Intelligent Transformer Monitoring System Utilizing Neuro-Fuzzy Technique Approach

Intelligent Substation Final Project Report

Power Systems Engineering Research Center

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Executive Summary

Maintaining the health and reliability of the power substation has been a concern for many years. For this reason, maintenance crews would periodically take transformers and circuit breakers off-line, in order to assess whether the equipment is operating normally. With this method, there are still catastrophic failures, not to mention much unneeded maintenance. With a growing need for lower cost and more efficient diagnostic tools, the advent of on-line monitoring and artificial intelligence analysis techniques have been applied to the electrical power substation. This report details development of an advanced predictive maintenance and diagnostic system that can be used to monitor the health of the transformer and other substation equipment. Thus, maintenance can be performed on a needed rather than scheduled basis.

A portable, on-line diagnostic module is designed that is able to collect current, temperature, and vibration data from non-invasive sensors, condition the signals appropriately, send the data to the substation computer for storage, and then have the ability to remotely access the data for analysis and health assessment. An artificial intelligent architecture utilizing neuro-fuzzy techniques is used for non-linear system identification, output estimation, and fault detection. Experimental results are presented from the application of the diagnostic module and neuro-fuzzy system on three, single-phase 166 MVA transformers. The system has been successfully able to identify the equipment dynamics, estimate the outputs, and detect a simulated thermal fault, as well as distinguish between sensor and system failures. The foundation for a hybrid neuro-fuzzy expert system is also detailed. The potential for transformer and substation equipment health diagnosis and life expectancy prediction using this system is immense.

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1. Introduction

This introductory chapter describes the importance of this research topic, its impact, and the goals and objectives of the project. A short outline for the rest of the report is also provided.

1.1 Motivation

In recent years, increased emphasis has been placed on power reliability. In particular, major changes in the utility industry, primarily caused by restructuring and re-regulation, have caused increased interest in more economical and reliable methods to generate and transmit power. The health of equipment constituting the substation is critical to assuring that the supply of power can meet the demand. As has been seen recently in California and more dramatically in the recent blackout in the northeast, the United States is already beginning to reach a point where the transmission and distribution system cannot handle the instantaneous demanded power load.

The equipment making up the foundation of a substation, primarily circuit breakers and transformers, are expensive, as is the cost of power interruptions. The savings that would be accrued from the prevention of failures in substation equipment would be in the millions of dollars (Cournoyer, 1999). In the past, most maintenance of large substation transformers was done based on a pre-determined schedule. Maintenance crews would inspect a transformer at set intervals based on its past age and performance history. As can be expected, this leads to many catastrophic failures of improperly diagnosed transformers and the over inspection of other healthy transformers. Because of the cost of scheduled and unscheduled maintenance, especially at remote sites, the utility industry had begun investing in instrumentation and monitoring of substation equipment. On-line transformer diagnostics is the key to greatly reducing the cost and increasing the reliability of providing the needed electrical energy to a growing society. In this report, the on-line monitoring and health diagnostics of transformers is investigated. Transformers are the most expensive piece of equipment in the substation and; therefore, preventing transformer failures is critical. Transformers are continuing to become larger and larger with some handling over 1000 MVA (see Figure 1.1). For this reason, assuring power reliability entails the proper running of these transformers.

1.2 Research Objective

The main objective of this research is to develop the foundation of an intelligent substation in terms of self-diagnostic, self-data analysis and self-informing equipment. While the fundamental and analytical techniques for an intelligent substation are presented, the results are implemented on real-life transformers for an actual substation. The purpose of this research is to develop a sample diagnostic system that outlines the sensors needed and the analytical software used to extract information about the health of the large substation transformer from this sensor data. This system needs to be able to collect and manipulate the data from the sensors, send it to the substation host computer, and then be able to remotely access from a maintenance computer that can perform the automatic fault detection. The goal is then to use the neuro-fuzzy system to identify equipment dynamics through training to a sample data set. It will then be shown how the system can detect failures and distinguish between system failures and sensor failures. This diagnostic system would be implemented on a set of large 166 MVA transformers. A large set of sample data will be collected that can be used as a baseline for future expansion of the diagnostic system to multiple substations. In addition, the foundation for an expert system developed based on the latest transformer expertise will be described that can complement the neuro-fuzzy diagnostic system. This foundation sorts through the many different possible sensor thresholds that could be used in an expert system and details the most used and accepted thresholds.

The on-line monitoring of transformers or other substation equipment is only part of what is needed for fault detection. The sensors merely provide massive quantities of real time data. Thus, a mechanism is needed for analyzing this data and providing useful diagnostic information about the health of the equipment. The analysis can be as simple as placing certain limits and thresholds on the range of sensor measurements. This is a simple method that can prove helpful for certain conditions. However, when the system that is being monitored is more complex and exhibits non-linear dynamic behavior, as a transformer does, simple threshold analysis is not sufficient. In this case, more sophisticated methods should be employed. This is because dynamic systems have changing relationships between the system variables that characterize both normal and faulted states. For example, a certain temperature rise may be a sign of impending failure in a new transformer but not in an older one. The problem then becomes how to symbolize these changing relationships in a practical and reliable way.

As systems become more complex and interconnected, it becomes difficult to maintain them. Components wear and fail, or operating conditions change, causing performance degradation. To meet this challenge, fault detection and isolation strategies have been developed over the past decades to enable automatic detection of faulty conditions, so that measures can be taken before the failure becomes catastrophic. In the case of large power transformers (see Figure 1.1), a catastrophic failure costs millions of dollars. Thus, there is a real need to be able to monitor these transformers and set alarms if there are any impending failures. This should be done with the minimum number of sensors, while still providing reliable diagnostic information. This research attempts to accomplish the goal of an affordable and reliable system that can easily be installed to monitor large transformers. Results form this research can be expanded to circuit breakers, a complete substation, and a transmission and distribution system.

1.3 Report Outline

This report will begin with an extensive review of the current techniques and diagnostic hardware that are being used for transformer monitoring. There will also be a comprehensive review of the different types of analytical methods that have been developed over the years and how they can be used to provide diagnostic information from large volumes of data. In addition to analytical methods, common artificial intelligence techniques for transformer diagnostics will be discussed. These topics will be overviewed in Chapter 2. Chapter 3 describes the neuro-fuzzy network that is used to analyze and extract diagnostic information from the data collected by the diagnostic module of Chapter 4. In Chapter 3, the ability of the neural network to act as a non-linear system identifier, an output observer, and a fault detector is illustrated. Chapter 4 gives a detailed description of the diagnostic module that was designed for this research.

Figure 1.1: **Typical large substation transformer**

A rule-base of thresholds for the different types of sensors used in transformer diagnostics, including those sensors not implemented in the diagnostic system of Chapter 4, is formed in Chapter 5. These thresholds are derived from the latest expert experience with transformer diagnostics and can later be used in the implementation of an expert system. Chapter 6 gives the experimental analysis from the application of the diagnostic module and analytical neuro-fuzzy system. The optimal location of sensors and determination of the appropriate inputs and outputs for the analytical system are given in this chapter and applied to the field data to illustrate the proper functioning of the diagnostic system. Finally, a summary of the results from this report, the future work planned for this research, and conclusions are provided in Chapter 7.

2. Literature Review

The area of substation diagnostics, and in particular transformer diagnostics, has become increasingly important in recent years with more and more strain being placed on the transmission and distribution (T & D) system. A key component for the reliability of a T & D system is the transformer. Much effort has been made in recent years to formulate techniques to diagnose the health of transformers. The work presented in this thesis centers around three major areas of study in transformer diagnostics. These three main areas can be divided into diagnostic hardware and what failures they indicate, expert system with a rule-base of if-then statements for different types of failures, and artificial intelligence that can be used as a system identifier, non-linear observer, and fault detector. The predominant literature on these three areas is discussed in this chapter and in Chapter 5.

2.1 Diagnostic Hardware

In recent years, many new devices have been developed to help in providing information that can be used in diagnosing the health of transformers. There are many key measurements that can help in indicating if a transformer is healthy or not. These measurements include the water in oil, combustible gas in oil, temperature, gas pressure, insulation properties, partial discharge, acoustic signatures, motor current profiles, bushing leakage current detection, moisture in insulation, spectral content of shell vibration, and load current and voltage (Farquharson, 2000). The above quantities can all help in detection of many different types of failures. An explanation of the quantities, what they infer about the health of a transformer, and the common hardware used to obtain the above quantities is given below.

2.1.1 Dissolved Gas Analysis

Dissolved gas analysis has become a very popular technique for monitoring the overall health of a transformer. As various faults develop, it is known that different gases are generated. By taking samples of the mineral oil inside a transformer, one can determine what gases are present and their concentration levels. Work has been done to theoretically connect the gaseous hydrocarbon formation with the thermodynamic equilibrium (Halstead, 1973). Work by Haltstead indicated that the hydrocarbon gases with the fastest rate of evolution would be methane, ethane, ethylene, and acetylene. Halstead's work further proved that there is a relationship between fault temperature and the composition of the gases dissolved in the oil. Much effort has been made into creating a diagnosis criteria for the types and amounts of gases that are present in the oil (Zhang et al., 1996).

Some studies have focused on key gases and what faults they can be used to identify (Griffin, 1988). A summary of the relationship between fault types and the key gases is given in Table 2.1.

Table 2.1: Key gases for DGA and their fault type

Key Gas	Chemical Symbol	Fault Type
Hydrogen	H_2	Corona
Carbon Monoxide and Carbon Dioxide	CO CO_2	Cellulose insulation Breakdown
Methane and Ethane	CH_4 C_2H_6	Low temperature Oil breakdown
Acetylene	C_2H_2	Arcing
Ethylene	C_2H_4	High temperature oil breakdown

In the case of key gas analysis, a fault condition is indicated when there is excessive generation of any of these gases. For this to be effective, much expert experience is still needed. As an alternative, research has been done in the area of the ratios between different gases. In this method, the ratio between the concentrations of different dissolved gases is used for the fault diagnosis. For example, acetylene concentrations that exceed the ethylene concentrations indicate that extensive arcing is occurring in the transformer, since arcing produces acetylene (Ward, 2001a). Extensive arcing is a sign of insulation degradation and possible failure in the transformer. Likewise, there are many other ratios that can be used. The problem with ratio analysis is the knowledge base that is required to properly diagnose a transformer from the ratio of its dissolved gases must be very large and complex (Zhang et al., 1996).

In addition to key gas analysis and ratio methods, researchers have developed a formula for the equivalent gas content in the oil, which weights the amount of hydrogen, carbon monoxide, acetylene, and ethylene present in the oil to produce a single number. This number can then be used to identify abnormal conditions when comparing it to some pre-determined threshold value. A set of standards for limits on these gases has been created and will be discussed in more detail in the rule-base section of Chapter 5. The trends in the gases is often more important than the absolute concentrations and many dissolved gas sensors have a trending algorithm that will put more emphasis on abrupt changes in concentrations, especially in the key gases such as acetylene.

Several different dissolved gas sensors have been created. The most commonly used on-line dissolved gas analyzer is the Hydran by GE-Syprotec. It detects six of the major dissolved gases present in the oil. In addition, it is programmed with a trending algorithm for assistance with transformer diagnostics. The Hydran detects the hydrogen, carbon monoxide, acetylene, and ethylene content in the oil. It connects directly to the load tap changer and provides daily values and trending information (Reason, 1995). Besides the Hydran, Severon makes a TrueGas on-line analyzer as does Morgan Shaffer. Morgan Shaffer's online analyzer also monitors the water content in the oil, which we shall discuss next. Advanced Optical Controls, Inc has developed a more complicated gas analyzer. Advanced sensor monitors the actual concentration of six gases using near infrared spectroscopy. Samples can be taken every half hour and an associated microprocessor can store data for up to two months. It should be noted that the aforementioned types of sensors and monitoring systems cost several thousand dollars each, with prices ranging from a little over $6000 to nearly $17000 (Reason, 1996).

2.1.2 Moisture Analysis

In addition to gas in the oil, it is an accepted fact that the presence of water is not healthy for power transformers. Water in the oil indicates paper aging, since the cellulose insulation used in power transformers is known to produce water when it degrades (Ward, 2001b). Water and oxygen in the mineral oil further increases the rate at which the insulation will degrade. This means that a high concentration of water in the oil not only indicates that the insulation has been degrading but it will degrade more quickly in the future due to increased presence of water in the oil. Water in the oil is also a sign that the mineral oil itself is deteriorating. When the mineral oil deteriorates, the dielectric constant of the oil decreases. Reduction of the dielectric constant can lead to a flashover and consequential failure of the transformer.

The relationship between the oil in the mineral oil and the insulation paper is a complex equilibrium. Water is constantly moving from the oil to the insulation and vise-versa. The migration of water inside the transformer is a very complicated process (Ward, 2001b). Work has been done using a fuzzy-logic identification tool to detect the water-in-paper activity. This tool then takes into account the moisture available for transfer to the oil. On-line measurements of the water saturation in the oil, top and bottom oil temperatures, and load are used to determine this activity (Davydov, 1998).

As with the dissolved gas analyzer, several companies make on-line moisture sensors that give measurements of the amount of water present in the oil. One of the most commonly used is the Aquaoil by GE-Syprotec. Other companies also have moisture-in-oil analyzers, such as Doble’s Domino. These moisture-in-oil sensors cost around $5000 each.

2.1.3 Partial Discharge Monitoring

Though moisture and dissolved gas analysis is helpful in detecting many types of failures that can occur in a transformer, the measurement of partial discharges is probably the most effective method to detect pending failure in the electrical system (Ward, 2001b). As the electrical insulation in a transformer begins to degrade and breakdown, there are localized discharges within the electrical insulation. Every discharge deteriorates the insulation material by the impact of high-energy electrons, thus causing chemical reactions. During these discharges, ultra-high frequency waves are emitted. Most incipient dielectric failures will generate numerous partial discharges before the catastrophic electrical failure. Partial discharges may occur only right before failure but may also be present for years before any type of failure. A high occurrence of partial discharges can indicate voids, cracking, contamination, or abnormal electrical stress in the insulation (Ward, 2001b). Because of the importance that partial discharge measurements have in diagnosing potential catastrophic failures in a transformer, it is critical that partial discharge measurements be able to be made in the field.

