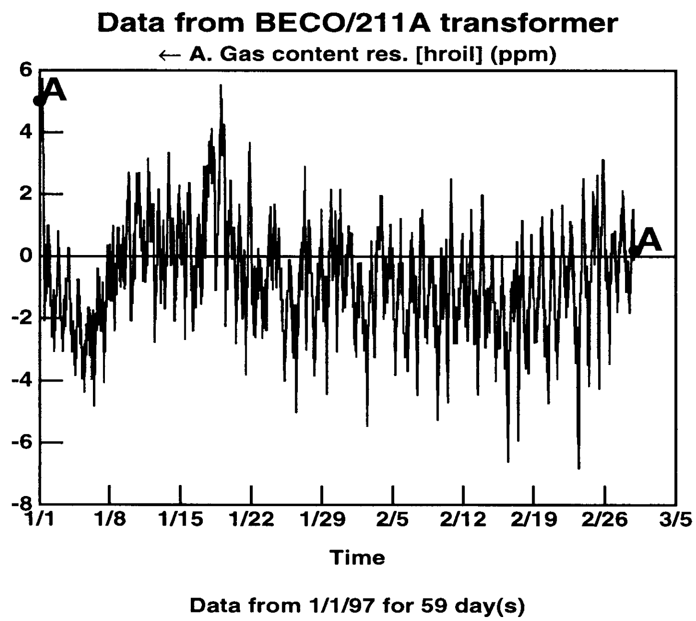


Figure 6-26: Station 211: Composite Gas Residual for January and February 1997

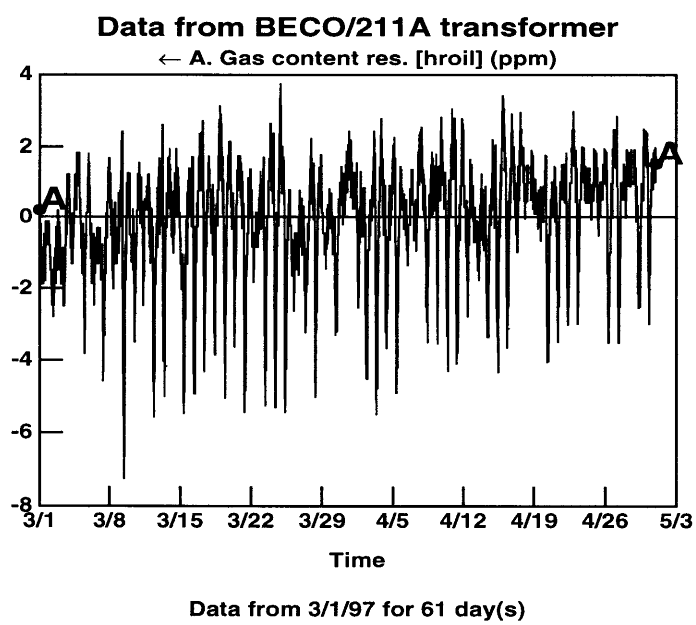


Figure 6-27: Station 211: Composite Gas Residual for March and April 1997

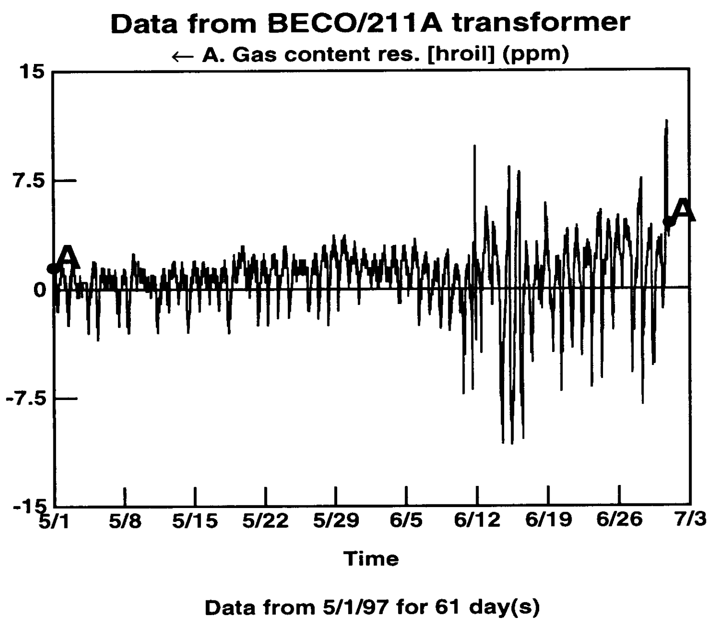


Figure 6-28: Station 211: Composite Gas Residual for May and June 1997

compares the sensitivity of the point-wise to the proposed detection scheme in detecting events. To test the sensitivity, the upper and lower spatial thresholds were set at the mean residual value, plus or minus two, three, and then four standard deviations. The number of positives (events), false positives, and undetected positives were tabulated for both schemes when appropriate and are shown in the Table. At tighter threshold settings, it becomes increasingly more difficult to distinguish between false positives and positives. Therefore, no direct measure is included in the Tables from here on out. There is a clear reduction in the number of false positives with the proposed method by an order of approximately 70% for all threshold settings. The 3 positives (events) detected at the mean plus four standard deviation setting, were due to Hydran® 201R sensor starvation and can be considered a signal for turning the heaters off. They are not considered false, since they indicate a sensor failure for a prolonged period. In comparison, for the point-wise scheme, 14 positives were detected at the same level, but the majority represented very brief periods of sensor starvation that the human would not be interested in.

The ROC method described extensively in Section 6.2.4 was used as a guide to set up

Data Processing	*Value*	*Descriptor(s)*
Sampling Period (T)	5	min
Data Filtering	24 hour mean	ppm (calculated every 3 hours)
ROC Calculation	7 day change	ppm (calculated every 3 hours)
Spatial Classification	*Value*	*Descriptor(s)*
Fuzzy Sets (s)	3	abnorm decr, normal, abnorm incr
Mean ($\overline{ROC}_{R_{gas}}$)	0.14	ppm
Standard Deviation ($\sigma_{ROC_{R_{gas}}}$)	1.06	ppm
Transition Region (width)	$\sigma_{ROC_{R_{gas}}}$	ppm
Transition Region (shape)	S	sigmoid
Temporal Classification	*Value*	*Descriptor(s)*
Validation Window (V[k]) (length)	3	3 points (6 hours)
Validation Window (V[k]) (shape)	S	sigmoid
Alarm Generation	*Value*	*Descriptor(s)*
Alarm Level LA	0.8	abnormal decr
Alarm Level UA	0.8	abnormal incr

Table 6.5: Station 211 Detection Setup Parameters: Gas Residual ROC

th UA and th LA	*Gas Residual ROC*	*Proposed*
$\overline{ROC}_{R_{gas}} \pm 4\sigma_{ROC_{R_{gas}}}$	Positives (Events)	0
	False Positives	0
	Undetected Positives	0
$\overline{ROC}_{R_{gas}} \pm 3\sigma_{ROC_{R_{gas}}}$	Positives (Events)	0
	False Positives	–
	Undetected Positives	–
$\overline{ROC}_{R_{gas}} \pm 2\sigma_{ROC_{R_{gas}}}$	Positives (Events)	4
	False Positives	–
	Undetected Positives	–

Table 6.6: Station 211 Sensitivity of Proposed Method: Gas Residual ROC

Data Processing	*Value*	*Descriptor(s)*
Sampling Period (T)	5	min
Data Filtering	–	none
ROC Calculation	–	none
Spatial Classification	*Value*	*Descriptor(s)*
Fuzzy Sets (s)	3	low, normal, high
Mean ($\overline{R}_{gtoil}$)	0.61	°C
Standard Deviation ($\sigma_{R_{gtoil}}$)	3.60	°C
Transition Region (width)	$\sigma_{R_{gtoil}}$	°C
Transition Region (shape)	S	sigmoid
Temporal Classification	*Value*	*Descriptor(s)*
Validation Window (V[k]) (length)	25	25 points (120 min)
Validation Window (V[k]) (shape)	S	sigmoid
Alarm Generation	*Value*	*Descriptor(s)*
Alarm Level LA	0.8	low
Alarm Level UA	0.8	high

Table 6.7: Station 211 Detection Setup Parameters: Top Oil Temp Residual Magnitude

the detection scheme parameters in Table 6.5, Station 211 Detection Setup Parameters: Gas Residual ROC. Analysis of the data yielded a mean, $\overline{ROC}_{R_{gas}}$, of 0.14 ppm and a standard deviation, $\sigma_{ROC_{R_{gas}}}$, of 1.06 ppm. This shows that little change in the gas residual occurs over a weekly time frame for the six month period. As shown in Table 6.6, Station 211 Sensitivity of Proposed Method: Gas Residual ROC, there were no events detected for the four and three standard deviation alarm threshold settings. There was only one false positive alarmed for the two standard deviation setting. This once again confirms that the weekly changes in the gas residual data are well behaved and that the proposed detection scheme does a good job by eliminating undesired events. It is difficult to compare the weekly ROC with the point wise rate of change method presently implemented in the field-deployed system. The point wise rate of change can be described as a noise detector since it picks up large step changes and impulses from sensor failures, cooling state changes, and other communication systems problems between the monitoring computer and the data acquisition system. Therefore no direct comparison is being made here.

Choices for the proposed detection scheme parameters were discussed extensively in

th UA and th LA	*Top Oil Residual Magnitude*	*Point-Wise (number)*	*Proposed (number)*	*Reduction (%)*
$\overline{R}_{gtoil} \pm 4\sigma_{R_{gtoil}}$	Positives (Events)	0	0	0
	False Positives	0	0	0
	Undetected Positives	0	0	0
$\overline{R}_{gtoil} \pm 3\sigma_{R_{gtoil}}$	Positives (Events)	2	0	100.0
	False Positives	–	–	—
	Undetected Positives	–	–	–
$\overline{R}_{gtoil} \pm 2\sigma_{R_{gtoil}}$	Positives (Events)	16	1	93.8
	False Positives	–	–	–
	Undetected Positives	–	–	–

Table 6.8: Station 211 Comparison and Sensitivity of Methods: Top Oil Temp Residual Magnitude

Sections 6.1 and 6.2. Therefore the actual choices will not be justified, but will be explained in detail when necessary.

Figures 6-29, 6-30, and 6-31 show the top oil temperature residual for the period of interest separated into two month periods. The top oil temperature residual was evaluated by the same method as the gas residual. Table 6.7, Station 211 Detection Setup Parameters: Top Oil Temp Residual Magnitude, shows the values either calculated or chosen for the four major detection scheme steps shown in Figure 6-2. Analysis of the top oil temp residual for the entire data set, yielded a mean value, denoted by $\overline{R}_{gtoil}$, of 0.61°C, and a standard deviation, denoted by $\sigma_{R_{gtoil}}$, of 3.60°C. This residual or error term is close to zero centered and has only slight variation about the mean. Here the raw top oil temp measurements and the model predictions were closely matched over the six months.

Table 6.8, Station 211 Comparison and Sensitivity of Methods: Top Oil Temp Residual Magnitude, compares the sensitivity of the point-wise to the proposed detection scheme for detecting events. Once again the mean plus or minus two, three, and four standard deviations were used to set the upper and lower spatial thresholds. The number of positives (events), false positives, and undetected positives were tabulated for both schemes and are shown in the Table. For four standard deviations, both the point-wise and proposed method detected no events. For three and two standard deviations, there is a clear reduction of

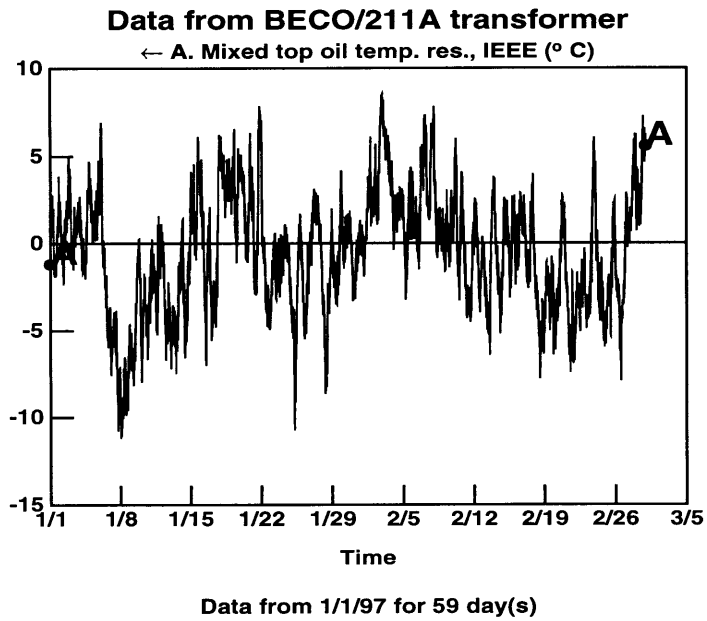


Figure 6-29: Station 211: Top Oil Temperature Residual for January and February 1997