At first, techniques to be able to detect partial discharges were few and far between. Luckily, because of the ultra-high frequency (UHF) waves produced during partial discharge, sensors have been developed that use UHF couplers to detect frequencies from 300-1500 MHz. Scottish Power and Strathclyde University first developed these types of sensors (Judd, 2000). In addition to UHF sensors, the UHF waves produced by the partial discharge produce pressure waves that are transmitted through the oil medium. Piezoelectric sensors can be used to detect these waves. These sensors can be placed on the outside of the tank to detect the acoustic wave impinging on the tank or in it, and the oil itself. The problem with placing it in the oil is that the sensor than becomes invasive. The external and internal partial discharge sensors both cost about $2000 each.

The advantage of partial discharge sensors is the ability to detect the actual location of insulation deterioration, unlike with dissolved gas sensors. By placing several partial discharge sensors around the transformer tank, it becomes possible to pinpoint the exact location of the discharges (Reason, 1995). Most often the deterioration occurs on the first several coils of the high side voltage of the transformer. The one disadvantage to partial discharge sensors is that they are greatly affected by the electromagnetic interference in the substation environment. Therefore, signal processing techniques are often used to improve the signal to noise ratio in order to make the measurements effective (Bengtsson, 1997).

Another on-line partial discharge detection technique that involves a fiber optic sensor has been developed recently at Virginia Polytechnic Institute and State University.

In this technique, a laser diode transmits light into a fiber optic coupler that has the light propagate across an air gap inside a self-contained diaphragm, lined with reflective gold. The reflected light combines with the small, reflected wave inside the fiber optic coupler to produce an interference pattern that differs as the air gap changes. In this way, the acoustic waves produced by partial discharges can be detected (Wang, 2000).

2.1.4 Temperature Monitoring

One of the simplest and most effective ways to monitor a transformer externally is through temperature sensors. Abnormal temperature readings almost always indicate some type of failure in a transformer. For this reason, it has become common practice to monitor the hot spot, main tank, and bottom tank temperatures on the shell of a transformer.

It is known that as a transformer begins to heat up, the winding insulation begins to deteriorate and the dielectric constant of the mineral oil begins to degrade. Likewise, as the transformer heats, insulation deteriorates at even a faster rate. As the next section describes, monitoring the temperature of the load tap changer (LTC) is critical in determining if a LTC would fail. In addition to the LTC, abnormal temperatures in the bushings, pumps, and fans can all be signs of impending failures.

Recently, thermography has been used more widely for detecting temperature abnormalities in transformers. In this technique, an infrared gun is taken to the field and used to detect temperature gradients on external surfaces of the transformer. Infrared guns make it easy to detect whether a bushing or fan bank is overheating and needs to be replaced. The method is also useful in determining whether a load tap changer (LTC) is operating properly (this will be discussed more in the section on LTC monitoring). Thermography is effective for checking many different transformers quickly to see if there is any outstanding problem (Kirtley, 1996).

However, thermography is not conducive to on-line measurements and; therefore, is prone to miss failures that may be developing between the periods when the transformers are checked.

In order to make on-line monitoring possible, thermocouples are placed externally on the transformer and provide real-time data on the temperature at various locations on the transformer. In many applications, temperature sensors have been placed externally on transformers in order to estimate the internal state of the transformer. These temperature readings can be used to determine whether the transformer windings and oil are overheating or running at abnormally high temperatures. High main tank temperatures have been known to indicate oil deterioration, insulation degradation, and water formation (Kirtley, 1996).

The state of the art currently in thermal detection comes in the form of transformer models. Mathematical models have been used to accurately predict oil and winding temperature for varying conditions, using exclusively external thermal detectors. The parameters for these models include main tank temperature, hot spot temperature, and ambient temperature. The IEEE had developed a model, but did not properly account for changes in the ambient temperature and thus set off alarms when there was no fault. In the past several years, researchers at MIT have developed a model that accurately predicts the thermal state of a transformer (Lesieutre, 1997). Here at CSM, we have also developed a thermal model, which used extended Kalman filters and adaptive Hopfield networks in order to develop an observer that could estimate the state of the transformer from a few temperature measurements. The Kalman filter and Hopfield networks were used to calculate various parameters, which could be used to estimate the state of the transformer and determine whether it was in a failure mode (Ottele, 1999).

2.1.5 Vibration Monitoring

The diagnostic methods described thus far have all dealt with trying to detect a failure in the electrical subsystem of the transformer, namely the electrical insulation around the coils. There has also been research carried out in regards to mechanical malfunctions in a transformer. The cellulose insulation on the coils of the transformer shrinks with aging. The shrinkage causes a loosening in the clamping pressure. If the coils are not retightened, the decreased pressure can often lead to a short-circuit between turns (Berler et al., 2000). Short circuits often can lead to the catastrophic failure of the transformer and thus must be monitored closely. Studies of transformer breakdowns have shown that between 70 and 80% of failures are caused by a short circuit between turns in the transformer.

2.1.6 Current Monitoring

Though not part of the new diagnostic tools that have been developed recently, monitoring the currents on the primary, secondary, and tertiary coils has been done for quite a while. In addition, monitoring the current being drawn by the fans and pumps can also indicate when there might be a failure in these accessory units. Monitoring these currents may often be an easier and cheaper alternative than thermography or other types of thermal monitoring. It is important to monitor the appropriate functioning of the cooling system. Should a fan bank fail and not be detected and corrected, the increased temperature in the transformer will greatly increase the deterioration in the transformer insulation and thus greatly reduce the life of the transformer. Furthermore, monitoring the currents on the primary, secondary, and tertiary coils can often indicate if there is an imbalance in the transformer that might indicate a developing problem or impending failure (Farquharson, 2000).

2.1.7 Bushing and CT Monitoring

Though the breakdown of the insulation can cause catastrophic failure in a transformer, the life of a transformer is predominantly shortened by the deterioration of its accessories. These accessories include the bushings, load tap changers (LTC), and cooling system. Nearly 50% of defects are from these accessories, while only 20% are from the failure of the insulation system (Sokolov et al., 2001). More notably, 70% of transformers have revealed problems with the bushings. Therefore, one can realize the value in monitoring the health of the bushings.

Similar to the insulation around the transformer coils, there is also layers of foil and oil-impregnated insulation that surround the transformer bushings and current transformers (CTs). There is a small amount of charging current that flows when the system is running. Changes in this charging current can indicate degradation in the insulation. As the insulation degrades, carbon deposits can short circuit some of the layers and increase the stress on the remaining layers. This leads to a decrease in the capacitance and the charging current increases. Eventually, the remaining layers of insulation cannot take the strain and the system fails, often catastrophically (Reason, 1995). Some of the causes of bushing failures include changing dielectric properties with age, oil leaks, design or manufacturing flaws, or the presence of moisture (Traub, 2001). Sensors have now been created to monitor the health of bushings. Transformer bushings have a finite life, but these on-line sensors can inform the utility company when a bushing may be ready to fail. The InsAlert monitoring probe from Square D Co. and the Intelligent Diagnostic Device (IDD) for bushings and current transformers from Doble have the ability to detect abnormalities and possible failure conditions in the bushings and CTs. These sensors cost around $3300 to monitor three bushings, but have been shown to work effectively.

2.1.8 LTC Monitoring

Similar to the monitoring of bushings and CTs, the health of the load tap changer (LTC) has also been emphasized. Overheated LTCs can result from many different phenomena. These causes include coking, misalignment, and loss of spring pressure. Though the contact temperature cannot easily be measured directly, the overheating will generally result in an increase in the LTC oil temperature. Therefore, wear in an LTC can be detected by monitoring the temperature differential between the oil of the load tap changer and the oil of the main tank. By monitoring the LTC temperature closely, the flashover between the contacts can be avoided, which usually results in a short circuit of the regulating winding and subsequent failure of the transformer.

J.W. Harley, now a part of GE, has developed a temperature differential monitor for this purpose. Many similar sensors have now been developed based on this principle (Reason, 1995). Monitoring of transformers has spread to different techniques and hardware that try to monitor the health of the electrical (insulation) portion of the transformer, which can lead to catastrophic failures, but has also spread to the transformer accessories (bushings, CTs, LTC, pumps, and fans) which account for 46.2% of transformer defects (Sokolov et al., 2001). In addition to the accessory and electrical monitoring of the transformer, several methods for detecting mechanical failures, such as the loosening of the clamping pressure on the coils, has also been researched and developed recently. The monitoring system described later in this report utilizes some of the hardware monitors described above and forms a rule-base for warnings on some of the other sensors not present in our diagnostic system.

2.2 Approaches to Fault Detection

In order to avoid the knowledge requirement of an expert system, much research has been done on data analysis through more analytical and artificial intelligence techniques. In these methods, models or artificial learning techniques are used to try to identify the transformer dynamics and detect failures from this identification. Many different methods have been tried, some with more success than others. In the following sections, analytic and artificial intelligence techniques will be described in more detail. First, a comparison of the different types of fault diagnosis methods will be given.

2.2.1 Fault Diagnosis Methods

Fault diagnosis is a concept that has been studied and utilized extensively. In both the medical and engineering fields, researchers have been trying to determine when a system, biological or otherwise, would fail. Many different methods for detection of an impending failure in a system have been developed. These methods can be classified into two broad categories. One is the knowledge-based approach. The expert system described in Chapter 5 is based on human knowledge of transformers. From the human knowledge, rules are formed and decisions are made based on the rules. This is one type of knowledge-based diagnosis. The knowledge-based approach can also utilize artificial intelligence. Namely, by using artificial intelligence techniques, rules can be generated automatically and decisions would be made. The other broad categorization is the analytic model-based approach to fault detection. In this case, linear or nonlinear system theory is used to develop system models. The model can represent electrical, mechanical, thermal, or hybrid dynamics that take place in the system. These analytic models attempt to represent the system by mathematical expressions. From these models, fault detection may be achieved analytically by comparing the model's reconstructed and estimated measurements with the actual behavior of the system, depicted by available sensor measurements. If analytic evaluation of the residuals is not suitable, fault detection may be made by an expert system based on heuristic rules. In this case, the final fault decision will be made by the human operator, as might be the case with the knowledge-based approach as well. Figure 2.1 is a block diagram showing the steps that are taken for both the knowledge-based and analytic model-based approaches.

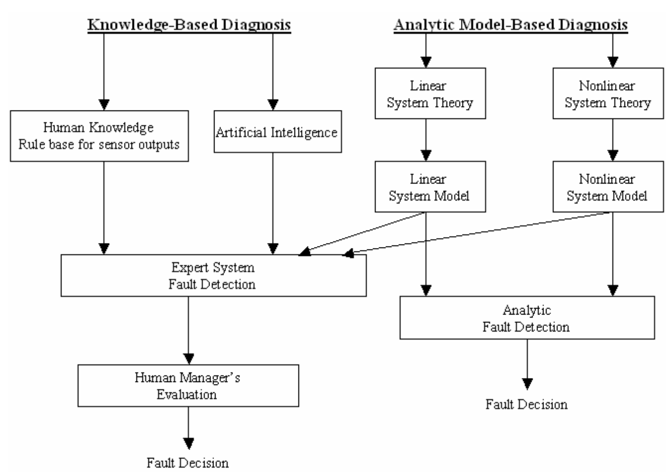


Figure 2.1: Various approaches to fault diagnosis

2.2.2 Analytic Models for Transformer Diagnostics

In the beginning, most attempts in transformer diagnostics focused on analytic models. As mentioned in the previous section, analytic models attempt to represent the system through mathematical equations. Depending on the complexity of the system and the desired model accuracy, both linear and nonlinear models have been developed. These models attempt to use physical principals to model a system. In the case of transformers, nonlinear models are needed in order to describe the inherent complexities of the system.

Model-based monitoring of transformers was introduced by MIT researchers (Hagman, et. al., 1996). It has subsequently been implemented on several transformers around the United States. In this model-based monitoring, actual measurements are compared with predictions based on operating conditions and ambient temperatures to provide a better assessment of the actual transformer condition. A schematic of the idea behind model-based monitoring is given in Figure 2.2. Parameter estimates for the model of the transformer system are calculated given a set of inputs and outputs. Once the model is developed, residuals are generated between the model outputs and the actual outputs. These residuals are put into an adaptive mechanism that recalculates the system parameters. The parameter estimation allows the diagnostic system to tune itself to each given transformer. Rapid deviation of model parameters indicates a developing fault. Slow changes in the parameters may only signify a slow developing fault or normal aging. Through trending of the parameter changes for a properly operating transformer, it also becomes possible to make life expectancy predictions (Hagman, et al., 1996).

For transformers, many different types of models have been developed to try to identify the system and detect failures. The transformer system is very complex. It contains thermal, mechanical, electrical, and fluid systems. Though most effort was made at linear models of the transformer systems, it quickly became evident that non-linear models provided for more accurate system identification (Archer et al., 1994). Using these models, it has become possible to detect faults by noticing abrupt and slowly developing changes in the model parameters. The added complexity that non-linearity introduces to system modeling renders it impractical in most cases.

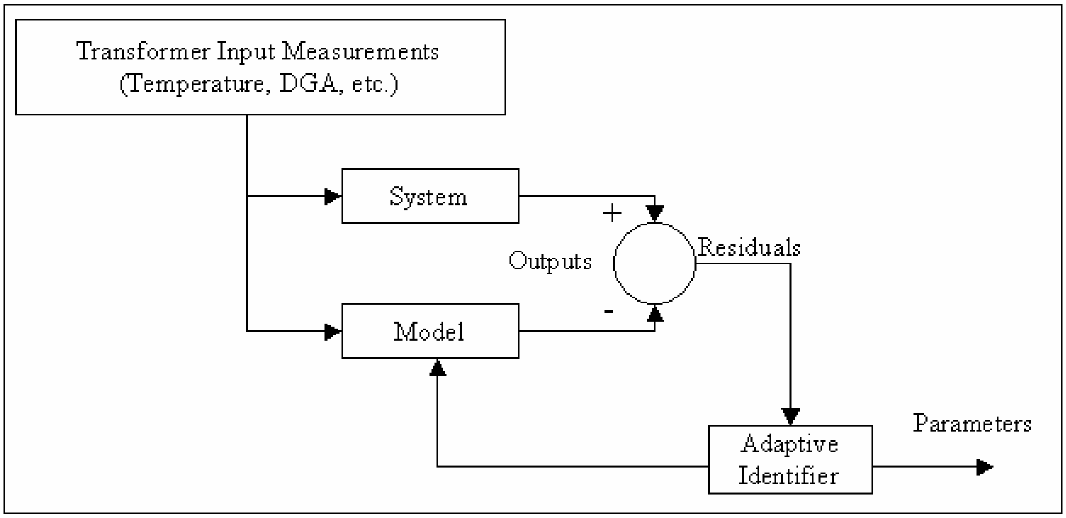


Figure 2.2: Model-based monitoring scheme for transformer

The most common models that have been experimented with are thermal models. The IEEE had developed a model for the top oil temperature rise above ambient temperature. As later researchers found, the IEEE model did not accurately account for changes in the ambient temperature that may occur. Subsequently, research was done at MIT to find a replacement for the MIT model. They developed a top oil model that incorporated ambient temperature variations to provide a system that was suitable for on-line monitoring and diagnostics (Lesieutre et al., 1997). In addition, the system used top oil temperature measurements in coordination with dissolved gas content to form an adaptive and intelligent monitoring system, utilizing thermal modeling (Kirtley et al., 1996).

Much like the system developed at MIT, Ottele presented a thermal model of the transformer using a physical based mathematical approach. An electrical circuit modeled the transformer, where capacitors and resistors represented the different thermal masses and thermal conductivities, respectively. The challenge was to determine the proper value for these critical transformer parameters. Ottele used both a Hopfield based adaptive observer and a modified extended Kalman filter to solve for the unknown states and parameters. The Hopfield network would give the least squares solution, while the Kalman filter would give a linear approximation based on Newton's method. In both cases, the solution resulted in the values for the unknown states and parameters of the system. Large state variations indicated failures or developing failures (Ottele, 1999).

For protection against overloading, transformer thermal models have also been developed, which use two exponential equations and non-linear time constants determined from transformer data (Zocholl & Guzman, 1999). These models are used to predict top-oil rise over ambient temperature, hottest-spot conductor over top-oil temperature, and hottest-spot winding temperature given a specific load. This allows the utility to predict the damage that can be done from running a transformer at a given load but also can be used to detect failures when there is a discrepancy between predicted temperatures and the actual measured temperatures.

Many models have been formed that combine temperature measurements with current, voltage, and other transformer measurements. Meliopoulos proposed a monitoring system that would estimate the transformer hot spot temperature, the loss of life (LOL), and the transformer coil integrity. State estimation methods were used, such as Cholesky factorization, to provide accurate estimates using oil, tank, and ambient temperatures in addition to the voltages and currents on all the phases as well as the LTC position (Meliopoulos, 2001).

In addition to the thermal models, many mechanical, electrical, and even fluid models have been developed for the transformer. On the mechanical side, a mathematical model has been derived to express the mechanical stresses due to forces on the transformer windings. This model provides critical information on the possible damage that is caused from radial short-circuit forces and gives an assessment of the possibility that a catastrophic fault from a winding short circuit could occur (Weselucha, 1995). Likewise, diagnostics of the electrical system have been developed using the transfer function method. Though the method uses ratios of the transformers electrical voltages and currents, the method actually detects defects in the mechanical system. The transfer function method is a quotient of the Fourier transformed input and output signals. These quotients are used to model the system electrically, and through comparison with previous fingerprints, can detect developing defects (Christian et al., 1999). In addition to the mechanical and electrical modeling strategies, fluid models have been developed for the transformer oil and its gas content. For bubbles to form, they must press against the surrounding liquid (i.e. mineral oil). The formation of bubbles inside the transformer is critical because the causes of bubbles are all linked to developing failures in the transformer. Supersaturation of the oil by gas, decomposition of the cellulose insulation, and vaporization of water in the oil all produce bubbles. The model indicates the temperature levels at which the bubbles form and thus allows for warnings when the temperature reaches the levels indicated by the model (McNutt et al., 1995). Finally, chemical models of the transformer insulation have also been developed. The insulation model uses degree of polymerization and tensile strength of the insulation to make fairly accurate estimations of the aging and life expectancy of the insulation (Pansuwan et al., 2000).

The thermal models and many of the others given above are based in the time domain. In the past few years, subspace-based identification of power transformer models have been formed from frequency response data (Ackay et al., 1999). In this study, transformers are identified through the use of a subspace-based algorithm in coordination with non-linear least squares technique. The identified transformers have a dynamic range of 1 MHz and still produce accurate models. In this method, mathematical frequency-based models are formed from which equivalent circuits can be derived to match the frequency response of the model. The resulting models are usually higher order but can be reduced through model reduction and still produce highly accurate mathematical representations of the system.

2.2.3 Artificial Intelligence Diagnosis of Transformers

There are several different techniques for fault detection and diagnostics. The knowledge required for the fault detection engine varies greatly with the technique used. The modeling techniques described above require significant knowledge about the system. The physics behind the operation of the device (i.e the transformer) has to be derived. This type of modeling is known as white box modeling. For the model to be successful, there must be information available about the inner workings of the system. On the other side of the spectrum, there is black box modeling. Black box modeling does not require knowledge of the inner workings of the system. Artificial intelligence is the prime example of the black box model. The artificial intelligence trains itself to the system and provides diagnostic information based on a set of inputs and outputs. The actual mapping that the artificial intelligence develops or how this relationship relates to any physical principles is usually not defined. For the user, the inner working of the fault detector is not important, rather only the output of the fault detector is of interest. Figure 2.3 illustrates the difference between white box and black box monitoring.

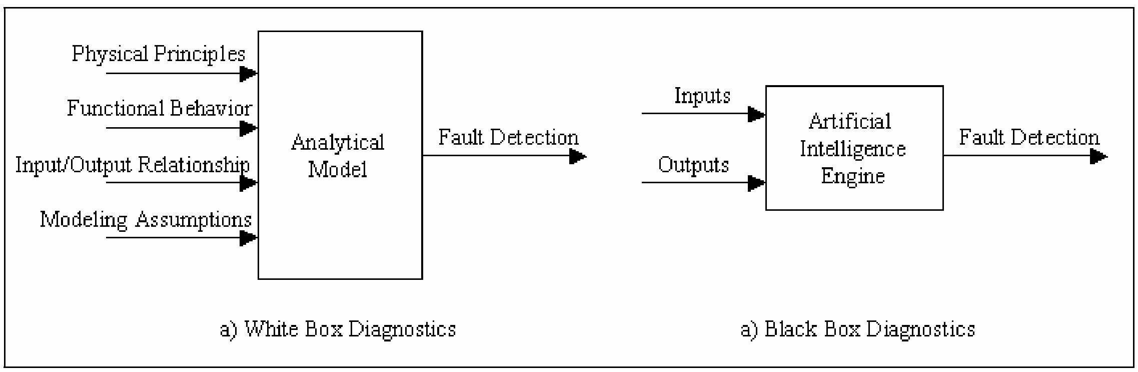


Figure 2.3: Comparison between white and black box diagnostics

As noted earlier, the non-linearity of transformers makes it exceedingly difficult to create white box models that provide a high level of accuracy. In addition, the many subsystems (thermal, mechanical, electrical, fluid) present in a transformer make the system modeling very complex. It is not feasible to determine the physical principles that inter-relate the subsystems and accurately formulate a model system. For this reason, black box modeling, centered around various artificial intelligence techniques, have become more popular for transformer diagnostics (Jota et al.,1998). In this case, the artificial intelligence can solely be used or a hybrid of knowledge-based and artificial intelligence techniques can be used (gray box diagnosis).

The most common forms of artificial intelligence used for transformer diagnosis are neural networks and fuzzy logic. Petri nets and genetic algorithms have also been tried but with less success. An overview of some of the artificial intelligence techniques that have been developed for transformer diagnostics is discussed below.

Due to the complexity of the numerous phenomena, it is difficult to formulate a precise relationship relating the different contributing factors. This uncertainty naturally lends itself to fuzzy set theory. For this reason, most black box and gray box diagnostic techniques have used fuzzy logic to some extent. Xu et al. developed a transformer diagnostic system that utilized both an expert system and a neural network to detect failures in a transformer. The knowledge of the expert system has many uncertainties, and therefore fuzzy logic is employed. In this case, the neural network employs sampled learning to complement the knowledge-based diagnosis of the expert system. The two techniques are integrated by comparing the expert system conclusion with the neural network reasoning using a consultative mechanism (Xu et al., 1997). A block diagram for this type of hybrid system is given in Figure 2.4.

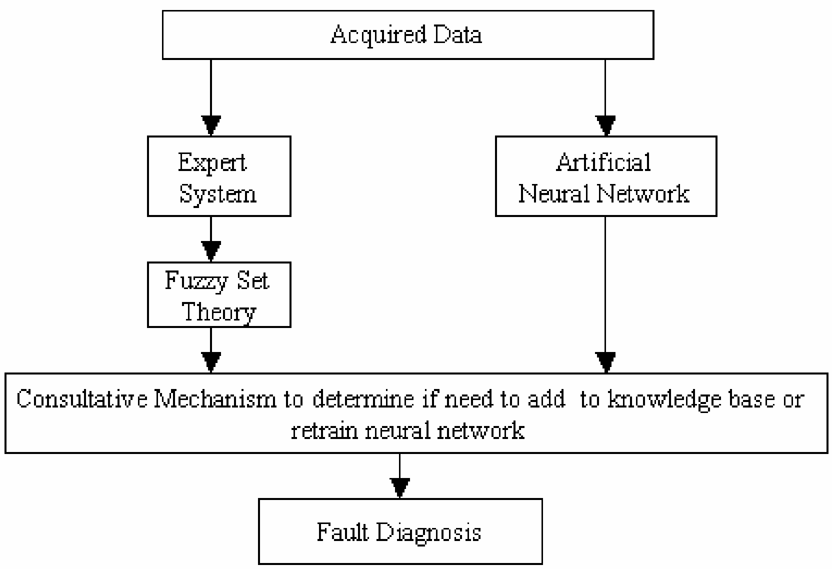


Figure 2.4: Strategy for combined fuzzy logic, expert system, and neural network

Much like Xu, Gao and Yan also developed a comprehensive system that included fuzzy logic, expert system, and an artificial neural network to detect faults in the insulation system. In this case, fuzzy logic is implemented in coordination with the neural network. The output of the neural network is numerical values between 0 and 1, which are placed in membership functions based on a set of fuzzy rules (Gao & Yan, 2002).

The combination of an expert system with neuro-fuzzy techniques is not the only diagnostic tool used in transformer systems. An integration of an artificial neural network and an expert system has been developed for power equipment diagnosis. The system uses the neural network to form implicit diagnostic rules and has the added benefit of logic regression analysis for fault location (Wang et al., 2000). In addition, work has been done in predicting the moisture content in the transformer oil using a neuro-fuzzy system, similar to the one presented and tested later in this thesis. This method trains the network to the moisture content and then compares expected and predicted values of the moisture content to detect failures (Roizman & Davydov, 2000). The strategy for this diagnostic system is given in Figure 2.5.

Though many methods have employed some combination of fuzzy logic, artificial neural networks, and expert systems, this is not always the case. A highly accurate two-step artificial neural network has been used for transformer fault diagnosis using dissolved gas data. In this system, two neural networks are used. One is used to classify the major fault types, while the other determines if the cellulose insulation is involved (Zhang et al., 1996). In addition, a DGA based diagnostic system has been developed that employs a single neural network that is trained with an improved back propagation algorithm utilizing data pre-treating for higher accuracy (Yanming & Zhang, 2000).

Fuzzy logic has also been used to diagnose the health of a transformer and foresee any developing failures. Fuzzy logic has been used to smooth out some of the problems that can appear when using the cut and dry rules of expert system knowledge. By forming fuzzy membership functions for the different measurements (gases, generation rates, electric current, temperature), it is possible to overlap the individual membership functions into one large fuzzy matrix that can be used for diagnosis (Denghua, 2000). A fuzzy logic diagnostic system has also been developed for the transformer that utilizes evolutionary programming and different shaped membership functions to get a more accurate fuzzy diagnostic system. This is formulated as a mixed-integer combinatorial optimization problem (Huang et al., 1997).

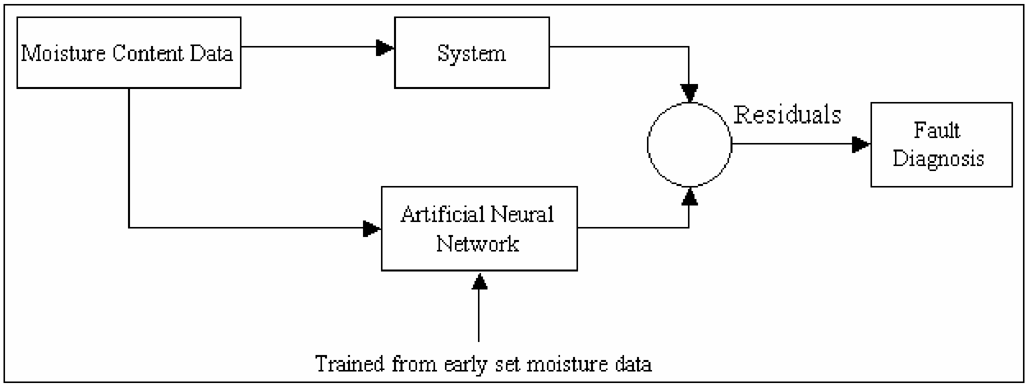


Figure 2.5: Fault diagnosis method utilizing neural network on moisture data

Another artificial intelligence based approach utilizes a genetic algorithm in coordination with an artificial neural network. One of the weaknesses of the artificial neural network approach is the tendency to find only a local minimum in its training due to improper initial value. In this case, the genetic algorithm is used to optimize the initial value and thus increase the accuracy of the neural network training (Wen et al., 1997). Likewise, genetic algorithms have been used in the training of a fuzzy controller that forms diagnostic rules based on dissolved gas data. In this case, the fuzziness helps define diagnostic operating conditions and the genetic algorithm decreases the amount of rules needed (Szczepaniak, 2001).