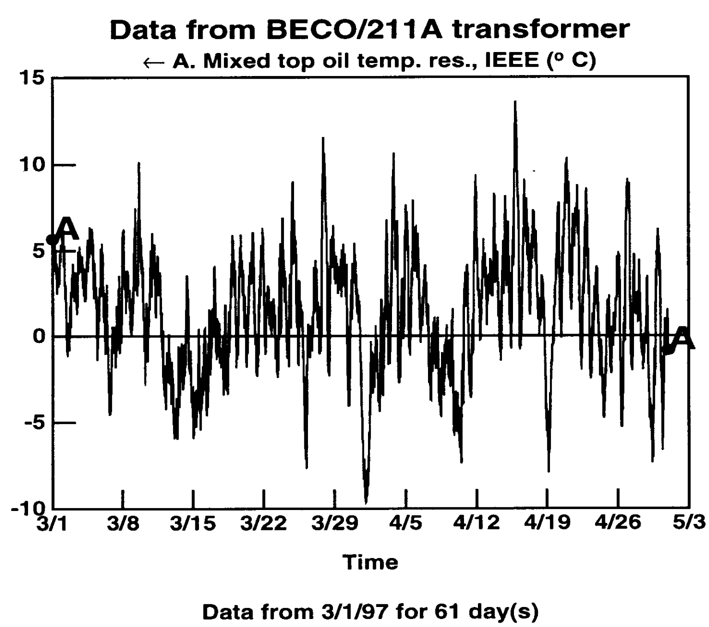


Figure 6-30: Station 211: Top Oil Temperature Residual for March and April 1997

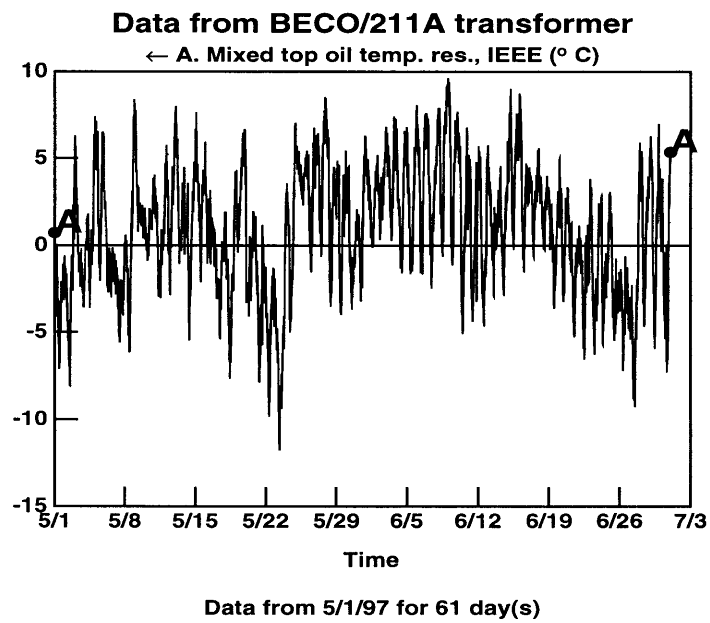


Figure 6-31: Station 211: Top Oil Temperature Residual for May and June 1997

100% and 94% respectively in the number of events detected with the proposed method.

The ROC method described extensively in Section 6.2.4 was used as a guide to set up the detection scheme parameters in Table 6.9, Station 211 Detection Setup Parameters: Top Oil Temp Residual ROC. Analysis of the data yielded a mean, $\overline{ROC}_{R_{gtoil}}$, of -0.01°C and a standard deviation, $\sigma_{ROC_{R_{gtoil}}}$, of 3.81°C. This shows little change in the top oil temp residual occurring over a weekly time frame for the six month period. As shown in Table 6.10, Station 211 Sensitivity of Proposed Method: Top Oil Residual ROC, there were no events detected for the four and three standard deviation alarm threshold settings. There was only one false positive alarmed for the two standard deviation settings. This once again confirms that the weekly changes in the top oil temperature residual data are extremely well behaved and that the proposed detection scheme does a good job by eliminating undesired ROC events.

Data Processing	*Value*	*Descriptor(s)*
Sampling Period (T)	5	min
Data Filtering	24 hour mean	°C (calculated every 3 hours)
ROC Calculation	7 day change	°C (calculated every 3 hours)
Spatial Classification	*Value*	*Descriptor(s)*
Fuzzy Sets (s)	3	abnorm decr, normal, abnorm incr
Mean ($\overline{ROC}_{R_{gtoil}}$)	-0.01	°C
Standard Deviation ($\sigma_{ROC_{R_{gtoil}}}$)	3.81	°C
Transition Region (width)	$\sigma_{ROC_{R_{gtoil}}}$	°C
Transition Region (shape)	S	sigmoid
Temporal Classification	*Value*	*Descriptor(s)*
Validation Window (V[k]) (length)	3	3 points (6 hours)
Validation Window (V[k]) (shape)	S	sigmoid
Alarm Generation	*Value*	*Descriptor(s)*
Alarm Level LA	0.8	abnormal decr
Alarm Level UA	0.8	abnormal incr

Table 6.9: Station 211 Detection Setup Parameters: Top Oil Temp Residual ROC

th UA and th LA	*Top Oil Residual ROC*	*Proposed*
$\overline{ROC}_{R_{gtoil}} \pm 4\sigma_{ROC_{R_{gtoil}}}$	Positives (Events)	0
	False Positives	0
	Undetected Positives	0
$\overline{ROC}_{R_{gtoil}} \pm 3\sigma_{ROC_{Rgtoil}}$	Positives (Events)	0
	False Positives	–
	Undetected Positives	–
$\overline{ROC}_{R_{gtoil}} \pm 2\sigma_{ROC_{R_{gtoil}}}$	Positives (Events)	1
	False Positives	–
	Undetected Positives	–

Table 6.10: Station 211 Sensitivity of Proposed Method: Top Oil Temp Residual ROC

6.3.3 Transformer #2 (BECo Station 509, Transformer 345A)

The second transformer, a 3-phase 345/115 kV shell-form autotransformer, is in a critical location in BECo's transmission system. It is triple rated, 202/269/336 MVA, OA/FOA/FOA, for 65°C rise over ambient. It has a 13.8 kV tertiary winding that is loaded with 100 MVA of reactors for power factor control during times of light system load. It was manufactured by McGraw-Edison and originally installed during 1973. It has been continuously monitored by the MIT system since July 12, 1995.

This particular transformer design has a known susceptibility to through-fault damage and has flaws in its magnetic design. The susceptibility is caused by a lack of support for the bottom of the pancakes in the shell-form winding. When a through-fault generates large transient JxB forces, the bottoms of the pancakes tend to distort plastically, resulting in an uneven electric stress distribution where the high voltage winding is in relatively close proximity to the tank wall and bottom. This can lead to tracking and flashover. Also, when the winding moves, if the paper is brittle due to age and heating, it can fracture, again leading to dielectric failure. The magnetic design problems stem from the fact that this transformer has been used for voltage and power factor control through loading of the tertiary winding by shunt reactors. Under certain tertiary loading conditions, portions of the core saturate, resulting in leakage flux passing through the oil and tank wall. The combination of increased magnetic losses due to core saturation, and eddy current losses in adjacent metal parts caused by the leakage flux, has resulted in overheating of the oil and paper at certain locations in the transformer [14].

For the first twenty years of service, the transformer ran with no reported problems. During the next five years, the tertiary was loaded with 100 MVA of reactors which resulted in overheating and gassing. Based on MIT's monitoring experience and subsequent recommendations, the utility reset the thermostats 5°C lower and began using only half (50 MVA) of the reactors. After these changes in October 1995, the transformer stopped overheating and gassing.

Overall this transformer has been abused and is suspect because of its overheating and gassing history combined with the design flaws. The Hydran® 201R sensor oftentimes experiences severe starvation, due to the placement and piping configuration of the oil flow loop, which adversely affects the gas reading and the accompanying residual. The J. W. Harley^{TM} DAS and accompanying sensors, shown in Table 6.2, in addition to the adaptive mathematical models work as well as can be expected given the severe starvation, but rarely experience other types of problems. The overall result is that periodically large numbers of "flags" or error messages are generated by the gas module in the monitoring system.

The data to be analyzed was taken from the period of April 1 until September 30, 1997. This period was selected since the most problems typically occur during that time of the year due to the loading patterns and accompanying cooling state changes. Before setting up the general run for the proposed detection scheme, the "errors" file for this transformer, described in Chapter 3, was manually examined in order to get an idea of the number of and types of problems that occurred during the 6 month period. This was also done in order to ensure that the data from the chosen period was valid.

Observation of the "errors" file revealed several important messages. On April 6, during the daylight savings time change, no data was or could be recorded during the hour in which the clocks were set ahead. "No New Data" messages were recorded in the file, followed immediately by "New Data" messages. Therefore one hour of data starting at 2 a.m. appears to be missing, although in reality data was still being recorded. On May 13, the monitoring system was shutdown for maintenance for one hour and thirty four minutes, resulting in no data being received or recorded during this time. There was only one other ten minute period on July 17 in which data was missing. This was caused by a mistaken connection to the DAS. These periods of missing data are not a significant problem in setting up and evaluating the detection schemes.

During the six month period, there were numerous gas residual magnitude, gas residual ROC, and gas ROC flags generated by the field-deployed monitoring system. The majority of the gas residual flags had a negative sign indicating that the measured value was lower than that predicted by the gas model. The numerous gas and gas residual ROC flags resulted mainly from the Hydran® 201R sensor either going into or coming out of starvation. On July 12, the Hydran® 201R heater was finally turned off for the season

Data Processing	*Value*	*Descriptor(s)*
Sampling Period (T)	5	min
Data Filtering	–	none
ROC Calculation	–	none
Spatial Classification	*Value*	*Descriptor(s)*
Fuzzy Sets (s)	3	low, normal, high
Mean ($\overline{R}_{gas}$)	-0.68	ppm
Standard Deviation ($\sigma_{R_{gas}}$)	5.73	ppm
Transition Region (width)	$\sigma_{R_{gas}}$	ppm
Transition Region (shape)	S	sigmoid
Temporal Classification	*Value*	*Descriptor(s)*
Validation Window (V[k]) (length)	25	25 points (120 min)
Validation Window (V[k]) (shape)	S	sigmoid
Alarm Generation	*Value*	*Descriptor(s)*
Alarm Level LA	0.8	low
Alarm Level UA	0.8	high

Table 6.11: Station 509 Detection Setup Parameters: Gas Residual Magnitude

in order to avoid severe starvation problems. During the summer months, cooling state transients were occasionally detected by the gas model which resulted in several ROC flags. Observation of the "errors" file shows numerous changes in the gas model flag generation thresholds in order to minimize the number of useless flags while still preserving some degree of sensitivity. There were only a few top oil temperature residual flags on June 9 which were caused by a rapidly falling ambient temperature late in the afternoon, coupled with a poorly performing thermal model. Otherwise, all of the other four measurements (top oil temperature, Hydran® 201R oil temperature, primary current, and ambient temperature) did not exceed their respective preset thresholds used by the monitoring system to detect abnormal levels.

For BECo Station 509, Transformer 345A, the proposed detection is being evaluated in the same way as for Station 211. Therefore only the magnitude and ROC detection for the residuals is being performed. The choices for the proposed detection scheme parameters were discussed extensively in Sections 6.1 and 6.2. Therefore the actual choices will not be justified, but will be explained in detail when necessary.

th UA and th LA	*Gas Residual Magnitude*	*Point-Wise (number)*	*Proposed (number)*	*Reduction (%)*
$\overline{R}_{gas} \pm 4\sigma_{R_{gas}}$	Positives (Events)	142	73	48.6
	False Positives	0	0	0
	Undetected Positives	0	0	0
$\overline{R}_{gas} \pm 3\sigma_{R_{gas}}$	Positives (Events)	162	82	49.4
	False Positives	–	–	–
	Undetected Positives	–	–	–
$\overline{R}_{gas} \pm 2\sigma_{R_{gas}}$	Positives (Events)	324	104	59.6
	False Positives	–	–	–
	Undetected Positives	–	–	–

Table 6.12: Station 509 Comparison and Sensitivity of Methods: Gas Residual Magnitude

Data Processing	*Value*	*Descriptor(s)*
Sampling Period (T)	5	min
Data Filtering	24 hour mean	ppm (calculated every 3 hours)
ROC Calculation	7 day change	ppm (calculated every 3 hours)
Spatial Classification	*Value*	*Descriptor(s)*
Fuzzy Sets (s)	3	abnorm decr, normal, abnorm incr
Mean ($\overline{ROC}_{R_{gas}}$)	-0.34	ppm
Standard Deviation ($\sigma_{ROC_{R_{gas}}}$)	1.46	ppm
Transition Region (width)	$\sigma_{ROC_{R_{gas}}}$	ppm
Transition Region (shape)	S	sigmoid
Temporal Classification	*Value*	*Descriptor(s)*
Validation Window (V[k]) (length)	3	3 points (6 hours)
Validation Window (V[k]) (shape)	S	sigmoid
Alarm Generation	*Value*	*Descriptor(s)*
Alarm Level LA	0.8	abnormal decr
Alarm Level UA	0.8	abnormal incr