In addition to genetic algorithms, Petri nets have found some applications in transformer diagnostics. The type of system affects how the Petri net operates and fails and what can be diagnosed from the failure of the net. One method is to construct redundant Petri net embeddings, which can then be used to identify place or transition failures. A transition failure models a failure in the hardware performing a certain transition (in a discrete event system), since no tokens are deposited to their appropriate output places or none are removed from the input places. The first is a failure of the post conditions; the second is a failure of the preconditions. A place failure, on the other hand, corrupts the number of tokens in a single place (Hadjicostis, 2000). Coloured Petri net (CPN) models have the added benefit that the tokens are distinguishable. These can be used even more effectively to diagnose a complex system. The structure of the Petri net is a graph describing the structure of a discrete event system and the dynamics of the system is described by the execution of the Petri net (Szucs et. al., 1998). The Petri net in essence models the whole system, both the system states and error states. Once the Petri net model is formed, a reachability tree starting from the initial state can be formed.

In Petri net diagnostic systems, predictive learning is also possible. In this case, the diagnostic system archives all events measured online. If an unmodeled event or state occurs, the Petri net adds the description to the system. It might be possible to apply these techniques to transformer diagnostics. However, the transformers lack of discrete event makes the problem more difficult. A fast and accurate transformer diagnostic system has been developed in China. The Petri net operation matrix is used for knowledge representation and inference. From this matrix, a relationship between the fault warning and the fault itself can be formulated (Wang and Ji, 2002).

3. Neuro-fuzzy Fault Detection Engine

In Chapter 2, many different diagnostic techniques were described. Analytical models can be used to describe dynamics of the transformer system. However, it can be realized that modeling of the entire transformer system, in order to accurately diagnose failures, is not feasible. For this reason, artificial intelligent techniques are employed to detect developing faults in transformers. As described in Chapter 2, the combination of neural networks and fuzzy logic is common in transformer diagnostic systems. The neuro-fuzzy engine proposed in this thesis utilizes neural network and fuzzy logic for the purpose of non-linear system identification, output observation, and fault detection. This neuro-fuzzy system has been implemented and tested by the research team in their prior investigation related to the development of an Intelligent Substation, and has been found to successfully detect failures in such non-linear thermofluid systems as refrigerators and distribution transformers.

The description of the neuro-fuzzy system used in this research is given below. A mathematical description of the inner workings of the system and how the final fault detection decision is made is also described. The work described here is part of the effort of the research team headed by Dr. Shoureshi and his graduate students, Hu (2000) and Fretheim (2000).

3.1 Overview of Diagnostic Approach

The diagnostic approach developed by the research team can be divided into several parts. First, relevant, diagnostic data must be collected from sensors. From this set of data, measurements are chosen to be either inputs or outputs. The neuro-fuzzy network then receives the data and performs several tasks. Non-linear system identification is the first step performed by the network. Through training, the neuro-fuzzy network identifies the non-linear system dynamics, so that future estimations can be made. Once trained, the network can serve as an output observer. The trained network processes data and estimates the output. These estimates can then be compared to the measured outputs to form residuals. The final step is to analyze the residuals produced by the neural network in order to detect faults. The assessment of the transformer health and any need for maintenance can be established. A block diagram of this approach is shown in Figure 3.1.

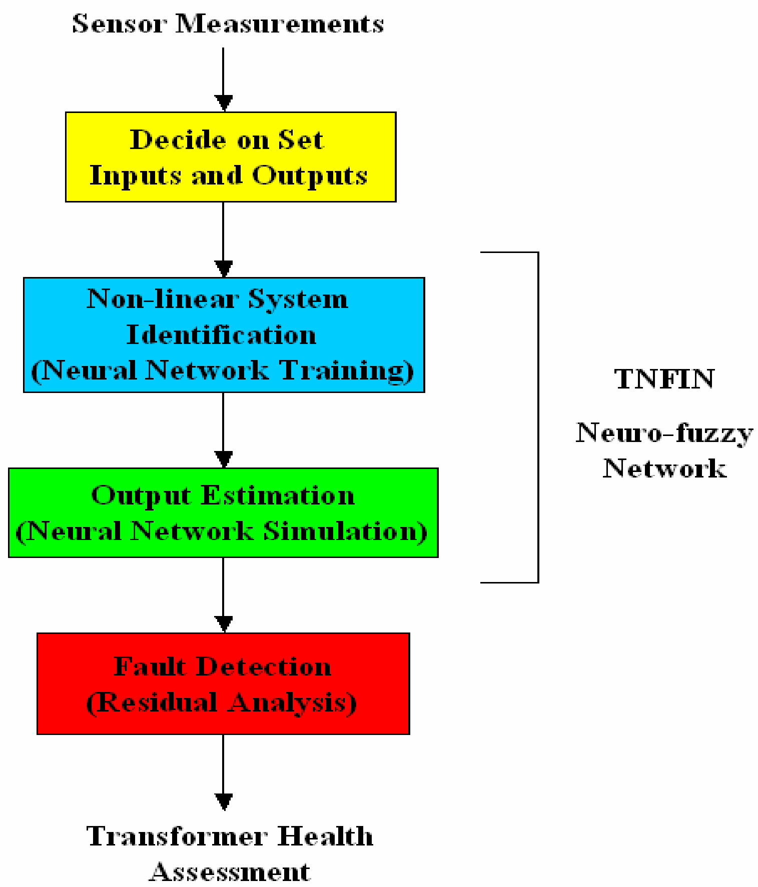


Figure 3.1: **Block diagram of diagnostic approach**

The following sections describe the architecture of the neuro-fuzzy network used in the research and give the mathematical foundation for the non-linear system identification, output observation, and fault detection.

3.2 Non-linear System Identification

This section focuses on the theoretical basis for non-linear system identification, which is applied to the transformer. The purpose of system identification is rather simple. Through observing the system, a model is formed that attempts to duplicate the behavior of the system. As the size and complexity of the system increases, it becomes more difficult to develop analytical models. The more accurate the model the smaller the error will be between the model estimates and the actual outputs. A block diagram of the operation of a system identification technique is depicted in Figure 3.2.

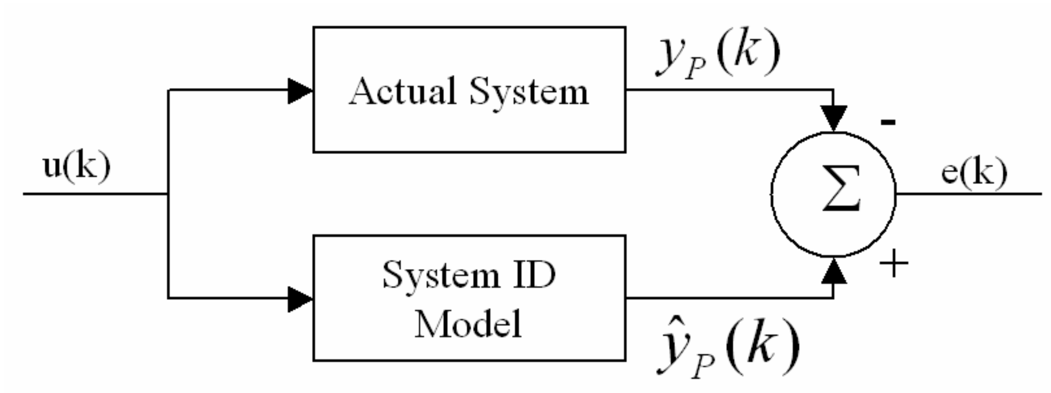


Figure 3.2: Process of system identification

In the case of the transformer, simple analytical models often cannot accurately portray its dynamics. Therefore, neural networks are commonly used for non-linear system identification of transformers. A summary of previous research related to non-linear system identification using neural networks is discussed below.

3.2.1 Background of Neural Networks for System Identification

As mentioned in Chapter 2, one alternative to complex analytical modeling is system identification through other means, such as artificial intelligence (Ljung, 1999). In more general terms, system identification is the name given to the various methods which use input output data to develop dynamic models for a system.

Until about the mid-1980s, non-linear models of systems were primarily derived empirically or from first principles. If these analytic models were too complex to derive, a linear approximation could be made through input output data, or nonlinear systems could be linearized around an operating point. For example, the extended Kalman filter uses a linearization around a certain point to try to approximate the non-linear behavior. By applying techniques based on complex variables, linear algebra, and ordinary differential equations, complex systems could be identified.

Despite the growing expertise and experience that had been formed in the area of linear system theory, non-linear system identification was still a relatively new topic. Few people had focused their attention on non-linear system identification. In the case of non-linear systems, stability, system behavior, and robustness had to be analyzed differently for each case. There were no general rules that could be applied as in the case of linear systems. In the 1980's with the introduction of neural networks, non-linear system identification received much more attention. A neural network is meant to operate like a human brain. Just as the human mind makes decisions based on past learning experiences, a neural network produces outputs by processing a set of inputs based on past learning. Narendra and Parthasarathy (1990) published the first, feasible neural-based method for non-linear system identification. Two categories of neural networks have been considered for this application: 1) multilayer neural networks and 2) recurrent networks. Multilayer neural networks represent static non-linear maps, while recurrent networks represent non-linear dynamic feedback systems. Using back propagation techniques for training, non-linear system identification was found to be feasible through neural networks.

Neural networks were first used to identify process dynamics in nuclear power plant components (Parlos and Atiya, 1991; Parlos et al., 1994). A recurrent multilayer perceptron network is used, where the architecture is a mix between feedforward and feedback. In the nuclear power plant case, the network is compared to an analytic white box model derived from physical principles. The results of the neural network compared well with the analytic model and showed that for this specific application, neural networks can succeed in non-linear system identification. Though it is not clear whether the recurrent feature in the neural network improved the results, most subsequent research is aimed at these recurrent networks.

Qin and McAvoy (1992) compare recurrent networks versus feedforward networks and batch learning versus pattern learning. Four neural network learning algorithms are used in their experiments. The results show that the recurrent network is more robust to noise but has a more complicated training routine. The same experimental result is achieved by an independent experiment (Nerrand et al., 1994), where a discussion of training recurrent neural networks for process modeling is described. The ultimate decision on the type of training that should be employed for non-linear system identification should be based on the noise involved in the process. Batch learning is appropriate for white noise or noiseless systems.

For systems where the noise varies or is not deterministic, many different methods have been developed for training. Das and Olurotimi (1998a; 1998b) discuss how to train recurrent neural networks with noise present. There are many different architectures and training algorithms to choose from and careful effort should be taken in picking the algorithm appropriate for the system at hand.

The question is often posed as to whether a recurrent network is worth the added complexity. A recurrent network does add many more connections than a feedforward/feedback architecture. It has been proven that a recurrent network can serve as a universal approximator of an arbitrary non-linear mapping, provided a few conditions are met, whereas the same cannot be said of the feedforward/feedback networks (Chen and Chen, 1995).

The training algorithm of both multi-layer feedforward neural networks (MNN) and recurrent neural networks (RNN) are usually based on a back propagation (BP) algorithm, as were the first neural networks used for non-linear system identification (Rummelhart et al., 1986). The BP algorithm for MNN's are better understood than RNN's (Das and Olurotimi, 1998a). As such, there has been much more success in using MNN's for non-linear system identification, pattern recognition, controls, and signal processing than there has been using RNN's. Over the years, many improvements have been made on the standard BP algorithm, such that it would have a faster convergence. Despite the improvements, the major disadvantage of BP based neural networks is the slow convergence and the susceptibility to falling in a local minimum.

In order to try to compensate for the problem of slow training, radial basis function neural networks (RBFNN's) (V.T. and Shin, 1994), which can approximate any static non-linear function to some desired accuracy (Haykin, 1994), was introduced. In most cases, the RBFNN has faster training, since it does not use a BP algorithm. However, the training can often result in an ill-conditioned least mean squared (LMS) problem. In addition, the memory requirements can get extremely large when dealing with larger data sets. In general, RBFNN has two major disadvantages: computational complexity, and lack of spatial varying resolution (Suykens and

Vandewalle, 1998). Despite these problems, RBFNN has been found to be effective for non-linear system identification as discussed by Juditsky et al. (1995).

The above forms of non-linear system identification only use neural network architectures. As noted in Chapter 2, it has become common to incorporate fuzzy logic with neural networks. Much like neural networks, fuzzy logic can also be used to form models for non-linear systems based on input output data (Suykens and Vandewalle, 1998). A structure that holds increased potential for fuzzy modeling is the Takagi-Sugeno (TG) system. This system combines an artificial neural network with fuzzy logic to create a neuro-fuzzy system for non-linear system identification. This hybrid system is known as a Tsukamoto-Type Neural Fuzzy Inference Network (TNFIN), which is an extension to the TS fuzzy system (Hu et al., 2000). It is this form of black box modeling that is used in the present research for system identification and fault detection. This technique displays a fast and accurate training and has compared well with the MNN's and RBFNN's in previous studies (Fretheim, 2000).

3.2.2 Neural Network Architectures

As shown in the preceding section, there are many different types of neural network architectures that can be used for non-linear system identification. They all have their strengths and weaknesses. When choosing the appropriate algorithm, there are two properties that are crucial. First, the training algorithm should be fast and the parameters space must not be too large that the architecture cannot be implemented in a real-time scenario. Fretheim (2000) did a study of the different types of neural network architectures, including MLPNN, RBFNN, and TNFIN. Through experimental studies with a refrigerator diagnostics and distribution transformer systems, it was found the MLPNN is well understood but has the tendency to fall into local minima. The RBFNN performed comparatively with the TNFIN with respect to accuracy. However, the RBFNN requires nearly three times as many parameters as the TNFIN. This is computationally expensive and undesirable for the purposes of non-linear system identification for the transformer. Due to the results with the small distribution transformer, the TNFIN is used for this research, where a larger transformer is being identified.

The TNFIN was developed and first implemented by Zhi Hu (2000). The TNFIN was originally implemented as a load forecaster but was later applied to non-linear system identification (Fretheim, 2000). Experience with non-linear systems has shown that the TNFIN does not have the tendency to fall into local minima as is the case for the MLPNN. The training algorithm for the TNFIN has also been improved to make it comparable with the RBFNN. With this fast training capability of the TNFIN, non-linear system identification became possible. To better understand the TNFIN architecture and how it can be used for system identification, an overview of the TNFIN is given below.

3.2.3 TNFIN Architecture

TNFIN is a multi-layer feedforward neural network. The number of layers in the TNFIN is held constant at 4. The TNFIN can handle any number of inputs and outputs, which makes it applicable for many different systems. The architecture used in this research is a slight variation of the original network presented by Hu et al. (2000), which had five layers.

A schematic of the general architecture of the TNFIN is presented in Figure 3.3. The figure is shown for the case of two inputs and two outputs. The network can be adjusted for any number of inputs and outputs. The equations and constraints given below are for the two input, two output case. The parameters that are adapted during training show up in the functions of layers 1 and 3.

Layer 1: This is the fuzzification layer. Each node of the first layer gives a membership degree of a linguistic value. For a network with N inputs, the first layer places each input into a fuzzy set. The total number of nodes in this layer is equal to the number of inputs (N) times the number of membership functions in the fuzzy set. The kth node in this layer performs the following operation:

$$O_k^1 = \mu_{A_{ij}}(x_i) \tag{3.1}$$

where

$$k = 2*(i-1)+j \qquad (1 \le i \le 2, 1 \le j \le 2)$$

x_i is the ith input variable, and A_{ij} is the jth linguistic value associated with the input variable x_i. Thus, O_k^1 denotes a membership function related to x_i and specifies the degree of x_i belonging to A_{ij}. $\mu_{A_{ij}}$ is chosen as a bell-shaped function without an exponential parameter. There must be at least as many membership functions as there are inputs to the TNFIN.

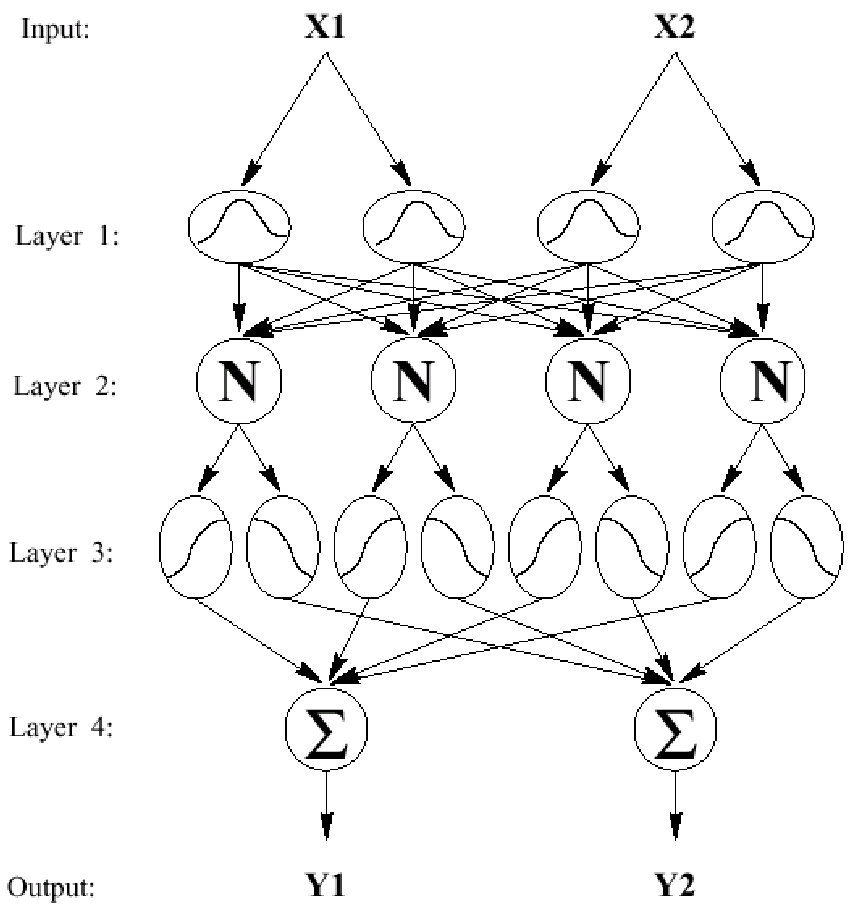


Figure 3.3: Architecture of the TNFIN

Once the number of membership functions has been decided for layer 1, the network structure for all the remaining layers is established as well, and layer 1 becomes:

$$O_k^1 = \mu_{A_{ij}}(x_i) = \frac{1}{1+[(\frac{x_i - a_{ij}}{b_{ij}})^2]} \tag{3.2}$$

where

$$k = 2*(i-1)+j \qquad (1 \le i \le 2, 1 \le j \le 2)$$

and the set of parameters $\{a_{ij}, b_{ij}\}$ associated with the jth membership function of the ith input variable is referred to as antecedent parameters and is used to adjust the shape of the membership functions in layer 1. Since there is both a and b parameters, the number of adjustable parameters is twice the number of membership functions.

Layer 2: Layer 2 serves as the normalization layer. The weighted outputs from the nodes of layer 1 are normalized. The total number of nodes in layer 2 is equal to the number of nodes in layer 1. The output is simply given by:

$$O_k^2 = \frac{O_k^1}{\Sigma_k O_k^1} \qquad (1 \le k \le 2N) \tag{3.3}$$

Layer 3: Once the inputs have been fuzzified and normalized, they must once again be defuzzified. Therefore, layer 3 serves as the defuzzification layer. The total number of nodes in this layer is equal to the number of nodes in layer 1 times the number of outputs. Each node from Layer 2 expand into two (number of outputs) same type nodes in layer 3, which contain two types of functions, either a monotonically increasing or monotonically decreasing function. Tsukamoto-type fuzzy reasoning (Tsukamoto, 1979) is used for fuzzification.

Thus, the defuzzified values for the output of this layer are specified as follows:

$$O_m^3 = \begin{cases} O_k^2 (c_{kl} - d_{kl} \sqrt{\dfrac{1}{O_k^2} - 1}) & \text{if } \mathrm{k} = \text{odd} \\ O_k^2 (c_{kl} + d_{kl} \sqrt{\dfrac{1}{O_k^2} - 1}) & \text{if } \mathrm{k} = \text{even} \end{cases} \tag{3.4}$$

where

$$\mathrm{m} = 2 * (\mathrm{k} - 1) + 1 \qquad\qquad (1 \le \mathrm{k} \le 4, 1 \le \mathrm{l} \le 2)$$

Layer 4: The fourth and final layer in the network architecture is the summation layer. It sums the outputs of layer three together into an output. There are as many nodes in this layer as there are outputs. There is only one connection between each node in layer 3 and a node in the output layer. The output of this layer is simply:

$$O_l^4 = \sum_k O_{2*(k-1)+l}^3 \tag{3.5}$$

3.2.4 Hybrid Learning Algorithm

Training of the TNFIN network is done with a hybrid learning algorithm that incorporates both error minimization and supervised learning. Hu (2000) provides a detailed description of the training algorithm used for the TNFIN. A few of the unique parts of the training algorithm are discussed here.

As noted above, the training of the network is done using supervised learning and error minimization. When p is the number of training sets and l is the number of inputs, training is performed by:

$$\begin{aligned} &\min E = \frac{1}{2} \sum_p \sum_l (T_{p,l}^* - O_{p,l}^4)^2 \\ &\textit{and} \qquad E_{p,l} = \frac{1}{2} (T_{p,l}^* - O_{p,l}^4)^2 \end{aligned} \tag{3.6}$$

where E is the mean squared error between the training and the output, $O^4_{p,l}$ is the *l*th output of the network for the *p*th training set, and $T^*_{p,l}$ is the measured target.

The parameters *c, d* in layer three are updated using a LMS algorithm. The following steps are performed during each complete iteration of the TNFIN training algorithm:

Step 0:

Initialize parameters *a, b* to a predefined value, and set parameters *c, d* equal to **zero.**

Step 1:

Calculate the consequent parameters *c, d* using LMS algorithm.

Step 2:

Calculate a range of learning rates to use.

Step 3:

Use GD (gradient descent) algorithm to minimize the output with respect to *a, b*, followed by LMS algorithm to calculate the respective *c, d*. For all the learning rates calculated in step 2, repeat starting from the minimum after step 1.

Step 4:

The final parameters to be used for the network are chosen from the minimum of step 3. If the value is not small enough, further training may be done by repeating steps 2 and 3.

Due to the linear relationship between the parameters in layer three and the error *E,* the training of the consequent parameters through the LMS algorithm is fast. In addition, the GD approach, that adjusts the antecedent parameters with different learning rates from the same starting point, helps to avoid falling into a local minima.

Training of this network was used for a small 10kVA transformer that was anticipated to simulate a larger transformer, similar to the ones used in this research (Fretheim, 2000). It was found that large data sets were necessary to capture the full dynamics of the transformer system. When these larger sets of input output data were used, the TNFIN trained quickly and with a small error of less than .05 (normalized). It is found that the problems of slow convergence and local minima were avoided. With the positive results from the small transformer already documented, it was the natural choice to use the TNFIN for system identification on the larger transformers used in the present research.

3.3 Neural-Based Non-linear Observer

In addition to system identification, the neural network will also serve as an output observer. This observer problem can be defined as a solution to a set of non-linear equations, and solved using non-linear least mean squares (LMS), the same method used in the training of the neural network. Newton's algorithm and Levenberg-Marquardt's method, two well known LMS techniques, are considered. This neural-based observer will serve as the foundation for the fault detection approach of the next section.

3.3.1 Observer Introduction and Background

The goal of an observer is to provide an estimate of the state of a dynamic system using only input output data. Work in attempting to find the solution to a state estimator for a linear, time invariant system first began in the mid 1960s (Luenberger, 1963). To understand the mathematical basis of an observer, first consider the *n*-dimensional linear time invariant system:

$$\begin{aligned} x(k+1) &= Ax(k+1) + Bu(k+1) \\ y(k+1) &= Cx(k) \end{aligned} \tag{3.7}$$

where A,B, and C are respectively $n \times n$, $n \times p$, and $q \times n$ matrixes, $x(k) \in R^n$ is the state vector, $u(k) \in R^p$ is the system input, and $y(k) \in R^q$ is the system output. If we are given the measurements $[y(k)\ y(k\text{ -}1) \cdots y(k\text{ -}l)]$, and the inputs
$[u(k)\ u(k - 1) \cdots u(k - l)]$, the problem for the observer is to find an estimate of the state trajectory $[\hat{x}(k), \hat{x}(k-1) \cdots \hat{x}(k-l)]$, where $\hat{x}(.)$ indicates an estimate of the true states $x(\cdot)$.

After success of observer designs with linear, time invariant systems, widespread work has been devoted to expand the observer design to time-varying linear systems, and to non-linear systems. Due to their lesser amount of complexity, most effort has focused on linearizable systems (Baumann and Rugh, 1986). Stable observers have also been developed using quadratic Lyaponov functions (Thau, 1973). In addition, there has also been some success using Hopfield neural networks for state observers (Chu et al., 1989; Chu and Shoureshi, 1994). Likewise, Kalman-type and Luenberger observers have also been extended to incorporate the non-linear systems in continuous time (Gauthier et al., 1993; Deza et al., 1992).

Non-linear observer design is still an active research topic. Methods are currently being developed to try to apply to broad classes of non-linear systems. Michalska and Mayne (1995) have proposed an optimized moving horizon observer, while Grizzle and Moraal (1995) derived an approach to solving systems of non-linear equations applicable to a wider class of non-linear observer design. The observer problem can also be analyzed by solving a set of differential algebraic equations (Nikoukhah, 1998).

In finding an observer, it is not always necessary to have a system model, as utilized in the case of linear observers. Using a neural network to train itself to estimate the states from input output data, it is possible to create an observer that uses only input data (Levin and Narendra, 1996). For this to work, however, the dynamic system trajectory must be limited. This is feasible for control systems where one knows the outputs and inputs that are available.

For the purposes of diagnostics, state observers may also be used. Observers used for fault detection are quite similar to those used for state estimations. The main difference is there is no need for a comprehensive knowledge of the state space in diagnostic applications of observers. For diagnostics, an output observer is used to help determine changing relationships between signals so that an output value may be estimated. This estimated value can then be used to determine any developing abnormalities or dramatic changes in the system.

In fault detection, the difficulty is associated with determining which sensor measurements to use as inputs and outputs of the system. In the case of the diagnostic module designed in this research, the current, temperature, and vibration data must be used to train the network. The goal is to choose inputs and outputs chosen that would cover the range of normal operating conditions. The key for fault detection is that the observer be able to detect changing dynamics.

In this section, a new analytic technique for output observer design for non-linear systems is described where the intended application is fault detection. Instead of identifying the inverse mapping directly, a neural network will be used to determine the forward dynamics of the system. The observer then uses the identified model to estimate unknown outputs from known outputs and inputs. The neural network is only used to represent the system dynamics and thus the observer can be used to solve for different outputs depending on the available inputs. The inputs and outputs to the observer are not fixed and, therefore, there is a greater flexibility.

Later in this chapter, it will be shown that this flexibility is a requirement for a new fault detection approach. The TNFIN network discussed earlier is used to model the system. However, any neural network architecture can be used for the observer design that is described below.

3.3.2 Nonlinear Observer Using Neural Network Dynamic Models

The class of systems to be considered can be described by:

$$x(k+1) = f(x(k), u(k))$$
$$y(k) = g(x(k), u(k))$$

where $x \in R^n$, $u \in R^m$, $y \in R^p$.