Table 6.13: Station 509 Detection Setup Parameters: Gas Residual ROC

th UA and th LA	*Gas Residual ROC*	*Proposed*
$\overline{ROC}_{R_{gas}} \pm 4\sigma_{ROC_{R_{gas}}}$	Positives (Events)	50
	False Positives	0
	Undetected Positives	0
$\overline{ROC}_{R_{gas}} \pm 3\sigma_{ROC_{R_{gas}}}$	Positives (Events)	52
	False Positives	–
	Undetected Positives	–
$\overline{ROC}_{R_{gas}} \pm 2\sigma_{ROC_{R_{gas}}}$	Positives (Events)	62
	False Positives	–
	Undetected Positives	–

Table 6.14: Station 509 Sensitivity of Proposed Method: Gas Residual ROC

Data Processing	*Value*	*Descriptor(s)*
Sampling Period (T)	5	min
Data Filtering	–	none
ROC Calculation	–	none
Spatial Classification	*Value*	*Descriptor(s)*
Fuzzy Sets (s)	3	low, normal, high
Mean ($\overline{R}_{gtoil}$)	4.64	°C
Standard Deviation ($\sigma_{R_{gtoil}}$)	5.37	°C
Transition Region (width)	$\sigma_{R_{gtoil}}$	°C
Transition Region (shape)	S	sigmoid
Temporal Classification	*Value*	*Descriptor(s)*
Validation Window (V[k]) (length)	25	25 points (120 min)
Validation Window (V[k]) (shape)	S	sigmoid
Alarm Generation	*Value*	*Descriptor(s)*
Alarm Level LA	0.8	low
Alarm Level UA	0.8	high

Table 6.15: Station 509 Detection Setup Parameters: Top Oil Temp Residual Magnitude

th UA and th LA	*Top Oil Residual Magnitude*	*Point-Wise (number)*	*Proposed (number)*	*Reduction (%)*
$\overline{R}_{gtoil} \pm 4\sigma_{R_{gtoil}}$	Positives (Events)	1	0	100.0
	False Positives	1	0	100.0
	Undetected Positives	0	0	0
$\overline{R}_{gtoil} \pm 3\sigma_{R_{gtoil}}$	Positives (Events)	16	1	93.8
	False Positives	–	–	–
	Undetected Positives	–	–	–
$\overline{R}_{gtoil} \pm 2\sigma_{R_{gtoil}}$	Positives (Events)	112	16	85.7
	False Positives	–	–	–
	Undetected Positives	–	–	–

Table 6.16: Station 509 Comparison and Sensitivity of Methods: Top Oil Temp Residual Magnitude

Data Processing	*Value*	*Descriptor(s)*
Sampling Period (T)	5	min
Data Filtering	24 hour mean	°C (calculated every 3 hours)
ROC Calculation	7 day change	°C (calculated every 3 hours)
Spatial Classification	*Value*	*Descriptor(s)*
Fuzzy Sets (s)	3	abnorm decr, normal, abnorm incr
Mean ($\overline{ROC}_{R_{gtoil}}$)	0.006	°C
Standard Deviation ($\sigma_{ROC_{R_{gtoil}}}$)	4.44	°C
Transition Region (width)	$\sigma_{ROC_{R_{gtoil}}}$	°C
Transition Region (shape)	S	sigmoid
Temporal Classification	*Value*	*Descriptor(s)*
Validation Window (V[k]) (length)	3	3 points (6 hours)
Validation Window (V[k]) (shape)	S	sigmoid
Alarm Generation	*Value*	*Descriptor(s)*
Alarm Level LA	0.8	abnormal decr
Alarm Level UA	0.8	abnormal incr

Table 6.17: Station 509 Detection Setup Parameters: Top Oil Temp Residual ROC

th UA and th LA	*Top Oil Residual ROC*	*Proposed*
$\overline{ROC}_{R_{gtoil}} \pm 4\sigma_{ROC_{R_{gtoil}}}$	Positives (Events)	0
	False Positives	0
	Undetected Positives	0
$\overline{ROC}_{R_{gtoil}} \pm 3\sigma_{ROC_{Rgtoil}}$	Positives (Events)	0
	False Positives	–
	Undetected Positives	–
$\overline{ROC}_{R_{gtoil}} \pm 2\sigma_{ROC_{R_{gtoil}}}$	Positives (Events)	7
	False Positives	–
	Undetected Positives	–

Table 6.18: Station 509 Sensitivity of Proposed Method: Top Oil Temp Residual ROC

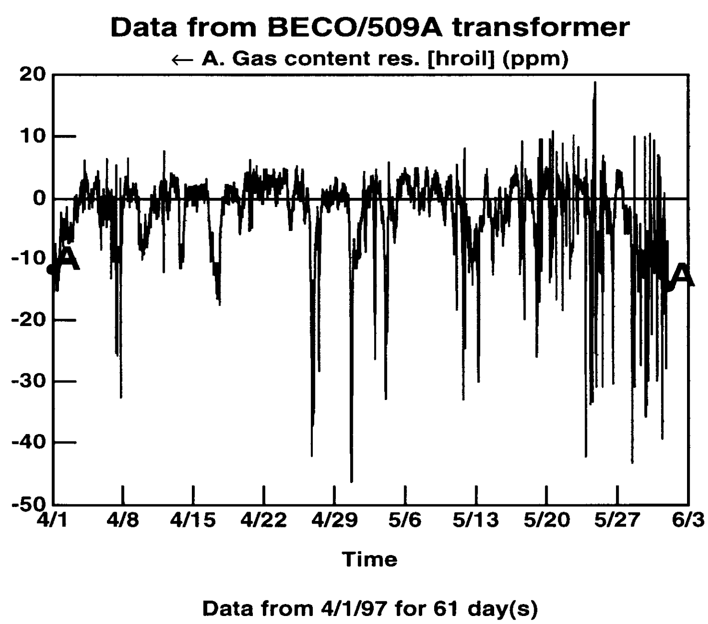


Figure 6-32: Station 509: Composite Gas Residual for April and May 1997

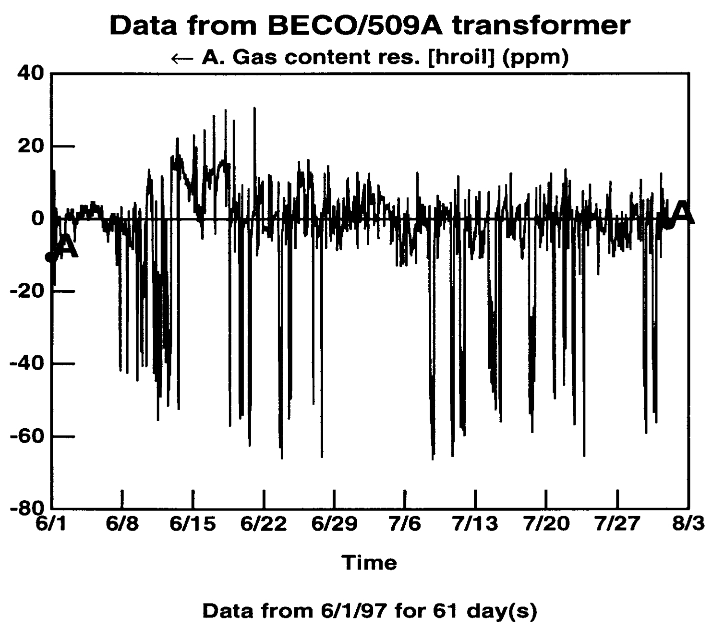


Figure 6-33: Station 509: Composite Gas Residual for June and July 1997

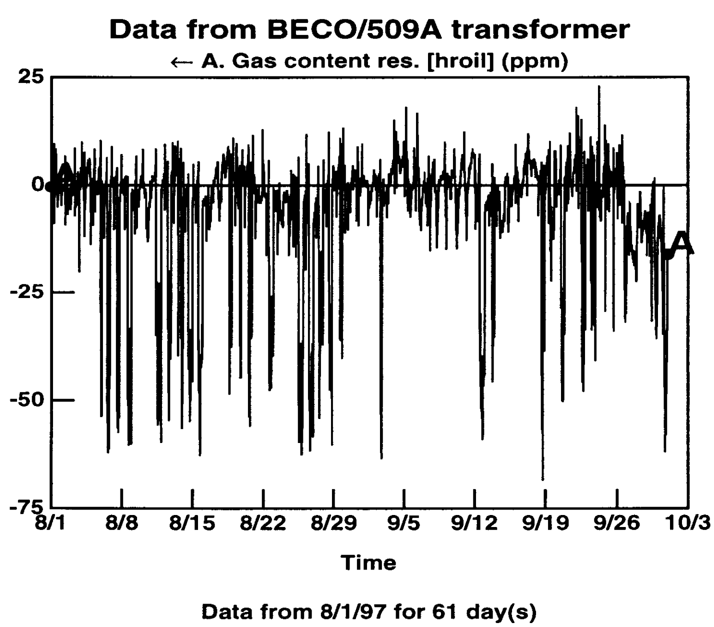


Figure 6-34: Station 509: Composite Gas Residual for August and September 1997

Figures 6-32, 6-33, and 6-34 show the gas residual for the period of interest separated into two month periods. Table 6.11, Station 509 Detection Setup Parameters: Gas Residual Magnitude, shows the values either calculated or chosen for the four major detection scheme steps shown in Figure 6-2. This Table lists the four steps as Data Processing, Spatial Classification, Temporal Classification, and Alarm Generation and should be self-explanatory. Analysis of the gas residual for the entire data set, yielded a mean value, denoted by $\overline{R}_{gas}$, of -3.95 ppm and a standard deviation, denoted by $\sigma_{R_{gas}}$, of 12.63 ppm. These values were not used or shown in the Table. This residual or error term is definitely not zero centered as would be expected and it has sizable variation about the mean. Therefore the raw gas data and the model prediction were not closely matched for the six month period. This negative mean and wide variation stems from the Hydran® 201R sensor experiencing severe starvation on a regular basis, thus resulting in sizeable negative residual values. These calculated values were not used in setting up the detection scheme due to the presence of severe starvation which caused the mean to be biased downward and the standard deviation to be excessively large which was caused by the sensor going in and out of starvation. The gas residual histogram indicated that residuals below -22 ppm were caused by starvation. Therefore, residuals below -22 ppm were eliminated from the data set in order to yield more consistent results. Analysis of the gas residual for the modified data set, yielded a mean value, denoted by $\overline{R}_{gas}$, of -0.68 ppm and a standard deviation, denoted by $\sigma_{R_{gas}}$, of 5.73 ppm. These results are better since the residual is approximately zero centered and has a much smaller standard deviation.

Table 6.12, Station 509 Comparison and Sensitivity of Methods: Gas Residual Magnitude, compares the sensitivity of the point-wise to the proposed detection scheme in detecting events. To test the sensitivity, the upper and lower spatial thresholds were set at the mean residual value, plus or minus two, three, and then four standard deviations. The number of positives (events), false positives, and undetected positives were tabulated for both schemes and are shown in the Table. Clearly both methods pick up the sensor starvation with 142 and 73 events detected for the point-wise and proposed detection scheme respectively. As before, the proposed scheme only picks up long lasting and severe starvation. There is a clear reduction in the number of events with the proposed method. The reduction goes from 49%, to 49%, and then to 60% for four, three, and two standard deviations respectively for the threshold settings.

The ROC method described extensively in Section 6.2.4 was used as a guide to set up the detection scheme parameters in Table 6.13, Station 509 Detection Setup Parameters: Gas Residual ROC. Analysis of the entire data set yielded a mean, $\overline{ROC}_{R_{gas}}$, of -0.21 ppm and a standard deviation, $\sigma_{ROC_{R_{gas}}}$, of 9.51 ppm. While the mean change is negligible, the large standard deviation indicates that the change can vary significantly over a weekly time frame for the six month period. These values were not used due to the continuing severe starvation problem. During the six month period, there were not enough consecutive days without starvation in order to get a statistically significant number of independent ROC values in order to compute the statistics. Therefore, data was taken from January 1 until February 14, 1997 when starvation was not present. Analysis of this 45 day period, yielded a mean, $\overline{ROC}_{R_{gas}}$, of -0.34 ppm and a standard deviation, $\sigma_{ROC_{R_{gas}}}$, of 1.46 ppm. These values are listed in the Table and were used for the detection runs. As shown in Table 6.14, Station 509 Sensitivity of Proposed Method: Gas Residual ROC, there were 50 events detected for the four standard deviation alarm threshold setting. There were 52 and 62 events detected for the three and two standard deviation settings respectively. This once again confirms that the weekly changes in the gas residual data are extremely large and erratic and that the proposed detection scheme picks up large ROC caused by starvation problems. Once again, there is no direct comparison with the point wise ROC method being made here due to lack of similarity.