An alternative representation for the system is as a predictor equation of the following form:

$$\begin{bmatrix} y_1(k+1) \\ y_2(k+1) \\ \dots \\ \dots \\ y_n(k+1) \end{bmatrix} = F(y_1, y_2, \dots, y_p, u_1, u_2, \dots, u_m) \tag{3.8}$$

where:

$$y_j \overset{\Delta}{=} y_j(k), y_j(k-1), ..., y_j(k-jl)$$
$$u_j \overset{\Delta}{=} u_i(k), u_i(k-1), ..., u_i(k-il)$$

The model representation given by (3.8) has been discussed in (Shoureshi et al., 2000). The identification of a non-linear system involves training the neural network to approximate the mapping described by equation (3.8). The spaces defining the input and output sequences of the system are represented by U $\in$ R^r, Y $\in$ R^p, and Y_{in} $\in$ R^q, where

$$U(k) \overset{\Delta}{=} [u_1(k), u_1(k-1), ..., u_1(k-1l), u_2(k), u_2(k-1), ..., u_2(k-2l), ..., \\ u_m(k), u_m(k-1), ..., u_m(k-ml)]^T$$
$$Y(k) \overset{\Delta}{=} [y_1(k), y_2(k), ..., y_p(k)]^T$$
$$Y_{delay}(k) \overset{\Delta}{=} [y_1(k-1), ..., y_1(k-1l), y_2(k-1), ..., y_2(k-2l), ..., y_p(k-1), ..., y_p(k-pl)]^T$$
$$Y_{in}(k) \overset{\Delta}{=} \begin{pmatrix} Y(k) \\ Y_{delay}(k) \end{pmatrix}$$
$$Z \overset{\Delta}{=} \begin{pmatrix} U \\ Y_{in} \end{pmatrix}$$

Let $NN_f : Z^{r+q} \rightarrow R^p$ be a neural network representing the mapping given by Equation (3.8).

Let $NN_{fl} : (Y_{in}(k+l-1), U(k+l-1)) \rightarrow Y(k+l)$

Let one output y_i be measurable for all time k.

Let $C \overset{\Delta}{=} [1 \times p]$ where $C_i = 1$ and $C_j = 0$ where $j \neq i$

A sequence of *l* observations can be described by the following set of equations:

$$\begin{bmatrix} y_i(k+1) = C * NN_{f1}(Y_{in}(k), U(k)) \\ y_i(k+2) = C * NN_{f2}(Y_{in}(k+1), U(k+1)) \\ \dots \\ \dots \\ y_i(k+l) = C * NN_{fl}(Y_{in}(k+l-1), U(k+l-1)) \end{bmatrix} \tag{3.9}$$

where the $C*$ term selects out only the measurable output, which will later be compared with the actual output in the LMS algorithm.

Due to the forward prediction of the NN_f, the only unknown in equation (3.9) is the vector $Y_{in}(k)$. If there exists a unique solution to this set of equations for some value of *l*, it is stated that the system is output observable, and the vector $Y_{in}(k)$ can be recovered through a non-linear LMS algorithm.

The existence of the solution to Equation (3.9) is guaranteed if the output observability condition is satisfied. For a non-linear system, the concept of output observability becomes a function of the system trajectory, and hence, the existence of a solution to Equation (3.9) changes with time. Even if a solution exists, finding the inverse of the non-linear LMS problem can in many cases result in an ill conditioned solution. This is undesirable because any small disturbances or modeling errors can create large changes in the estimation of the unknown outputs.

An alternative approach to the non-linear neural network observer is to directly identify the inverse mapping using an artificial neural network (Shoureshi et al., 2001). The disadvantage of this approach is that all physical insight into the system dynamics is lost. Through identifying the system, any output can be considered the known measurement. This is extremely helpful in fault detection, where the dynamic model is used as a basis for fault detection.

3.3.2.1 Newton's Method

Newton's method (Shoureshi et al., 2001) was implemented to solve the set of Equation (3.9) as a root finding problem, and was implemented on a system with very little noise, and small modeling errors.

The algorithm converged quickly and reached a solution by selecting the best estimate of the output value and updating the value according to a standard algorithm.

In reality, the algorithm is terminated when the solution converges, or a fixed number of iterations have passed and the solution is not found. When no noise is present and the system has been accurately modeled, the algorithm worked suitably. However, noise in the system, or a poor initial guess had a tendency to make the algorithm diverge. The Levenberg-Marquard algorithm is found to be a more robust solution to the problem.

3.3.2.2 Levenberg-Marquardt Method

As a general nonlinear least squares equation solver, the Levenberg-Marquard algorithm (Shoureshi et al., 2001) has demonstrated good performance. The algorithm will always take a step in a descent direction and will not diverge as in the case of Newton's method when noise was present. The challenge is estimating a good initial state, when an acceptable local minimum or global minimum is desired. To be preferable over Newton's method, the observer must converge even in the presence of noise. By solving Equation (3.9) without regularization and then adding a regularization term, the observer becomes more robust in the presence of disturbances.

Let

$$R(\hat{Y}_{in}) \stackrel{\Delta}{=} [y_1^* - C * NN_{f1}(\hat{Y}_{in}, U), y_2^* - C * NN_{f2}(\hat{Y}_{in}, U), \ldots, y_m^* - C * NN_{fm}(\hat{Y}_{in}, U)]^T$$

$$minimize\ f(\hat{Y}_{in}) = \frac{1}{2} R(\hat{Y}_{in})^T R(\hat{Y}_{in}) = \frac{1}{2} \sum_{i=1}^{m} r_i(\hat{Y}_{in})^2 \qquad (3.10)$$

where $m > q, R(\hat{Y}_{in})$ is nonlinear in $\hat{Y}_{in}$ and

$\hat{Y}_{in} \in R^q$

$r_i(\hat{Y}_{in}) = y_i^* - C * NN_{fi}(\hat{Y}_{in}, U)$

where y_i^* is the observed value and $NN_{fi}(\hat{Y}_{in}, U)$ is estimated by the model.

If a solution exists, the global minimum = 0. However, modeling errors and noisy measurements will often result in a solution greater than 0. Let $\hat{Y}_{in}$ be the estimate of $Y_{in}(k)$ as a starting point. The recursive update of $\hat{Y}_{in}$ then becomes:

$$\hat{Y}_{+} = \hat{Y}_{in} - [J(\hat{Y}_{in})^T J(\hat{Y}_{in}) + \mu_c I]^{-1} J(\hat{Y}_{in})^T R(\hat{Y}_{in}) \tag{3.11}$$

where $\mu_c = 0$ if $\delta_c \geq \| (J(\hat{Y}_{in})^T J(\hat{Y}_{in}))^{-1} J(\hat{Y}_{in})^T R(\hat{Y}_{in}) \|_2$ and $\mu_c > 0$ otherwise.

Here, δ_c can change from one iteration to another, and will adjust the step size, $\hat{Y}_{in} = \hat{Y}_{+}$, for the next iteration. The solution to the minimization problem (3.10) represents the following mapping:

$$[y_i^*(k+1), y_i^*(k+2), ..., y_l^*(k+l), U(k), U(k+1), ..., U(k+l)] \to Y_{in}(k) \tag{3.12}$$

When there are noisy conditions present and the solution is poorly output observable, small deviations in y_i^* can cause large deviations in the estimate of Y_{in}.

It is possible to stabilize the solution even around poorly observable regions by adding a regularization term:

Let $D \overset{\Delta}{=} [1 \times p]$ where $D_i = 0$ and $D_j = 1$ where $j \neq i$, and i is the measured output

Let $\hat{Y}^{**} \overset{\Delta}{=} D * NN_{f1}(Y_{in}(k-1), U(k-1))$

Let $G(\hat{Y}_{in}(k)) \overset{\Delta}{=} \alpha(\hat{Y}_{in}(k) - \hat{Y}^{**})$, where α is a weighting factor.

Here, $G(\hat{Y}_{in}(k))$ represents the regularization term. Now, the minimization problem becomes:

$$minimize\ f(\hat{Y}_{in}) = \frac{1}{2}([R(\hat{Y}_{in}), G(\hat{Y}_{in})]^T [R(\hat{Y}_{in}), G(\hat{Y}_{in})]) \tag{3.13}$$

The observer problem with an inverse mapping now becomes a forward predictor by adding a regularization term. When the observer problem is ill-conditioned (i.e. the Jacobian of $R(\hat{Y}_{in})^T R(\hat{Y}_{in})$ is not full rank or poorly conditioned), there are some terms of $\hat{Y}_{in}$ that don't have a unique solution or are sensitive to noise in the data. When this problem occurs, the regularization term becomes dominant in the minimization algorithm for the terms of $\hat{Y}_{in}$ that are causing problems, and the forward prediction is used instead.

3.4 Fault Detection

In section 3.2, it was described how the TNFIN neural network can be used to identify a non-linear system, in the case of this research a transformer. The system is identified using just inputs and outputs to the system. In the previous section, the analytic background for a neural based observer was discussed. Once again, the TNFIN architecture was used by the observer to produce output estimates. From this observer design, a new fault detection approach can now be utilized. This new fault detection approach for non-linear systems is discussed in this section. The result of the new approach is a practical and general method of detecting abnormalities in a non-linear system. The benefits of this approach are described below.

3.4.1 Background of Fault Detection Approaches

For fault detection to occur, there must be the presence of constraints or redundancies that define normal operating conditions. In the analytic methods of redundancies, an observer, which contains a model of the system, is used to generate a residual. This residual is the difference between the observer estimate and the actual output, as given by some sensor measurement. In the ideal case, a non-fault condition would be indicated by a residual that is zero, while the presence of a non-zero residual would indicate a fault. However, the model of the system is not perfect, and as such, there will be some uncertainties present that will cause a residual to exist even under normal operating conditions. For this reason, some accommodations must be made and boundaries must be set for determining normal operating conditions. Many robust fault diagnostic methods have centered around this topic. Some have attempted to represent both the faults and model uncertainty as inputs and then try to decouple the residuals produced by faults and those produced by uncertainties in the model. In other approaches, the probability of a given set of outputs actually being produced by a system given knowledge about the noise, disturbances, and model error is determined. If the probability shows the data set is highly unlikely, the model is invalidated. If the model is representative of a normally operating system, then a fault has occurred when the residual becomes larger.

Using the results that have been achieved, based on the TNFIN, to identify and observe a small scale (10kVA) transformer system, a different approach can be derived for robust fault detection using neural networks (Fretheim, 2000). This fault detection method can be applied to a wide variety of non-linear systems. Work has been done in the past using neural networks for fault detection. In most of these scenarios though, the neural network is used for pattern recognition (Ficola et al., 1997). For this type of fault detection, the measured system outputs are actually the inputs to the neural network, and the fault classification or fault parameters are the outputs. In other schemes, neural networks are used to implement an observer that changes the parameters to approximate the maximum likelihood estimate (Alessandri and Parisini, 1997). Neural networks have even been applied to observers that can solve for inputs and predict forward (Krishnaswami et. al., 1994). The fault detection method proposed here uses the neural network for the purposes of modeling the dynamics of the transformer. A dead-beat observer is then implemented by solving a set of non-linear equations. Using this method, it becomes possible to introduce constraints into the system, which can improve the accuracy of the fault detection.

3.4.2 Observer Residual Generation

The observer design from Section 3.2 can now be used for generating residuals. By using this observer, a fault detection approach can be implemented. The details of this approach are given below. Figure 3.4 shows a simple block diagram for the implementation of the output observer. One should notice that there are two residuals in the diagram: $\varepsilon_1(k)$ is due to the uncertainty in the observer model, while $\varepsilon_2(k)$ is the difference between the estimated output and the actual output. For the purposes of the transformer fault detection, the output observer must be implemented on-line. For this implementation, the following are defined as:

$u(k) \overset{\Delta}{=}$ system input(s)

$\bar{y}^*(k) \overset{\Delta}{=}$ measured output, and input to observer

$y^*(k) \overset{\Delta}{=}$ any measured output, could be equal $\bar{y}^*(k)$ but does not have to be.

$\hat{y}^*{}_l(k) \overset{\Delta}{=}$ Observer estimate of $y_l(k-n)$

The term $\hat{y}_l(k-n)$ is shifted since in the real time scenario past values of the outputs are being calculated.

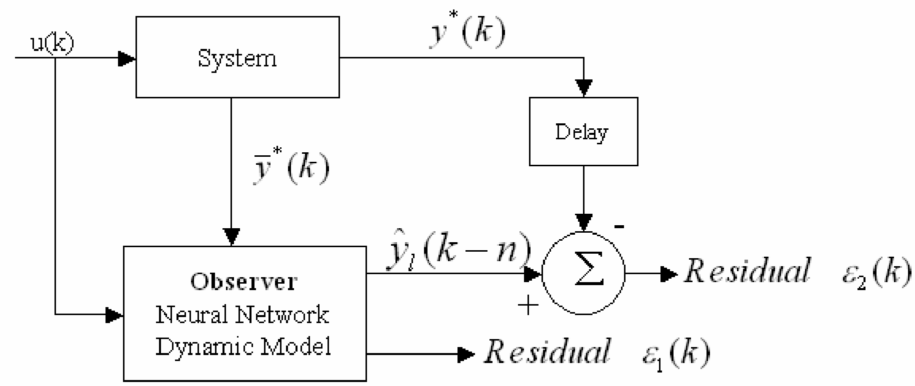


Figure 3.4: Block diagram for on-line observer with residual generation

There are two different ways to detect changes in the system dynamics.

$$residual \quad \varepsilon_1(k) \overset{\Delta}{=} \min_{y_l(k)} \| Y^n(k) - \overline{F}(u_{l+n-1}(k+n-1), y_l(k)) \| \tag{3.14}$$

$$residual \quad \varepsilon_2(k) \overset{\Delta}{=} \hat{y}(k) - y^*(k) \tag{3.15}$$

Residual $\varepsilon_1(k)$ is the minimum achieved through training of the neural network. A large value indicates that an accurate value of $y_l(k)$ could not be determined by the observer. Therefore, the observed outputs have difficulty in identifying dynamics of the system. This residual can be used to measure whether if there is a significant change in the dynamics. Output observability, noise and disturbances in the system, modeling errors also can contribute to the size of $\varepsilon_1(k)$. *Residual* $\varepsilon_2(k)$ is a measurement of the difference between measured and estimated values produced by the observer.