Figures 6-35, 6-36, and 6-37 show the gas residual for the period of interest separated into two month periods. The top oil temperature residual was evaluated by the same method as the gas residual. Table 6.15, Station 509 Detection Setup Parameters: Top Oil Temp Residual Magnitude, shows the values either calculated or chosen for the four major detection scheme steps shown in Figure 6-2. Analysis of the top oil temp residual for the entire data set, yielded a mean value, denoted by $\overline{R}_{gtoil}$, of 4.64°C, and a standard deviation, denoted by $\sigma_{R_{gtoil}}$, of 5.37°C. This residual or error term is not close to zero centered, but has

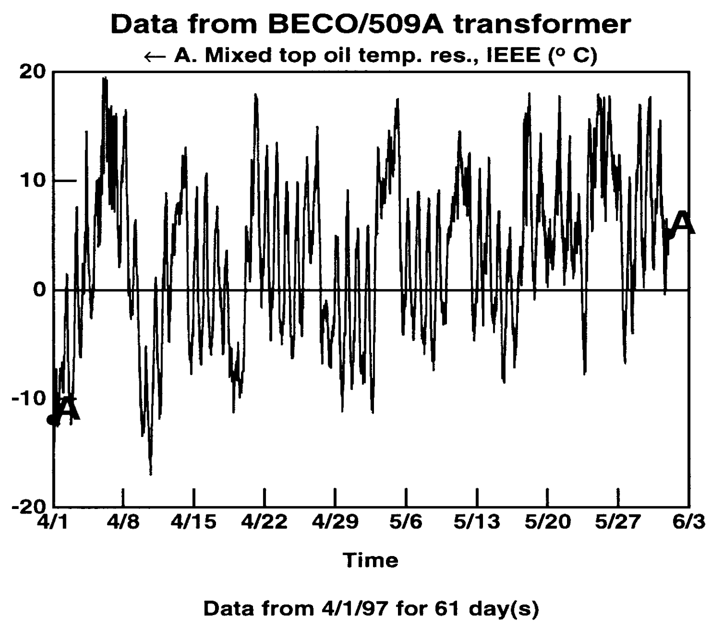


Figure 6-35: Station 509: Top Oil Temperature Residual for April and May 1997

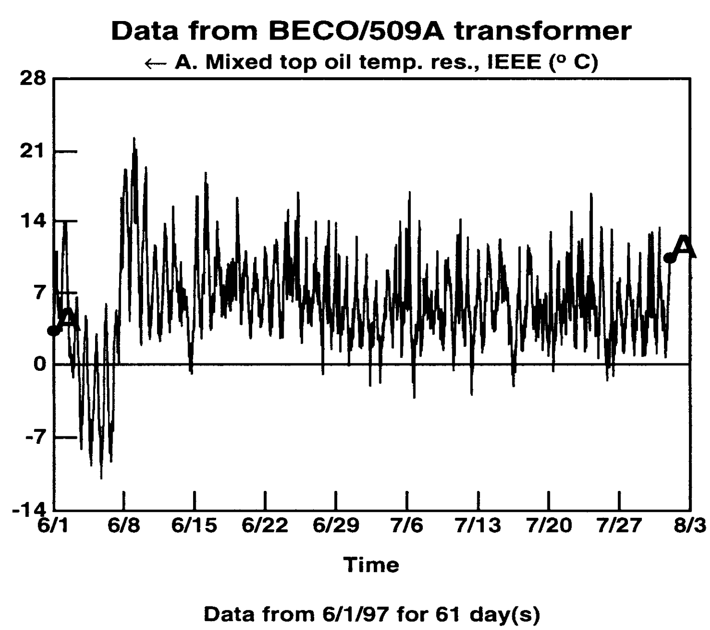


Figure 6-36: Station 509: Top Oil Temperature Residual for June and July 1997

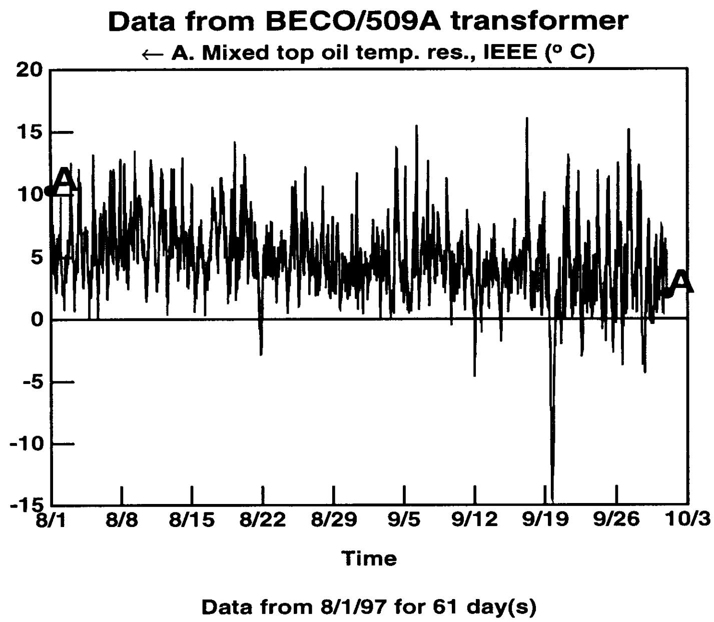


Figure 6-37: Station 509: Top Oil Temperature Residual for August and September 1997

an acceptable variation about the mean. The positive value of the residual could indicate slight overheating of the transformer. Here the raw top oil temperature measurements and the model predictions were not as closely matched over the six months as with the transformer from Station 211.

Table 6.16, Station 509 Comparison and Sensitivity of Methods: Top Oil Temp Residual Magnitude, compares the sensitivity of the point-wise to the proposed detection scheme for detecting events. Once again the mean plus or minus two, three, and four standard deviations were used to set the upper and lower spatial thresholds. The number of positives (events), false positives, and undetected positives were tabulated for both schemes and are shown in the Table. For four standard deviations, the point-wise and proposed method detected 1 and 0 events respectively. The point-wise event was due to the previously described rapidly falling ambient temperature, coupled with a poorly performing thermal model. In this case, the proposed scheme eliminated this false event. For four, three, and two standard deviations, there is a clear reduction of 100%, 94%, and 86% respectively in the number of positives detected with the proposed method.

The ROC method described extensively in Section 6.2.4 was used as a guide to set up the detection scheme parameters in Table 6.17, Station 509 Detection Setup Parameters: Top Oil Temp Residual ROC. Analysis of the data yielded a mean, $\overline{ROC}_{R_{gtoil}}$, of 0.006°C and a standard deviation, $\sigma_{ROC_{R_{gtoil}}}$, of 4.44°C. This shows little change in the top oil temperature residual occurring over a weekly time frame for the six month period. As shown in Table 6.18, Station 509 Sensitivity of Proposed Method: Top Oil Residual ROC, there were no events detected for the four or three standard deviation alarm threshold settings, although 7 events were picked up at the two standard deviation setting. This once again confirms that the weekly changes in the top oil temperature residual data are extremely well behaved and that the proposed detection scheme does a good job by eliminating undesired ROC events. No direct comparision is being made here with the point wise ROC method due to the lack of similarity.

6.3.4 Generalization of Results

From the specific examples and the general detection runs, it was clear that the proposed intelligent detection scheme is a significant improvement over the point-wise detection method currently implemented in the field-deployed system. The proposed scheme exhibited attributes of stability since it was insensitive to small random errors in the data values. It exhibited properties of robustness in that it was also insensitive with respect to a small number of big errors or outliers in the data set. Finally, the scheme exhibited attributes of importance since if any particular data point was suppressed from the data set, essentially no effect was seen on the final detection of anomalies.

The proposed detection scheme had excellent performance with a good data set as evidenced with the results from BECo Station 211, Transformer 345A. It had very good performance for the examples in Section 6.2 in which minimal or mild starvation was evident. Overall, it did not perform up to initial expectations in the face of severe and long lasting Hydran® 201R sensor starvation as exhibited at BECo Station 509, Transformer 345A. On the other hand, it did its job in detecting the severe starvation or accompanying sensor failure which the human should be aware of since it means the gas content is not being accurately monitored. One conclusion is that for gross sensor failures of this type, the detection scheme will not be useful unless the mounting of the sensor is corrected to give correct readings the majority of the time. This reemphasizes the technical and economic tradeoffs in on-line transformer monitoring which was previously depicted in Figure 5-16. In this case, the best economical solution is to correct the sensor mounting, rather than to change or develop new modeling/signal processing or artificial intelligence techniques. In order to reveal other unforeseen pitfalls and difficulties, the intelligent detection scheme should be implemented as part of the field-deployed monitoring system.

Overall, the key to the success of the method was the appropriate combination and use of both a discrimination and a validation step. Validation was essential for substantiating the seriousness of the violation by gathering additional observations or evidence of the same type before raising an alarm. In essence, both spatial and temporal information were necessary in order to accurately detect anomalous changes in the transformer's internal condition.

Chapter 7

Transformer Monitoring Incentives: Effect of Restructuring

This chapter examines the existing and potential incentives for the acquisition, utilization, and commercial development of transformer monitoring systems of the type discussed in this thesis. In general, on-line transformer monitoring has attracted considerable attention for many years. This interest has accelerated recently due to the structural changes in the electric utility industry. Historically, the electricity market in the United States has been dominated by national or regional monopolies. The Energy Policy Act of 1992 opened access to the transmission lines meaning wholesale marketers and traders could buy energy from any producer offering the most favorable conditions [1]. Today, many states are either implementing or considering implementing retail competition. This new competitive marketplace is now putting utilities and other related parties under severe pressure to reduce costs in order to survive.

Under regulation there have been very few incentives for performance improvements and cost cutting measures in the utility industry. Regulation allowed cost recovery to be secured through rate-of-return regulation. One consequence has been little, if any, incentive for innovation since the utility was not allowed to earn higher profits by reducing its costs. These incentives are now evolving and changing. Historically, the main incentive was to prevent the loss of expensive equipment. Today, it is shifting toward increasing the productivity of electric power generation and transmission, without compromising the reliability and safety of the electricity supply, while minimizing costs. This not only affects utilities, but also other for profit companies that are finding business opportunities in the industry. Opportunities may include the commercialization and utilization of new products such as a transformer monitoring system. If a low cost monitoring system can be developed that has a high probability of preventing a failure, commercial opportunities will emerge. This will directly impact both utilities and other organizations involved in the generation and transmission of electricity and will result in a cost consciousness among all participants.

As an example of an organization that is not a utility, consider a new entity called TransCo International [3]. TransCo is a regulated company with a profit motive that either owns or leases all of the transmission facilities within a specific market. TransCo is responsible for the reliability of the transmission system and has responsibilities for the operational resources required to maintain that position. The operating costs range from costs incurred in maintaining reserves on the system through the costs of providing ancillary services which basically are the services required to maintain the quality of supply and reliability of the system. It charges for services either as a function of capital ($/kW) or as a function of the throughput of the system ($/kWh). It is in a unique position in being able to make a trade-off between operational costs and investment in new facilities. TransCo would welcome an opportunity to achieve higher throughput or tremendous operational benefits without a decrease in the reliability. Thus, TransCo would have an incentive to invest in monitoring systems if the systems allowed it to economically operate its transformers at or beyond nominal capacity for long periods of time with no decrease in reliability.

Government actions, such as deregulation, stimulate innovation efforts by providing an incentive for new and improved products and processes. This could include improvements to existing technologies, new capabilities, higher reliability, and more versatility. The possibility of additional government actions, such as environmental restrictions, safety restrictions, research programs, wire charges, fines, or tax benefits, also influences or becomes an incentive for the innovation effort. Innovations, such as the transformer monitoring system, provide economic incentives and benefits to the utility and to the consumer. The utility

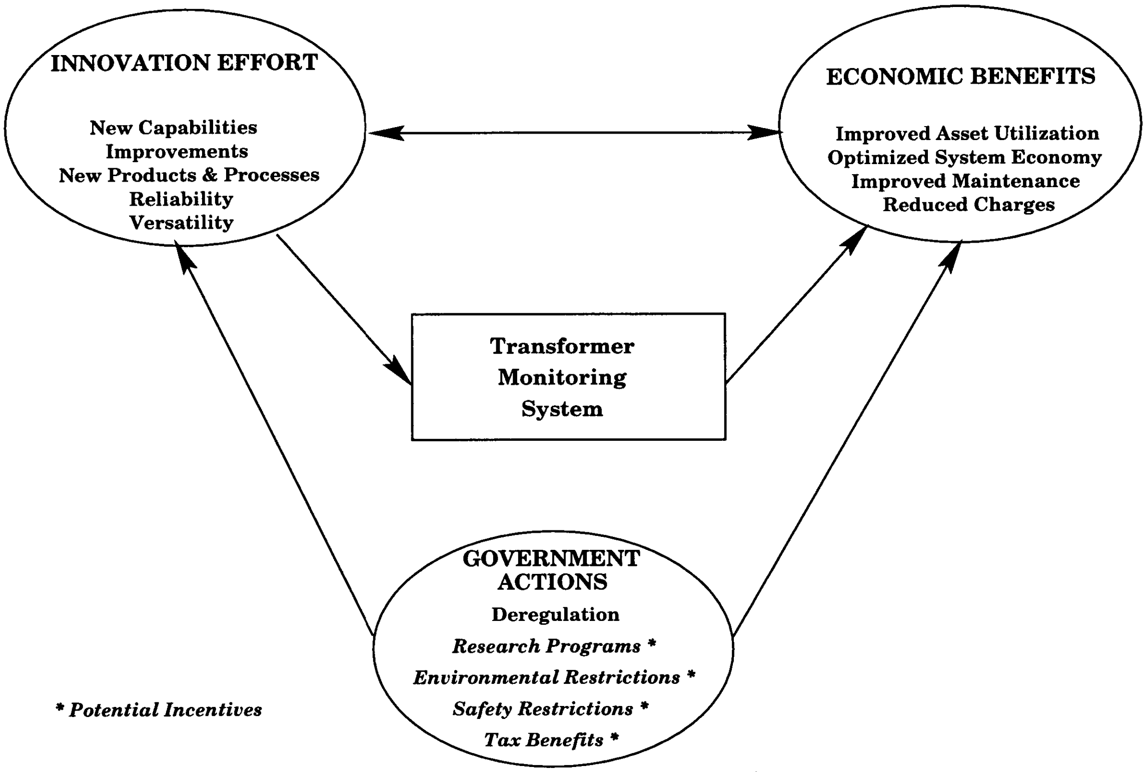


Figure 7-1: Effect of Deregulation on Transformer Monitoring

benefits by improved asset utilization, optimal system economy, and improved maintenance, while the consumer benefits by reduced electricity rates. Economic benefits and the innovation effort influence and drive one another. Government actions therefore indirectly and directly affect the economic benefits and the innovation effort.

A graphical depiction of the interactions between the innovation effort, the economic benefits, and government actions is shown in Figure 7-1, Effect of Deregulation on Transformer Monitoring. The components of this figure are discussed throughout this chapter. Section 7.1 examines the economic incentives for the acquisition and use of a transformer monitoring system. Section 7.2 examines what technical capability and changes are necessary for the monitoring system to be valuable. Potential government incentives are discussed in Section 7.3. From a utility's perspective, a rough cost and benefit analysis of the monitoring system is included in Section 7.4 using realistic values. Finally, the potential commercial viability of a monitoring system is analyzed from both a product and a service perspective.

7.1 Economic Incentives

Economic incentives are the driving forces behind most, if not all, decisions in business. Restructuring will ultimately result in a cost consciousness among utilities which must provide high quality, reliable power to the customers while minimizing total (short and long run) costs. Monitoring transformers and other electrical equipment is one way of optimizing existing assets. The driving forces are to prevent catastrophic failures, to avoid forced outages with related costs, to work existing equipment harder and longer, and to reduce maintenance costs. Note that the catastrophic failure of a large power transformer is very expensive. Just replacing the transformer may cost in excess of \$2,000,000. This capital cost will be represented as $K_c = \$2{,}000{,}000$ for use in Section 7.4. The utility must also consider additional expenses associated with replacing the failed equipment, such as generating power with more expensive units. Therefore, the monitoring system will help utilities to meet their constraints and allow them to safely supply reliable power at a competitive price.

7.1.1 Improved Asset Utilization

The implementation and use of a complete monitoring system with analysis and diagnostics will have a (tremendous) economic impact. It will reduce both long- and short-run marginal costs through improved operating performance. Improved utilization of the physical assets of the transmission system will result in lower investment requirements. Long-run marginal costs are reduced as a result of delaying investment or eliminating the need for specific future investments. For example, the field-deployed transformer monitoring system allowed 24 hour a day surveillance and analysis of a utility's high risk transformers that showed the existing transmission system, while short one critical transformer, could handle expected peak loads and contingencies with an acceptable risk. This allowed the utility to defer acquisition of an existing spare transformer from a neighboring utility at premium cost. The utility was able to save about \$800,000 from the cost of an emergency acquisition [5, 63].

7.1.2 Improved Maintenance

Improved on-line monitoring of the condition of transformers will permit them to be maintained or repaired prior to failure. On-line monitoring can reduce the incidence of catastrophic failures and will likely help to schedule repairs and retirements of apparatus in an orderly fashion. Monitoring systems may help alleviate the possible reduction in staff that typically performs periodic maintenance. Also, better monitoring will permit individual transformers to operate closer to their actual capabilities rather than at their name plate ratings or levels less than the name plate which many utilities choose to operate near. This will reduce the need for new investment as demand on the network increases. Continuous monitoring allowed the utility to uprate four of its transformers between 10% and 20%, a total of 184 MVA. Here the fractional increase in loading, $D_r = 20\%$. The utility evaluates this benefit for the upper increase in loading, alone to be $732,000 [5, 63].

7.1.3 Optimize System Economy

In addition to uprating, system economy can be optimized. During peak load periods, the increased transformer capacity allowed the utility to operate its most economical unit at peak capacity. The estimate is that during the summer of 1995 the company avoided purchasing about 70,000 MWH because of the close monitoring of its transformers. For the time period in question, the difference in cost between local generation and purchase was about $5.00/MWH, indicating a savings on the order of $350,000 [5, 63].

The system marginal operating costs are a more severe financial burden than the capital costs of the components. By monitoring the real time condition of the components and subsystems, appropriate decisions can be made to allow the operation of the components in such a manner as to reduce the total system operating cost. On-line monitoring will permit the system as a whole to be operated closer to its margin, thus reducing short-run marginal costs.

7.2 Technical Incentives

Monitoring systems must have a commercial value to the utility. Therefore, it is important to differentiate between what is technically "interesting" and what is economically "valuable". The rapid development of high performance computers, information technology, artificial intelligence, etc. has provided the tools and means for obtaining quick access to large quantities of "raw" transformer data. With these modern technologies, it is possible to observe a large number of parameters, however at a relatively high cost. Technically, the challenge is to determine the monitoring system requirements, that will produce an effective monitoring system at a moderate cost. This section examines the technical aspects of the monitoring system that increase the incentives for its use.

7.2.1 Analysis and Diagnostic Capabilities

Chapter 2 described four transformer monitoring systems that have been or are commercially available to utilities in varying stages of capability and usefulness in transformer monitoring. These systems included the Westinghouse TMS, the J. W. Harley^{TM} TPAS^{TM}, the QualiTROL SENTRY^{TM}, and USI "Transformer Monitor". As previously discussed, these systems function primarily as data acquisition and storage systems, as no automatic analysis of the data is being performed. Therefore there is little if any incentive and limited practical value for a utility to purchase and install these systems.

In general, the state of on-line transformer monitoring in real-time is underdeveloped. A commercially viable monitoring system must have the ability to perform analysis and make reliable recommendations concerning the operation and maintenance of the transformer. Here the monitoring system must be able to predict with an acceptable level of probability, incipient failure conditions. False alarms, or "false positives", must be kept to a minimum [13].

From the operation and 24 hour a day use of the field-deployed systems, MIT has developed the most comprehensive set of knowledge, expertise, and overall methods for interpreting the data and for giving recommendations. This type of research effort must be continued and and coordinated with a commercial vendor willing to shift its focus towards analysis, interpretation, and diagnosis of transformer data. Only an effort of this type will provide substantial enough incentives for the acquisition and use of monitoring equipment in the future.

7.2.2 Reliability & Versatility

The transformer monitoring equipment under consideration is on-line and permanently mounted on the transformer. It must be reliable and easy to install and maintain. Reliability of the sensor set, monitoring computer, communication mechanisms, etc. is critical. The monitoring equipment must be able to withstand the harsh environment of a substation and the weather it is subjected to. The maintenance of the monitoring equipment must be considerably less than that of the transformer it is mounted on.

The monitoring equipment must be versatile and designed for field installation on both new transformers and on those already in service. Since most of the transformer population is old, it is therefore most likely that emerging faults will occur on older rather than new transformers [53].

7.2.3 Proof of Concept

MIT's field-deployed monitoring system is currently monitoring five 345/115 kV autotransformers in a large utility transmission system. These monitoring systems are proof of concept that on-line transformer monitoring, incorporating adaptive models, is feasible and beneficial to the utility. Additional research and monitoring efforts are needed with a broader range of transformers and equipment. A larger set of transformers will yield more knowledge and information from which to be able to draw valid and broad conclusions.

7.2.4 Other Considerations

For a transformer monitoring system to be useful, it must be integrated with both new and traditional power substation automation efforts. As a start, the monitoring system should be integrated with SCADA (supervisory control and data acquisition), the station control, metering, and display, as well as with protection. In this way, information and data may be shared and the benefits of the integrated system to the utility and consumer will be greater than the sum of the components. Many efforts are underway to integrate substation automation in order to help utilities to extend operating areas and to cut operating and maintenance costs [62].

The location and purpose of the transformer must be identified and taken into consideration before installing monitoring equipment. For instance, consequential costs may be limited if redundancy is available or if the transformer is not in a critical location. On the other hand, if the reliability and quality of electric service are important, then extra capability is needed which leads to installation of protection devices, such as monitoring systems.

7.3 Potential Government Actions

Changes in government regulations in the future could include total government deregulation of the utility industry, tighter environmental regulations, and added safety restrictions. Utilities are being forced to develop internal policies that reflect the external policies of the regulating agencies. Policy decisions are vital to keep up with these changes, and therefore policy making becomes a multi-attribute function in this variable environment. Utilities must consider issues such as the cost of providing power, meeting the demand for power, and public perceptions of safety and environmental concerns. One way to address these concerns is to invest in monitoring systems for critical components.

7.3.1 Socially Desirable Capital Expenditures

The on-line monitoring and diagnostic systems will raise many issues in the area of public relations. These issues range from environmental to public welfare concerns. For instance, failures occur at a rate of approximately 2% per year for transformers in the 400-500kV range [2]. Therefore, safety becomes a major concern when transformers fail catastrophically in residential areas and the possibility of spilled oil or fire results. As an example, one of the utility's catastrophic failures caused a major oil spill very close to a drinking water reservoir.

This mandated an emergency environmental cleanup that cost in excess of \$600,000 [5, 63]. This environmental cost of a catastrophic failure will be represented as K_e = \$600,000 and the failure rate as $R_f = 2\%$ for use in Section 7.4. While a number can be put on the cleanup, it cannot ever "pay" for the neighborhood's concern over its safety. The only way to help their concern is to reduce catastrophic failures by the use of monitoring and diagnostic systems.

Under intense competition brought on by deregulation, the cost cutting measures, brought about by intense rivalry among competitors, should not sacrifice the reliability of electricity and the public's safety. Furthermore, the continuity of power to customers, especially ones such as hospitals, is critical. This raises the question of measuring the real utility of the on-line monitoring and diagnostic systems if their use predicts or prevents transformer failures with some probability. This may generate pressures on both corporate and public policy makers to require the installation of such monitoring systems in cases that may not be entirely economically driven.

The regulators might even devise methods for dealing with public welfare issues. These include building incentive mechanisms into the regulatory process that could range from tax breaks to fines. Tax breaks could be allowed for installation of safety measures, such as afforded by a transformer monitoring system. Therefore, socially desirable capital expenditures and programs would be encouraged through tax benefits which allow some cost recovery. Heavy fines could be levied in cases in which utilities cause bodily damage, harm to the environment, or a loss of power that could have likely been prevented. Utilities and independent power producers will expect government officials to make decisions in these areas. The major implication is that utility policy makers will face the fact that the on-line monitoring and diagnostic systems may help in resolving the issues that may or may not be purely economic.

7.3.2 Government Based Research Programs

Research programs on new power system technologies are critical, particularly in the face of deregulation. State and Federal regulators have been focusing on immediate issues raised by industry restructuring. Very little thought has been given to just how research will be supported in a restructured industry.

In the past, industries have tended to support only technologies near commercialization. For this reason, the Electric Power Research Institute (EPRI) was created in 1972 as a voluntary membership organization with the support of the majority of the large U.S. utilities. EPRI's traditional base of support is quickly fading as utilities trim costs. Research is one of the first things to go, as evidenced by EPRI cutting funding for the research included in this thesis [5].

Utilities are spinning off their generating plants into separate, for-profit firms, which have little interest in supporting collaborative research with their competitors such as the type EPRI supports. This is evidenced in EPRI's budget falling from roughly $600 million to $450 million. On the Federal side, the National Science Foundation (NSF) spends roughly $3.5 million per year on power-system engineering [61]. The majority of the research is for various generation technologies for large central stations.

A method for dealing with the issue of future research in the restructured industry must be devised. Regulators have vaguely discussed a "wire charge" that would create a fund to deal with public interest matters such as research. Just who would administer the funds and provide oversight is unclear since government bureaucracy would ultimately play a role. One suggestion is for a Federal law to require all electricity producers above a specific size to either pay a small "electric energy production charge" or to contribute an identical amount to a privately administered, nonprofit research program of their choosing [61].

7.4 Estimated Benefits

The on-line monitoring system is intended to improve the asset management of expensive and often critical large power transformers. Therefore, it is important to obtain a rough estimate of the benefits provided by the monitoring system as well as the costs. The approach adopted for estimating benefits is based on a variation of the method proposed in [5, 63]. All citations to [5, 63] will be suppressed from this point forward.

Four types of economic benefits are direct results of information-based asset manage-

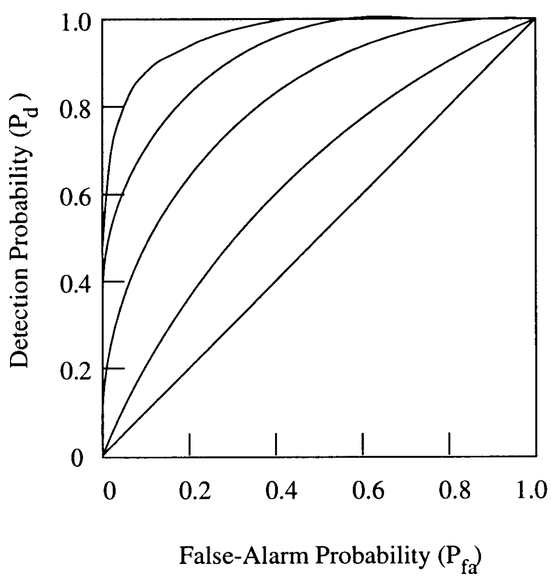


Figure 7-2: Operating Characteristic for the Scalar Gaussian Detection Problem

ment. These include capital cost avoidance, environmental cost avoidance, operational benefit, and maintenance cost reduction. Rough estimates are given for each of these benefits except for maintenance cost reduction where the economic benefits are currently unrealized by the utility using the present version of the field-deployed monitoring system.