To understand the observability property of the system, consider two different functions, *f*1 and *f*2. These two functions both minimize the first equation in (3.14), but occur on different points on the system trajectory. The system of *f*1 is poorly observable, while system *f*2 at the current trajectory is considerably more observable. As illustrated by Figure 3.5, the minimum of *f*2 is much more pronounced than the minimum of *f*1. The two residuals, $\varepsilon_1(k)$ and $\varepsilon_2(k)$, respond differently to a poorly observable system.

For a poorly observable system, small changes in the data y^* can cause large changes in $\hat{y}_l(k)$, but the error $\varepsilon_1(k)$ will not increase significantly. Thus, $\varepsilon_1(k)$ is robust in regards to disturbances in $\hat{y}_l(k)$. With this advantage, there is also the disadvantage that $\varepsilon_1(k)$ is not as sensitive to changes in system dynamics. The exact opposite is true for the residual, $\varepsilon_2(k)$. Small changes in data y^* can cause large changes in $\hat{y}_l(k)$. A small change in the data can cause relatively large $\varepsilon_2(k)$. In either case, the ability to use either residual $\varepsilon_1(k)$ or residual $\varepsilon_2(k)$ to detect a fault is decreased as the system becomes less observable. For poorly observable systems, $\varepsilon_1(k)$ might not detect a real fault, where $\varepsilon_2(k)$ could produce a false alarm. Due to this fact, the fault detection approach used in this research combines the properties of both the residuals to be able to increase sensitivity and robustness. The following section describes the approach used for this research.

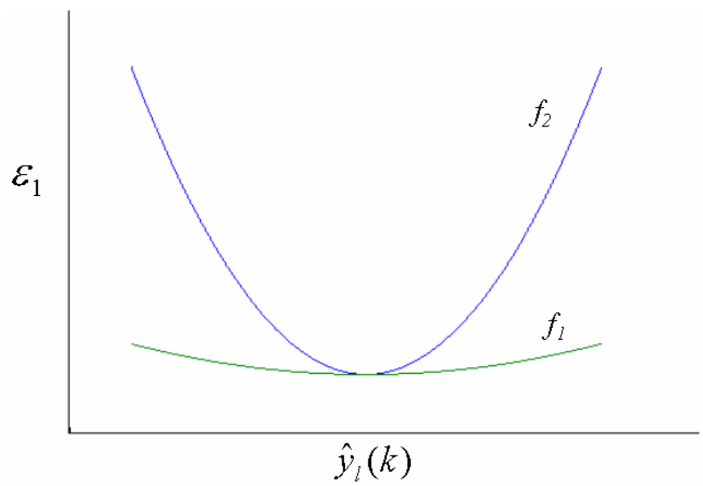


Figure 3.5: Comparison for degrees of observability

3.4.3 Optimization Based Fault Detection Approach

Since a solution to the minimization problem of Equation (3.14) has already been determined, the algorithm can be adjusted by taking into account previously known information, such as available measurements, noise level of the sensors used, parameter bounds, etc. By using this additional information, the reliability of the fault detection approach, as well as its applicability to other systems, is greatly enhanced.

Equation (3.14) is a solution to a deadbeat observer problem. As noted earlier, ideally (i.e. neural network mapping is an accurate representation of a system and there is no noise or disturbances present), a no-fault condition would exist when the solution to Equation (3.14) is equal to zero. In reality, there is inevitably going to be modeling errors, noise, and disturbances. Therefore, the solution to the minimization problem of Equation (3.14) will never be zero. Modifications must then be made to incorporate the uncertainties in the system. Thus, a no-fault condition can be said to exist when:

$$\min_{y_l(k)} \| Y^n(k) - \overline{F}^n(u_{l+n-1}(k+n-1), y_l(k)) \|_W < \varepsilon \qquad (3.16)$$

where $\| x \|_W = \sqrt{x'Wx}$. The goal now becomes to identify appropriate values for the parameters W and ε. For this purpose, a data set different from the data used for the system identification is used to represent the normal system behavior. Here W is a weighting matrix for x, and ε is set as an upper bound on the error during a no fault operation. In this way, W can weight the more important outputs. If the minimum of the solution to Equation (3.16) is less ε, there is strong evidence that the system is operating normally. Information about the type of sensor measurements used can determine an appropriate W. If the level of noise and the scaling of the data is approximately the same, then an identity matrix may be used for W. For example, if the scaling is different from one measurement to another, then W can be used to compensate for this effect in the minimization of Equation (3.16). When an identity matrix is used for W, it is assumed that the measurements are independent; hence, the non-diagonal terms are zero. There could be cases that correlation may exist between different sensor measurements, which would result in off diagonal terms in the matrix W. However, trying to determine the value of these terms can be extremely difficult, especially for non-linear systems.

A new output sequence can now be tested for possible faults by determining if Equation (3.16) is satisfied for the chosen values of W and ε. $Y^n(k), y_l(k)$ and $u_{l+n-1}(k+n-1)$ in Equation (3.16) are now based on values from the data sequence to be tested. If the minimum is less than ε, there is strong evidence of a no fault condition.

The minimization problem described by Equation (3.16) is generally exceedingly flexible. Not all the terms in $Y^n(k)$ need to be used, nor do all terms in $u_{l+n-1}(k+n-1)$, $y_l(k)$ need to be unknown.

Given a vector x of length r, and a finite set of integers $M = \{i1, i2, i3, \cdots, i_s\}$, $i_k \le r$ and $k = 1, 2, 3, \cdots, s$, let p_M be the projection operator such that

$$p_M * x = \begin{bmatrix} x_{i1} \\ x_{i2} \\ x_{i3} \\ \vdots \\ x_{is} \end{bmatrix}$$

From p_M, another projection operator can be defined as:

$$\pi_M^z \overset{\Delta}{=} \begin{bmatrix} p_M & 0 & \cdots & 0 \\ 0 & p_M & \cdots & \\ \vdots & & & \\ 0 & 0 & \cdots & p_M \end{bmatrix}$$

where π_M^z is a diagonal matrix of size $[(r*z)\times(r*z)]$. For a collection of several measurements of x, where $x_z = [x(k)\ x(k-1) \cdots x(k-z)]$, then

$$\pi_M^z * x_z(k) = [x_{i1}(k)x_{i2}(k)x_{i3}(k)\cdots x_{is}(k)x_{i1}(k-1)x_{i2}(k-1)x_{i3}(k-1)\cdots x_{is}(k-1)\cdots x_{i1}(k-z)x_{i2}(k-z)x_{i3}(k-z)\cdots x_{is}(k-z)]'$$

Using this operator, it is possible to select particular inputs or outputs from the vectors $u_{l+n-1}(k+n-1)$ or $y_l(k)$, etc.

The minimization for fault detection now becomes:

$$\min_{\pi_{U_u}^{l+n-1}u,\pi_{U_y}^{l}y} \| \pi_I^n Y^n(k) - \pi_I^n \overline{F}^n(u_{l+n-1}(k+n-1), y_l(k)) \|_W \tag{3.17}$$

Through this procedure, a subset of the prediction equations in the set l is chosen for evaluation. Meanwhile, the variables that are "known" in index sets K_u and K_y are fixed and the variables that are unknown in sets U_u and U_y are calculated. Some of the variables collected in $u_{l+n-1}(k+n-1)$ or $y_l(k)$ may be inputs, which are known, or outputs for which measurements are (or are almost) noise free. When trying to detect faults, it may be necessary to test for sensor failures by removing the data from a particular sensor. This fault detection approach easily allows for identification of sensor failures.

Additional information may also be available about $\pi_{U_u}^{l+n-1}u_{l+n-1}(k+n-1)$ and $\pi_{U_y}^{l+n-1}u_l(k)$, even if accurate measurements are not available. For example, the sensors may have a known noise level with a magnitude bound of η, or there may be some bounds on the acceptable values for other variables. This information can be expressed as a known set Ω, for which the unknown variables are known to lie:

$$\pi_{U_u}^{l+n-1}u_{l+n-1}(k+n-1), \pi_{U_y}^{l} y_l(k) \quad \in \Omega$$

For this case, the resulting problem is a constrained minimization, where:

$$\min_{\pi_{U_u}^{l+n-1}u,\pi_{U_y}^{l+n-1}y\in\Omega} \| \pi_I^n Y^n(k) - \pi_I^n \overline{F}^n(u_{l+n-1}(k+n-1), y_l(k)) \|_W \tag{3.18}$$

The power of this fault detection approach depends on the constraints imposed by the minimization problem in Equation (3.18), and, the observability properties of Equation (3.14), which was discussed earlier. The constraints placed on the minimization problem by Ω have a different impact on an ill-conditioned system as opposed to a well-conditioned system. For both cases, Ω improves the ability to detect changing dynamics in the system. In the case of a well-defined minimum (i.e. well conditioned), the constraints result in a large increase in the residual ε_1 and a greater detectability of a fault. In the case of a less defined minimum (i.e. ill conditioned), the residual ε_1 also increases but to a smaller degree. Therefore, the ability to detect a fault does not increase as greatly as for the well-conditioned system. Looking at Figure 3.5 and placing a constraint on the system that places the minimization problem to the left of the absolute minimum on the $f1$ and $f2$ curves illustrates this fact.

3.4.4 Non-linear System Fault Detection

Some approaches to fault detection implement an observer and then compare the estimated values directly to the measured values (Krobicz, 1997; Marcu and Mirea, 1997). The disadvantage to this approach is when one attempts to isolate the fault. The number of observers needed quickly becomes extremely high. This problem can be avoided by using a multiple model approach for fault isolation (Frank and Ding, 1997). To do this, the observer must be made invariant to a particular type of fault. In the case of sensors or actuators, this can be achieved by removing the dependence of the prediction on the variable in question. For optimization based fault detection, an index set of unknowns can be augmented to include the variable. A new observer has to be created for each set of variables for which the fault detection approach needs to be invariant. As one can see, this process becomes a considerable task when the number of sensors is large.

The structure of each individual observer also changes depending on the signals chosen. Once an observer has been identified, the structure is fixed. This will affect the accuracy of the observer when an input is changed or absent. From simple system theory, it is known that a system trajectory is affected by the states. To define a particular system, the number of outputs and delays needed is dependent on the observability of the system. For non-linear systems, the observability is dependant on the current operating position and the input. For regions of low observability, the terms that are needed may increase. Since the number of equations in the set l

in the optimization based approach is variable, this does not pose a significant problem. The optimization based method is flexible to the number of input terms in the observer.

One of the added benefits of using a forward approach for fault detection is the ability to incorporate analytical and gray-box models in to the system. The neural network can be used to identify the unknown part of the dynamics, while an analytical model can represent the other part of the system. A system that can use gray box modeling can be shown by:

$$\begin{aligned} x(k+1) &= Ax(k) + Bu(k) + \beta(x(k), y(k)) \\ y(k) &= Cx(k) \end{aligned} \tag{3.19}$$

Here the matrices *A, B, C* are known and could be the result of an analytic model, the function $\beta(\cdot)$ could be estimated using a neural network approach. For this system, simply finding the inverse model would eliminate the benefit of the information gained from the analytical model that had been developed for the system.

The above mathematical architectures will be used in coordination with the diagnostic module formed in the next chapter to form a complete diagnostic system. As seen from this chapter, the mathematics behind the non-linear system identification and fault detection posed in this chapter can be applied to a wide variety of systems, not simply the transformer diagnostic discussed in this thesis.

4. Design and Construction of Monitoring System

With the neuro-fuzzy software developed for the non-linear system identification, using the TNFIN neural network, the research progress has focused on field implementation and acquisition of the actual field data. First, an experimental prototype was required that could be used to test several large power transformers.

This prototype includes a sensor package, a DAQ system, and a computer, which stores the data that is then sent to a host computer in our research lab that simulates a remote diagnostic configuration, as foreseen for the implementation and application of the proposed monitoring system. The host computer runs the TNFIN neural network. In order for the full potential of the TNFIN to be realized, it must receive large volumes of data from several transformers, which have operated under normal conditions, as well as under various failure conditions. Through training of the network by data received from a transformer that has failed, the predictive power of the neural network can then be used to anticipate and prevent similar failures on other transformers in the future. The experimental data obtained and analyzed in this thesis may not be sufficient for establishing a baseline for transformers that may be used in diagnosing many different transformers in the future.

In order to produce the needed experimental results and ultimately develop a diagnostic system that could be used for transformers, it is necessary to develop a decentralized monitoring system that breaks down the substation into different zones to be analyzed separately and then interconnected. The idea behind a distributed system is that instead of one central processor there would be different data processing units, called nodes, which are typically connected across a shared network line (Linder & Dalassandro, 2000). In this project, there are several different nodes that will be used to increase the reliability and reduce the apparent complexity at any one node, as compared to the centralized monitoring scheme.