In estimating the benefits provided by a transformer monitoring system, it is important to take into consideration the fact that any failure detection method or algorithm will be imperfect. Assume that P_d represents the probability that the monitoring system detects the incipient failure in time for appropriate action to avoid catastrophic failure and P_{fa} represents the probability that there is a false-alarm. In general, a good detector is one with a large P_d and a small P_{fa}. However, these are competing objectives since a good P_d is generally obtained at the expense of a high P_{fa}. Figure 7-2 shows this graphically as the operating characteristic of the likelihood ratio test with suitably chosen thresholds for the scalar detection problem as defined in [64]. For the ideal detector, the P_d-P_{fa} curve approaches the ideal operating characteristic of $P_d = 1$ for all $P_{fa} > 0$.

In order to estimate the benefits, some speculation concerning P_{fa} is involved. There will be costs associated with false alarms that result in negative benefits. These costs will only affect the operational benefit calculation and will not impact either the capital cost avoidance or the environmental cost avoidance calculation. Sections 7.4.1-7.4.4 provide estimates of the potential benefits realized by a transformer monitoring system given basic assumptions.

7.4.1 Capital Cost Avoidance

Assume that a piece of equipment, in this case a transformer, has a capital cost given by K_c and a lifetime given by L. Also assume that the transformer has a failure rate per year of R_f and a probability of P_d that the monitoring system detects the incipient failure in time for appropriate action to avoid catastrophic failure. The expected value of the avoided capital loss due to a failure is:

$$V_{af}(t) = K_c P_d R_f. \tag{7.1}$$

The present value of V_{af}, using a discount rate of r, over the lifetime of the transformer is:

$$V_{pk} = \int_0^L V_{af} e^{-rt} dt. \tag{7.2}$$

Integration yields, V_{pk}, the present value of the avoided capital cost, which is given by:

$$V_{pk} = \frac{K_c P_d R_f}{r} \left(1 - e^{-rL}\right). \tag{7.3}$$

7.4.2 Environmental Cost Avoidance

A transformer failure will often have environmental consequences that are measurable and substantial. Assume that the probability of a failure having environmental costs associated with it is P_e. A few failures have tremendous environmental costs, while others have either minimal or no associated costs. Therefore, P_e is assumed to be 30%. As previously discussed, a transformer failure resulted in an oil spill near a wetland. This involved substantial costs for cleaning up the contaminated soil. This cost does not depreciate and therefore remains constant over time. If the estimated cost of a catastrophic failure is K_e, then the expected value of the avoided loss is:

$$V_{ae}(t) = K_e P_e P_d R_f. \tag{7.4}$$

The present value of this avoided environmental loss after appropriately integrating is:

$$V_{pe} = \frac{K_e P_e P_d R_f}{r}\left(1 - e^{-rL}\right). \tag{7.5}$$

7.4.3 Operational Benefit

Certain types of equipment can be operated in a non-conservative way that can result in extremely large benefits. For instance, transformers may be operated beyond the nominal capacity rating for short periods of time. This is often desirable when the transformer is in a location that turns out to be important for system operation. Utilities have traditionally found it cheaper to overload than to buy a new higher capacity transformer, although they neglect the damage that results from overload and excessive heat.

The economics of overloading transformers is a subject of research since manufacturers and users hold different criteria "parameters" concerning the same transformer. According to the IEC Loading Guide (354), the maximum winding overload should not exceed 150% of the rated load (hottest spot temperature less than or equal to 140°C; top oil temperature less than 115°C) [4]. The ANSI/IEEE NEMA Guides have stated 200%, short-time loadings maximum top oil temperature, 110°C; maximum hottest-spot temperature of 150 or 180°C; maximum short time loading for 30 minutes of 200% [4].

Suppose in this analysis that a transformer is loaded to its nameplate and that overloading it would enable more economical generation dispatch. Assume that no effect of the overloading is seen on the external transformer parts or associated equipment or on the lifetime of the transformer. In a simplistic approach, assume that the rating of the transformer is P_o, the fractional variation in loading (beyond nameplate) is D_r, the number of hours per year for which this overloading is used is H_y, and the incremental savings is $\delta\lambda$. The operational benefit over the lifetime of the transformer is still dependent on the probability of detecting failures. This is taken into consideration most easily by allowing

D_r to be a function of P_d.

In reality, the actual form and shape of the operational benefit curve is unknown. A straight line approach is easiest, although it is not entirely realistic for the entire range of P_d, especially for values near 0 and 1. Ideally, the curve should be based on several parameters, which cannot be measured accurately, such as the maximum winding overload, the effect on other parts of the system, the utility's willingness to overload, the utility's trust and use of the monitoring system, and etc. For a monitoring system with very high probabilities of detecting failures, the benefits can be quite large since the operator can take operational risks by heavily or overloading the transformer for short periods of time knowing that a failure can be avoided with an extremely high certainty. For a monitoring system that has a very low probability of detecting a failure, the operator is less likely to take operational risks.

The impact of the variational loading on operations is directly and highly influenced by the choice of the fractional loading capacity curve. Due to a lack of information, the fractional loading capacity curve is simply chosen as a linear function relating loading relative to nameplate to the P_d. At high values of P_d, the transformer could be loaded for short periods at approximately 200% of nameplate as given by the ANSI/IEEE NEMA Guides. At low values of P_d, the operator would be hesitant to overload even for short periods. Therefore the curve is assumed to pass through the origin and through 200% for $P_d = 1$.

Therefore the impact of the variational loading on operations per year is:

$$V_{ao}(t) = D_r P_o H_y \delta\lambda. \tag{7.6}$$

The present value of this after appropriately integrating is:

$$V_{po} = \frac{D_r P_o H_y \delta\lambda}{r}\left(1 - e^{-rL}\right) \tag{7.7}$$

where D_r is shown in Figure 7-3.

As previously discussed, a monitoring system will also have some probability of generating false-alarms given by P_{fa}. These false-alarms will result in operational costs which

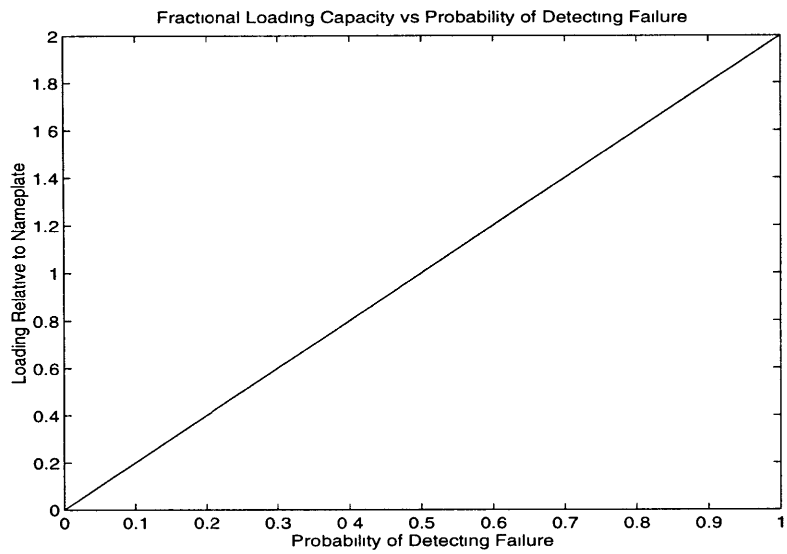


Figure 7-3: Hypothetical Fractional Loading Capacity (D_r)

reduce the benefits provided by the monitoring system. Assume that N_a is the expected number of alarms per year and that H_o represents the average number of hours the transformer is taken off-line for each alarm. Then the expected value of the operational cost due to a false-alarm, where the probability of a false-alarm is P_{fa}, is:

$$C_{fa}(t) = P_o \delta \lambda H_o P_{fa} N_a. \tag{7.8}$$

The present value of C_{fa}, using a discount rate of r, over the lifetime of the transformer is:

$$C_{pfa} = \int_0^L C_{fa} e^{-rt} dt. \tag{7.9}$$

Integration yields, C_{pfa}, the present value of the operational cost due to a false-alarm, which is given by:

$$C_{pfa} = \frac{P_o \delta \lambda H_o P_{fa} N_a}{r} \left(1 - e^{-rL}\right). \tag{7.10}$$

7.4.4 Example Benefits

The total benefits over the lifetime of the transformer, provided by a monitoring system, is the sum of the present values of the avoided capital cost, the avoided environmental loss, and the operational benefit due to variational loading minus the operational cost due to false-alarms. This present value of this total benefit due to a monitoring system may be written as:

$$V_{pms} = V_{pk} + V_{pe} + V_{po} - C_{pfa}. \tag{7.11}$$

In order to estimate V_{pms}, an example was chosen here that quite accurately describes a large power transformer of the type being monitored by MIT's field-deployed monitoring system. In order to get a rough idea of the benefits, realistic numbers have been assigned to the variables presented above. These numbers are in some cases quite accurate and were discussed in Sections 7.3 and 7.4. In other cases they are little more than rough guesses or assumptions.

The life of a transformer depends a great degree on adequate maintenance and knowledgeable operation. For this example, a transformer lifetime of 40 years and a discount rate of 10% are reasonable assumptions. The incremental savings (cost if the transformer is taken off-line), $\delta\lambda$ is chosen to be 10 mils per kWh, which is a very conservative number since the operational benefits are so heavily dependent on its actual value. The overload period, H_y, is assumed to be allowed to be 100 hours per year, although this is extremely conservative since it represents only about 1% of the total available hours per year. There are assumed to be 2 alarms per month where each alarm requires the transformer to be taken off-line for two hours for additional tests or maintenance. Two alarms per month is probably on the high side, although it could easily occur if the transformer is being heavily loaded for periods of time. The basic assumptions follow.

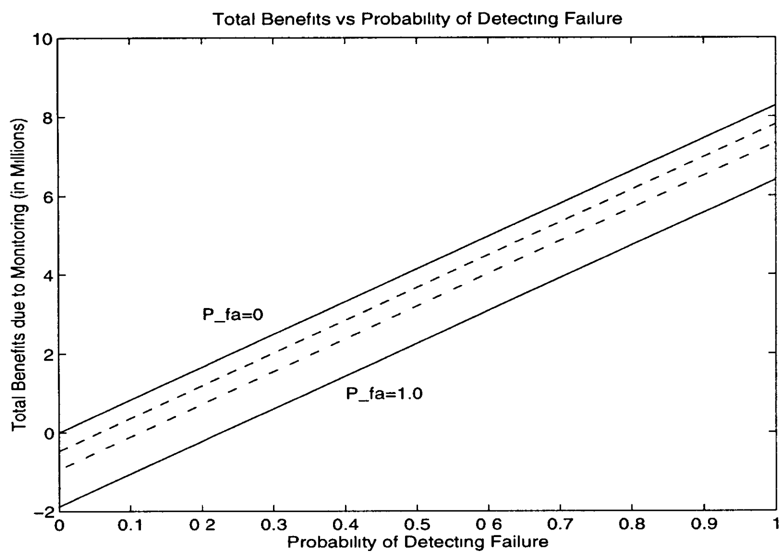


Figure 7-4: Total Cumulative (40 year) Benefits of Transformer Monitoring

Assumptions:

Transformer Capital Cost (K_c)	\$2,000,000	Each
Environmental Cost (K_e)	\$600,000	Each Occurrence
Lifetime (L)	40	Years
Failure Rate (R_f)	2%	Per Year
Probability of Environmental Costs (P_e)	30%	Per Failure
Discount Rate (r)	10%	Per Year
Transformer Rating (P_o)	400	MVA
Fractional Loading Capacity (D_r)	0 to 200%	
Overload Period (H_y)	100	Hours Per Year
Incremental Savings ($\delta\lambda$)	10	mils per kWh
Number of Alarms (N_a)	24	Per Year
Off-line Period (H_o)	2	Hours Per Alarm

In order to examine the total benefits provided by a monitoring system, the equations previously developed allow P_d to vary from 0 to 1. The avoided environmental and capital costs that are achieved for the different probabilities of detecting failures are linearly increasing functions and are positive for all values of P_d. The operational benefits can either be positive or negative depending on both P_{fa} and P_d.

Figure 7-4 shows the total cumulative benefits over the 40 year life of the transformer for the various assumptions while P_{fa} is allowed to vary from 0 to 1 by increments of 0.25. It is the combination of the environmental cost avoidance, the capital cost avoidance, and the operational benefits and costs. The benefits of the environmental and capital cost avoidance are negligible compared to that of the operational benefits. From the figure, P_d must be greater than 0.3 in order to achieve positive benefits for all values of P_{fa}. As expected, a monitoring system with a high P_d is much more valuable to a utility than one with a low P_d. In addition, a monitoring system with a low P_{fa} is much more valuable than one with a high P_{fa}.

7.5 Estimated Costs/Commercial Potential

The type of field-deployed transformer monitoring system described in this thesis is hopefully viable as a commercial product. Commercial entities will be evaluating the market opportunities in future years. In order to estimate the commercial potential of a transformer monitoring system and a utility's willingness to purchase such a system, a rough estimate of the cost of a monitoring system as well as potential profits from a commercial viewpoint must be determined. This determination is achieved by the development and comparison of three scenarios which follow.

7.5.1 Scenario 1: Utility Developed and Operated System

Scenario 1, shown as a spreadsheet in Figure 7-5, examines the case in which a utility chooses to develop and support a transformer monitoring system in-house. In this scenario, it is assumed that a utility in a region the size of Boston would have an incentive or need to monitor 10 transformers. In order to undertake such an effort, seven full time personnel are necessary for the software development, system installation and maintenance, and for 24 hour surveillance of the transformers. Isolated components, equipment, and monitoring computers to fit the 10 transformers must be purchased, installed, and maintained. The lifetime of the monitoring equipment is assumed to be 5 years. In determining the total costs of monitoring, all costs are assumed to occur on day one of each year. In order to obtain the average cost of monitoring per year, a present value calculation using a discount rate of 10% was performed using the expected monitoring costs over the 40 year lifetime of the transformer. This resulted in an average monitoring cost per transformer per year of $156,346. This option is unattractive due to the small number of transformers being monitored and the fact that the utility cannot benefit from economics of scale.

7.5.2 Scenario 2: Commercially Developed Product

Scenario 2, shown as a spreadsheet in Figure 7-6, examines the case in which a commercial vendor develops and sells a transformer monitoring system. In order to provide realistic numbers, it is assumed that the vendor installs a maximum capacity for delivering 100 systems per year. Due to the larger scale, but more experienced personnel, seven full time personnel are necessary for software development and system installation. In this case, no personnel are required for 24 hour surveillance of the transformers. Three additional full time personnel are needed for the sales and marketing, the general manager, and the secretarial positions. The larger scale provides economies which are reflected in the mass production cost reduction factor of 50%. An industry multiplier factor of 2 is assumed in order to determine the selling price of $100,000. A yearly licensing fee of 10% of the mass produced component cost is assumed. Additional administrative and liability costs are included.

From the perspective of the utility, it must pay $100,000 per monitoring system, with an assumed lifetime of 5 years, as well as a $5000 per year licensing fee. The utility must have five personnel in-house to provide 24 hour surveillance of the transformers and it must assume any additional maintenance costs beyond the initial installation. With the same assumptions as before, an appropriate present value calculation resulted in an average

Scenario 1:
Utility Developed and Operated Transformer Monitoring System

Mary Jane Boyd
20-May-98

Unit Cost	Number	Total	Description
$ 75,000	5	$ 375,000	5 people to provide 24 hour monitoring of 10 regional transformers/year
$ 75,000	1	$ 75,000	1 person to provide installation and maintenance
$ 93,750	2	$ 187,500	2 people for software development and updates and hardware specification
		$ 637,500	Subtotal (salaries)
		$ 212,500	Benefits (rate =33.33% of raw salaries)
		$ 850,000	Subtotal (salaries + benefits)
50%		$ 425,000	Overhead (rate = 50%)
		$ 1,275,000	Subtotal (salaries + benefits + overhead)
$ 100,000	10	$ 1,000,000	Cost of isolated components ($75K)* and monitoring computer ($25K)
15%		$ 150,000	Maintenance of equipment including phone lines, repairs, tapes, etc (15% of component cost)
		$ 2,425,000	Total Cost for first year
		$ 1,425,000	Total Cost for each of years 2-5

40 Year Total Cost for Monitoring Eqpt for 10 xfmrs	40 Year Total Cost for Maintenance for 10 xfmrs	40 Year Total Cost for 10 xfmrs	Average Cost per year	Average Cost per xfmr/year
($2,882,944.67)	($13,935,147.27)	($16,818,091.95)	$1,563,462 03	$ 156,346

Assumptions:

A utility company in a region the size of Boston typically has the incentive to monitor 10 critical large power transformers. It is assumed that the lifetime of the transformer monitoring equipment is 5 years.
For a transformer with a 40 year expected lifetime, the costs above will be incurred in a 5 year repeating pattern
Overhead includes administrative costs such as real estate, inventory, phones, etc.
A discount rate of 10% is assumed over the 40 year period.
* Cost of isolated components is based on the approximate purchase price of the QualiTROL SENTRY (TM)
All costs and expenses are assumed to occur on day one of each year.

Number of Units	10
Transformer Life	40
Equipment Life	5
Discount Rate	10%
Benefits Rate	33.33%
Overhead Rate	50%

Figure 7-5: Scenario 1: Utility Developed Monitoring System

Scenario 2:
Commercially Developed and Sold Transformer Monitoring System

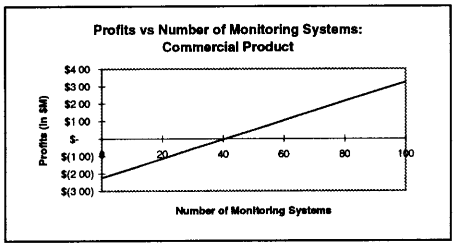
Mary Jane Boyd
20-May-98

Unit Cost	Number	Total	Description
$ 100,000	1	$ 100,000	Cost of isolated components ($75K)* and monitoring computer ($25K)
50%		$ 50,000	Mass production cost (reduction of 50% of costs)
2		$ 100,000	Selling Price per system (Industry multiplier is 2, typically 4-10 in manufacturing)
10%		$ 5,000	Licensing Fee (10% of cost of mass produced components)
	100	$ 10,500,000	Total Revenues for selling 100 systems
	100	$ 500,000	Total Revenues for each year (license fees only)
$ 75,000	5	$ 375,000	5 people to provide system setup and installation
$ 93,750	2	$ 187,500	2 people for software development, updates and hardware specification
$ 100,000	2	$ 200,000	Sales and Marketing
$ 100,000	1	$ 100,000	General Manager, Secretary, etc
		$ 862,500	Subtotal (salaries)
		$ 287,500	Benefits (rate=33 33% of raw salaries)
		$ 1,150,000	Subtotal (salaries + benefits)
50%		$ 575,000	Overhead (rate=50%)
		$ 1,725,000	Subtotal (salaries + benefits + overhead)
$ 50,000	100	$ 5,000,000	Cost of 100 systems
5%		$ 525,000	Liability Costs (5% of value of service selling price + license fees)
		$ 7,250,000	Total Cost for each year

Assumptions:
The company installs a total capacity for 100 units per year
Reasonable assumptions are made for salary and equipment
* Cost of isolated components is based on the approximate purchase price of the QualiTROL SENTRY (TM)
Overhead includes administrative costs such as real estate, inventory, phones, etc.
All costs and expenses are assumed to occur on day one of each year

Number of Units	100
Transformer Life	40
Equipment Life	5
Discount Rate	10%
Benefits Rate	33 33%
Overhead Rate	50%

# Units	Revenues	Costs	Profits (in $M)
0	$ -	$ 2,250,000	$ (2 25)
10	$ 1,050,000	$ 2,750,000	$ (1 70)
20	$ 2,100,000	$ 3,250,000	$ (1 15)
30	$ 3,150,000	$ 3,750,000	$ (0 60)
40	$ 4,200,000	$ 4,250,000	$ (0 05)
50	$ 5,250,000	$ 4,750,000	$ 0 50
60	$ 6,300,000	$ 5,250,000	$ 1 05
70	$ 7,350,000	$ 5,750,000	$ 1 60
80	$ 8,400,000	$ 6,250,000	$ 2 15
90	$ 9,450,000	$ 6,750,000	$ 2 70
100	$ 10,500,000	$ 7,250,000	$ 3 25



Utility Perspective (assume it buys 10 systems for comparison with Scenario 1)

Unit Cost	Number	Total	Description
$ 100,000	10	$ 1,000,000	Cost of 10 monitoring systems
$ 5,000	10	$ 50,000	Cost of 10 licenses
$ 75,000	5	$ 375,000	5 people to provide 24 hour monitoring of 10 regional transformers/year
		$ 375,000	Subtotal (salaries)
33 33%		$ 125,000	Benefits (rate=33 33% of raw salaries)
		$ 500,000	Subtotal (salaries + benefits)
50%		$ 250,000	Overhead (rate=50%)
		$ 750,000	Subtotal (salaries + benefits + overhead)
15%		$ 150,000	Maintenance of equipment including phone lines, repairs, tapes, etc (15% of component cost)
		$ 1,000,000	Total system cost for first year
		$ 950,000	Total additional cost every year

Assumptions:
The utility company buys 10 units the first year and pays license fees every year It incurs the costs above in addition to the monitoring system purchase price For a transformer with a 40 year expected lifetime, the monitoring system purchase costs will be incurred in a 5 year repeating pattern A discount rate of 10% is assumed over the 40 year period
Number of units 10

40 Year Total Cost for Monitoring Eqpt for 10 xfmrs	40 Year Total Additional Cost for 10 xfmrs	40 Year Total Cost for 10 xfmrs	Average Cost per year	Average Cost per xfmr/year
($2,882,944 67)	($5,068,180 35)	($7,951,125.03)	$ 739,161	$ 73,916

Figure 7-6: Scenario 2: Utility Developed Monitoring System

monitoring cost per transformer per year of $73,916 recognized by the utility.

From the perspective of a commercial vendor, it would receive revenues of $10,000,000 for the 100 monitoring systems and an additional $5000 per outstanding license per year. This can be compared with the $7,250,000 total cost of doing business per year. Assuming that there are 100 outstanding licenses per year, the vendor would have profits of $3.25M. Based on the proposed pricing schedule, an analysis revealed that the commercial vendor must sell 40 monitoring systems per year to break even.

At first glance, this appears to be a viable business opportunity. On the other hand, an initial ramp up in production was not included and it is uncertain what the actual product demand would be and whether 100 units is too optimistic. No effects of market saturation, competition, or pricing strategies were considered over the expected product life cycle. No effects of learning were incorporated into the model. Learning would eventually reduce the number of people needed for system setup and installation. For example, if the number was reduced from 5 to 2, the profits would increase from $3.25M to $3.7M per year. Clearly if a market demand develops and grows, this represents a profitable venture.

7.5.3 Scenario 3: Commercially Provided Service

Scenario 3, shown as a spreadsheet in Figure 7-7, examines the case in which a commercial vendor develops a system and provides a monitoring service for a set fee. For comparison purposes, it is assumed that the vendor provides a monitoring service for 100 transformers per year over a 40 year period. Once again, a lifetime of 5 years is assumed for the monitoring equipment. The vendor must assume all costs for the isolated components, equipment, and the monitoring computers. An effort of this scale requires seventeen full time personnel for software development, system installation and maintenance, and for 24 hour surveillance of the transformers. Three full time personnel are necessary for the sales and marketing, the general manager, and the secretarial positions. Additional operational expenses, administrative expenses, and liability costs are included.

With the same assumptions as before, an appropriate present value calculation resulted in an average monitoring system cost per transformer per year of $53,150. A margin of

10% was used to establish the service fee of $58,465 per transformer per year that the utility would be charged. The vendor achieves a total profit of $531,504 per year for 100 transformers. In Figure 7-7 the profits per year were examined as a function of the service fee charged. As expected, the service fee must be greater than $53,150 per year for positive profits.

As with Scenario 2, this appears to be a viable business opportunity. The service business at this level should be more sustainable over the long run than Scenario 2 in which a product is sold. In a sense, a service business locks in customers that pay relatively substantial yearly fees for future years, whereas a product is sold only once and the future yearly licensing fees are minimal. Once again, an initial ramp up in production, market demand, effects of learning, etc. were not take into consideration. For example, if the learning effects were substantial and the number of personnel for surveillance was reduced from 10 to 3, then the service fee would be reduced to $46,915 while the profits would increase to $1.36M.

7.5.4 Generalization of Results

In order to do a comparison of the costs and benefits, the total 40 year benefits for $P_{fa} = 0.1$ from Figure 7-4 was appropriately scaled to an average yearly benefit. Figure 7-8 shows the average yearly costs and benefits of transformer monitoring for a utility versus the probability of detecting a failure. The costs to a utility of monitoring, calculated for the three scenarios, is assumed to be fixed for all values of P_d.

There are real incentives for a utility to install transformer monitoring equipment. Utilities that have abnormally high failure rates or that would like to achieve operational advantages while almost eliminating the probability of failure, would be the most likely to install monitoring capability. Based on this analysis, any of the three scenarios for providing monitoring capability would be quite beneficial for the utility based on the difference between the benefits and cost curves. A utility would find the transformer monitoring service, with a profit margin of 10%, to be the most economical choice at $58,465 per transformer per year.

To be a viable business opportunity, a commercial monitoring system must achieve a

Scenario 3:
Commercial Transformer Monitoring System Service

Mary Jane Boyd
20-May-98

Unit Cost	Number	Total	Description
$ 100,000	1	$ 100,000	Cost of isolated components ($75K)* and monitoring computer ($25K)
50%		$ 50,000	Mass production cost (reduction of 50% of costs)
$ 75,000	5	$ 375,000	5 people to provide system setup and installation
$ 93,750	2	$ 187,500	2 people for software development, updates and hardware specification
$ 75,000	10	$ 750,000	10 people to provide 24 hour per day monitoring
$ 100,000	2	$ 200,000	Sales and Marketing
$ 100,000	1	$ 100,000	General Manager, Secretary, etc
		$ 1,612,500	Subtotal (salaries)
33 33%		$ 537,500	Benefits (rate=33 33% of raw salaries)
		$ 2,150,000	Subtotal (salaries + benefits)
50%		$ 1,075,000	Overhead (rate=50%)
		$ 3,225,000	Subtotal (salaries + benefits + overhead)
15%	100	$ 750,000	Operational Expenses including computers, laptops, etc. (15% of component cost)
$ 50,000	100	$ 5,000,000	Cost of 100 systems
5%		$ 448,750	Liability Costs (5% of value of service/costs)
		$ 5,000,000	Total system cost every 5 years for 100 systems
		$ 3,975,000	Total cost for non-equipment for years 1-5
10%		$ 5,315	Total Profit per xfmr (Margin = 10% of average 40 year cost)
		$ 531,504	Total Profit for 100 xfmrs per year
		$ 58,465	Service Fee per transformer/year (10% margin on avg costs)

40 Year Total Cost for Monitoring Eqpt for 100 xfmrs	40 Year Total Cost for non-equipment related expenses	40 Year Total Cost for 100 xfmrs	Average Cost per year	Average Monitoring Cost per xfmr/year	Total Profit per year for 100 xfmr service
($14,414,723.37)	($42,758,899.27)	($57,173,622.63)	$5,315,037.43	$ 53,150	$ 531,504

Assumptions:
The company provides service for 100 units per year. There is no ramp up in service.
Only the first year costs and expenses are given Reasonable assumptions are made for salary and equipment.
The service fee charged will be the total cost plus profit divided by 100 (assume 100 units for baseline).
* Cost of isolated components is based on the approximate purchase price of the QualiTROL SENTRY (TM)
Overhead includes administrative costs such as real estate, inventory, phones, etc.
All costs and expenses are assumed to occur on day one of each year.

Number of Units	100
Transformer Life	40
Equipment Life	5
Discount Rate	10%
Benefits Rate	33.33%
Overhead Rate	50%
Profit Margin	10%

Fee per Transformer (in $)	Revenues	Average Cost per year	Profits (in $M)
$ -	$ -	$5,315,037.43	$ (5 32)
$ 1,000	$ 100,000	$5,315,037.43	$ (5.22)
$ 20,000	$ 2,000,000	$5,315,037.43	$ (3.32)
$ 40,000	$ 4,000,000	$5,315,037.43	$ (1.32)
$ 60,000	$ 6,000,000	$5,315,037.43	$ 0 68
$ 80,000	$ 8,000,000	$5,315,037.43	$ 2.68
$ 100,000	$ 10,000,000	$5,315,037.43	$ 4 68

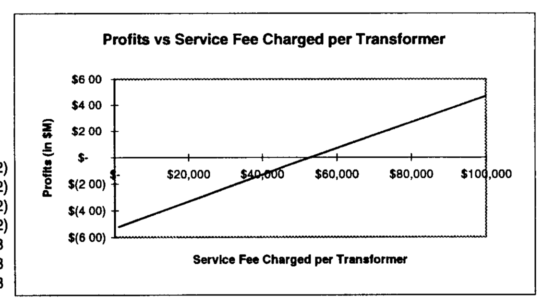


Figure 7-7: Scenario 3: Utility Developed Monitoring System

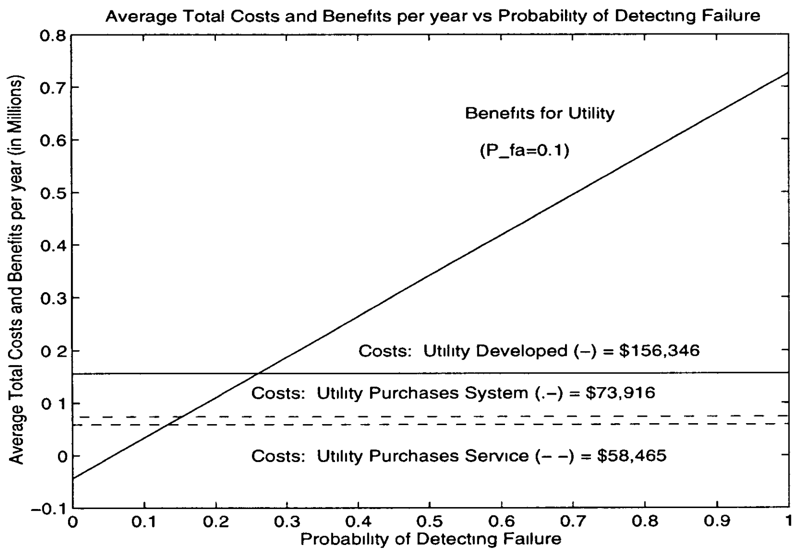


Figure 7-8: Average Yearly Costs and Benefits of Transformer Monitoring

probability of detecting failure greater than approximately 0.26 for positive net benefits for all three scenarios. This is shown in Figure 7-9 which zooms in on the critical region where the cost and benefit curves intersect. It must be emphasized that the cost and benefit curves shift up or down or change in shape depending on changes in the values used in the assumptions. It is important to use these numbers carefully in drawing specific conclusions.

A commercial vendor must carefully consider this information and incorporate technical capability into the systems to predict within an acceptable level of probability incipient failure conditions while minimizing false alarms. This capability must include analysis, interpretation, and diagnosis of transformer data, as well as recommendations for action. Only with technical capability of this level will there be substantial enough incentives for the acquisition and utilization of monitoring equipment.

Clearly there is a commercial opportunity in the area of transformer monitoring. Market research needs to be conducted in order to estimate the potential market demand as well as the price utilities and other commercial entities would be willing to pay for either the product or the service. For instance, if a utility is only willing to pay in the range of $20,000

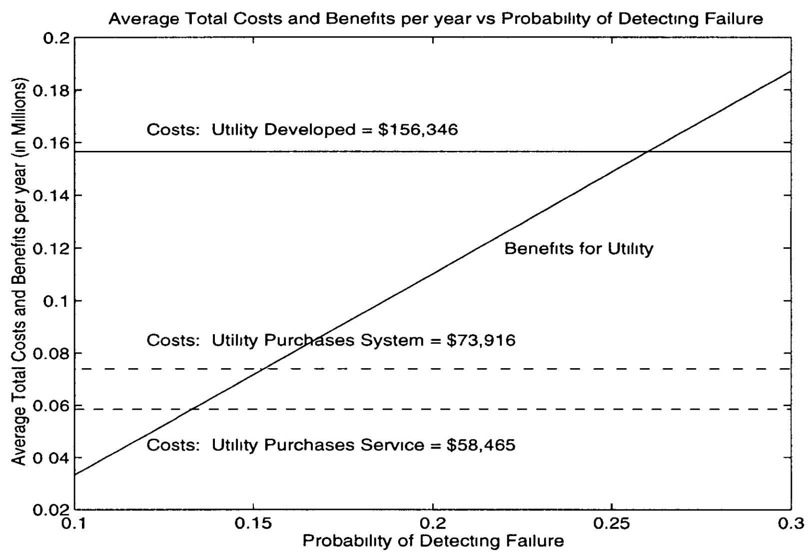


Figure 7-9: Critical Region: Average Yearly Costs and Benefits

for the service, the commercial vendor must carefully consider how to reduce the costs in order to meet this price. Cost reduction could come from reducing the number of personnel, from reducing the profit margins, through better deals on components and computers, etc. The spreadsheet models are helpful for roughly estimating how this may be accomplished and if it is feasible to meet the utilities price ceiling.

Finally, this analysis only hints at what the future may hold for new technologies such as transformer monitoring in the power industry. The prospect of dramatic technological developments with potentially large commercial payoffs is anticipated and expected in future years.

Chapter 8

Conclusions and Recommendations

This thesis expanded upon the body of transformer monitoring knowledge. The specific contributions to the field of transformer monitoring are summarized in Section 8.1. Section 8.2 provides general conclusions and makes recommendations for future work in the area of transformer monitoring and diagnostics that leverage knowledge and insights gained in performing the research for this thesis.

8.1 Contributions

This thesis makes five main intellectual contributions to the field of transformer monitoring. These are the:

- Development of an intelligent magnitude and rate of change detection scheme, utilizing both spatial and temporal information, that is based on fuzzy sets and on-line experience

- Development of simple economic models for the estimation of benefits and costs of transformer monitoring

- Development of a novel method (event reports) of obtaining, organizing, and structuring on-line transformer knowledge
- Development of an on-line transformer monitoring knowledge base
- Development of software that polls for error messages from the monitoring system, modifies their content, and interacts with appropriate software and hardware for transmission of messages to alpha-numeric pagers

8.2 Conclusions and Recommendations

The research and analyses of this thesis led to several general and specific conclusions. The most general conclusion is that the field-deployed transformer monitoring system is extremely sensitive to anomalous sensor, model, and transformer behavior. The drawback is that the sensitivity provided by the currently implemented point-wise detection scheme leads to numerous false alarms. In order to virtually eliminate the false alarms, an intelligent magnitude and rate of change detection scheme was invented and thoroughly tested. It accurately detects anomalous changes in the transformer's internal condition while eliminating nuisance alarms.

In order to automate the analytic, diagnostic, and prognostic capabilities currently performed by humans, an on-line transformer monitoring knowledge base is critical. At the onset of this thesis, no real on-line transformer monitoring experts were in existence. Therefore, traditional knowledge elicitation was not an option for obtaining knowledge. This led to the development of an event report method of obtaining, organizing, and structuring on-line transformer knowledge. These event reports efficiently and effectively capture in real time the knowledge generated by those who either are, or are becoming on-line experts.

The type of field-deployed transformer monitoring system described in this thesis has estimated benefits that substantially outweigh the costs as long as the probability of avoiding failure is greater than roughly 0.5. This positive difference between benefits and costs opens the door to commercial opportunities in the future.

Based on these conclusions, the research of this thesis should continue in several major directions as follows:

- The intelligent detection scheme developed and evaluated should be implemented as part of the field-deployed monitoring system.
- The event report procedure for capturing knowledge and for the development of the knowledge base must be continued, updated, and expanded as new knowledge becomes available.
- The advanced diagnostic system designed around the blackboard model should be further developed, tested, and eventually implemented as part of the field-deployed system.

8.2.1 Intelligent Detection Implementation

Chapter 6 presented and verified the general capability and usefulness of the intelligent detection scheme. The scheme was evaluated for specific magnitude and ROC examples as well as for two 6-month periods of data from two different transformers. The off-line testing of the scheme provided sufficient proof of concept. However, the scheme must be implemented as part of the field-deployed monitoring system in order to reveal pitfalls and difficulties that were not foreseen. By thoroughly exercising the scheme and then by tweaking the detection parameters if necessary, the scheme can be fine-tuned in order to add value to the monitoring system.

8.2.2 Knowledge Structuring

The event report method created a standardized procedure for acquiring and recording on-line expert transformer monitoring knowledge in close to real-time. Chapter 5 presented a general first attempt at structuring some basic knowledge obtained from the field-installations. This attempt at creating a knowledge base must be reexamined and updated as new knowledge becomes available. It must eventually be restructured for use with the appropriate artificial intelligence tools. Knowledge structuring is a necessary and critical task before a complete diagnostic and prognostic system can be implemented.

Three of the five transformers, all greater than 280 MVA and in a large utility transmission system, and the sensors sets attached to them are of the same type. It would be beneficial to use a broader range of transformers and sensors in order to develop a valid and broad knowledge base. A larger set of transformers should yield a lot of knowledge at relatively small incremental cost in total observation time.

8.2.3 Diagnostic System Automation

While this thesis focused primarily on detection, field experience indicates that it is possible and desirable to automate the diagnostic process. A design for a diagnostic system utilizing the blackboard model was presented at a block diagram level. This design should be further specified and incorporate information from the knowledge base derived from field experience. As a long term research goal, the entire transformer performance monitoring system incorporating detection, diagnosis, and prognosis described in Chapter 3 should be implemented as part of the field-deployed system.

8.2.4 Other General Recommendations

This thesis was a small part of a much larger group effort that was necessary for developing and implementing a functional transformer monitoring system as well as for providing twenty-four hour per day surveillance of the transformers, sensors, and various monitoring related equipment and devices. Out of this group effort, general recommendations which are extensively discussed in [5], spanned many dimensions and included:

- Develop and implement an intelligent transformer monitor
- Incorporate advanced modeling and sensor technologies
- Expand surveillance of in-service transformers
- Improve and implement better thermal, gas, partial discharge, and structural vibration models
- Develop a better economic evaluation method

In summary, the intelligent detection scheme along with the other research and analyses described in this thesis, serve as the first step toward a fully automatic on-line transformer monitoring, diagnostics, and decision making system.

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