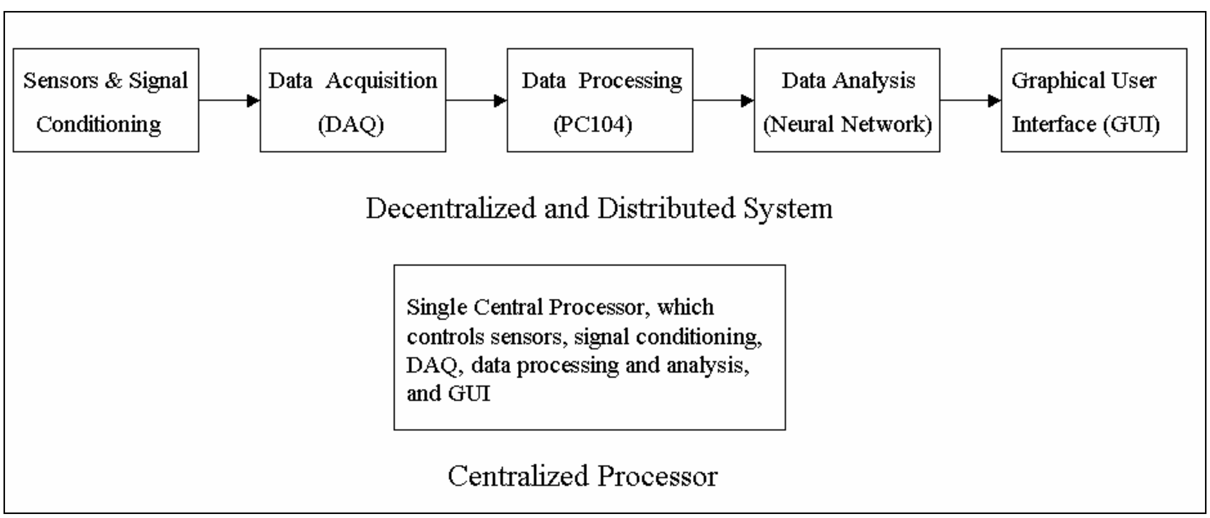


Figure 4.1: Comparison between distributed and centralized systems

The Intelligent Substation project will have essentially five different nodes. These nodes will be the sensors, signal conditioning, DAQ and storage, data analysis, and user interface nodes. A comparison of the distributed system to a single node system is shown in Figure 4.1. The purpose of the different nodes, their functions, and how they will be interconnected are presented in the following sections.

4.1 Sensor Node

The system begins with the simplest node in its distributed architecture. In order to monitor any machine, there needs to be a device to convert the physical operation of the machine to data that can be analyzed. There are a wide variety of sensors that can be placed on transformers and provide subsequent information on the health of the transformer. As detailed in Chapter 2, these include temperature, current, moisture, vibration, dissolved gas, acoustic, partial discharge, and dissolved gas sensors. In addition, there are sensors that can be used to monitor the proper functioning of many of the transformer accessories. In determining the sensors to be used in our system, it was necessary that the sensors be non-invasive, easily portable, and provide information that can be used to properly diagnose the health of a transformer. Using these qualifications, it was determined that moisture, dissolved gas, and partial discharge sensors would not be ideal. First, they are not easily transported from one transformer to the next. Likewise, the data obtained by the most common moisture and dissolved gas sensors are run through a trending program, usually in the lab, and the accessibility to the raw data is limited. As for the partial discharge sensors, they are invasive and thus not suitable for plans of a portable system. Lastly, the necessity for these sensors is diminished since the other sensors we will be using may be good indicators of the same types of failures.

To complete this task, a set of sensors will be placed externally on the transformer to monitor temperature (magnetic mount thermocouples), current (CTs), and vibration (accelerometers). In determining the specific sensors to be used in the experimental setup and as the basis for the substation diagnostics module, it was necessary that the sensor be able to withstand the harsh conditions in the substation (i.e. weather and electromagnetic interference). In addition, the sensors needed to be easy to install on a transformer so that the system could be portable. Many different companies and sensors were researched. The sensors finally chosen for the design of the experiment are described below.

To measure the temperature, magnetic mount thermocouples specifically designed for the power substation were chosen. The sensors are made by Substation Automation Solutions, a sub-division of General Electric Canada, Inc. and output 4-20mA. The magnet slides onto the shell of the transformer. A thin film of thermal compound coating used on the magnet increases the response and accuracy of the sensor. The temperature sensor comes with 40 ft. of cable, which is more than sufficient for taking measurements from the shell of the transformer and allows for easy installation by substation personnel. In the preliminary experiment, three of these sensors were placed on the shell of the transformer. They were placed on the shell of the transformer so as to provide information about the top and middle oil temperatures, as well as the ambient temperature. The sensors do require a +24V power supply, which was incorporated into the experimental prototype. A picture of a magnetic mount thermocouple placed on one of the test transformers is shown in Figure 4.2.

Figure 4.2: Magnetic mount temperature sensor placed on test transformer

In order to measure the low frequency vibrations on the shell of the transformer, accelerometers were needed that could magnetically mount to the shell of the transformer. These accelerometers have to withstand an industrial environment and be able to monitor low frequencies (i.e. 240-600 Hz). The accelerometers have a voltage output but come with a twisted shielded pair cable to help eliminate the electromagnetic noise present at the substation. The sensors chosen are made by PCB Piezotronics, an IMI division, and have a good resolution (100μg) (see Figure 4.3). A 1” flat magnet can be purchased to magnetically mount accelerometers to the transformer. For a three single-phase experimental setup, three accelerometers were used, one per transformer. These sensors require a constant current power supply for proper operation. A 24V power supply is connected in series with a constant current diode (2-20 mA) across the leads of the accelerometer. A capacitor (22μF) is then used to eliminate the DC bias voltage.

Figure 4.3: Industrial accelerometer used to measure shell vibration

The current transformers (CTs) are used to measure the currents of the primary, secondary, tertiary, as well as the currents in the pumps and fans. These sensors need to be easy to install and reliable. For this purpose, Magnelab, Inc. was chosen as the manufacturer of the CT to use in the module. For the currents to be monitored by the system, a turns ratio of 100:1 was needed in order that the output would be accepted by the DAQ card after passing through the signal conditioner. As with any current transformer, these sensors output a current that is at the same frequency as that measured but at 100th the magnitude. The sensors will be contained in the transformer cabinet and therefore do not need to withstand the weather elements or need extensive length of wire. For a three single-phase setup, 15 current transformers will be needed, while only 11 current transformers will be needed for a three-phase setup. Likewise, the Magnelab current transformers are split-core CTs, so they can easily be snapped around the appropriate leads in the transformer cabinet. Figure 4.4 shows the current transformers from Magnelab that are used in the diagnostic module.

Figure 4.4: Current transformer used to monitor currents in coils, pumps, and fans

4.2 Signal Conditioning Node

Due to the current output of all the sensors, circuitry is needed to convert the current signals into voltage signals in the range that can be accepted by the data acquisition system (DAQ). The signal conditioning card is used to perform these required conversions. Due to the unique number and different types of output (i.e. DC current for the temperature and AC current for the CTs), an in-house signal conditioner was designed for the specific sensors used in the diagnostic system. Channels 7 through 16 of the signal conditioner consist of simple resistor in parallel with a capacitor (Figure 4.5a). These channels convert all the 4-20 mA direct current output sensors to a 0-10V output. The capacitor serves to filter out high frequency noise that may be present. A 470Ω resistor and 10μF capacitor is used for all the non-accelerometer channels. For the accelerometer channels, a smaller capacitor needs to be used so that the frequencies that we desire are not filtered out. Therefore, for channel 10 and 11, a 100nF capacitor is used. For the current transformer channels (channels 1-6), a more complex circuit is needed since the input is an AC current. In this circuit (see Figure 4.5b), the output from the CT is input into the inverting output of an operational amplifier. The operational amplifier has negative feedback with a 1kΩ potentiometer in parallel with two diodes. The non-inverting input of the amplifier is tied to ground. The output of this amplifier is a half-waved rectified signal with a peak voltage that is determined by the potentiometer resistance. This output is then input into the standard low-pass active filter to produce a DC output. This output will not be as complete as the half-wave rectified peak given the time constants required to filter out a 60 Hz signal and still have insignificant ripple voltage. There is also the voltage drop due to the two diodes. Both operational amplifiers, shown in Figure 4.5b, are powered by +/-12V.

The present design is for a three single-phase setup. Some minor alterations would have to be made for a three-phase setup. Once the circuit was designed, an outside board manufacturer, Advanced Circuits, was contracted to perform the actual cutting of the boards. This provides for more reliable circuits that make the soldering required for populating of the components much simpler. Advanced Circuits' boards have solder mask that prevent damage to the circuitry while soldering.

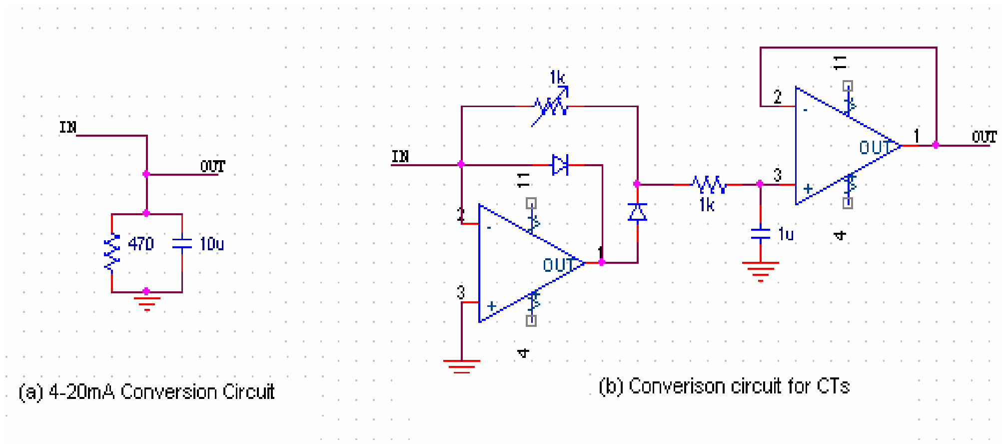


Figure 4.5: Two circuits used in implementation of signal conditioner

4.3 DAQ, Storage, and Transmittal Nodes

Once the physical operation of the machine has been obtained and conditioned, it is then sent to the next node of the system, which is the data acquisition node (DAQ). A DAQ card receives the voltage data and sends it to an embedded processing unit. In our research, we have utilized a PC104 for processing. The PC104 and DAQ chosen for the diagnostic module are both manufactured by Versalogic, Inc. and, therefore, are easily compatible (see Figure 4.6). The PC104 is in charge of receiving, processing, storing, and transmitting the data. Software modules, written in C, determine the sampling rate and number of samples to be received from each channel (i.e. each sensor). The PC104 then performs data processing on the outputs of the sensors, namely it takes the FFT of the vibration data, and converts the voltages to useful temperatures and currents that can be displayed to the user. Finally, the PC104 can then store up to 8 MB of data and transmit the data to a computer for analysis, using another software module that specifies how often data should be transmitted, in what size files, etc.

Figure 4.6: Versalogic PC104 and DAQ card used for the storing and transmittal of data

4.4 Portable Experimental Module

In order to fulfill the requirement of easy installation and portability, the hardware described in the previous three sections had to be integrated into a single module that could be placed in the transformer cabinet. Many designs were considered before the final module was completed. The module consists of the signal conditioning card with easy screw terminal access for the sensor inputs, the DAQ card, the PC104 processor, a AC-DC power supply, and a RS232 to single mode fiber optic converter, which is required to transmit the data from the PC104 to the computer located in the substation house. All of these components were mounted onto a metal plate. Magnets were placed on the back of this plate, which allows the entire hardware of the diagnostic module to be mounted inside the transformer cabinet. This design serves to protect the module from the elements and has the added benefit that there is a heater in the cabinet that runs during the winter. The diagnostic module provides for easy installation and maintenance. The system also can easily be removed from one transformer and placed on another. This portability is particularly useful for the experimental purposes, as it allows for collection of data from multiple transformers. As described later, the effectiveness of the data analysis is heavily dependant on the amount of data collected and the different failure and operating modes that are observed. Figures 4.7 and 4.8 show the diagnostic module that was designed and how it is easily mounted in the transformer cabinet.

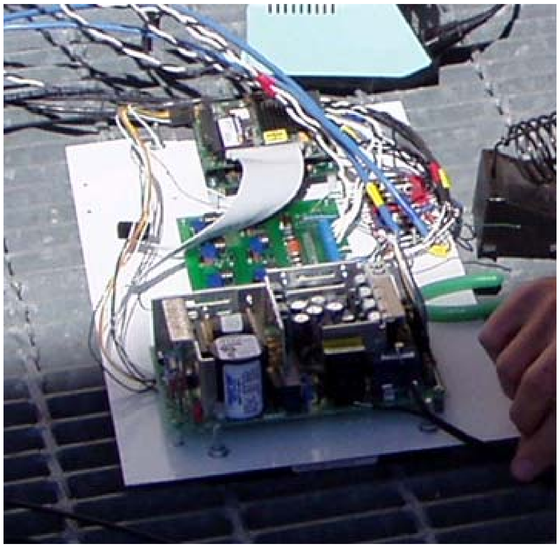
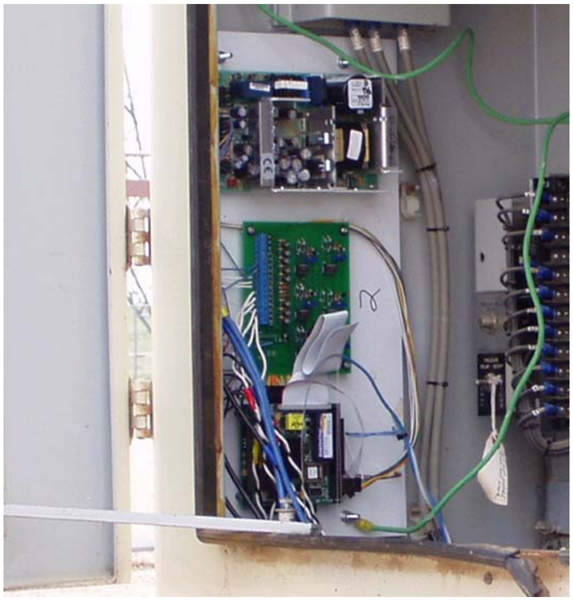


Figure 4.7: Designed portable diagnostic module with PC104 and signal conditioner



F**igure 4.8: Diagnostic module mounted inside transformer cabinet**

4.5 Data Analysis Node

The most important node in the distributed system is the data analysis node. This node processes all the data that is transmitted by the PC104 into useful diagnostic information that can be used to detect failures and make assessments regarding the health of the transformer. The substation computer is connected to the PC104 via fiber optic cable in order to reduce the electromagnetic interference that is extensively present in a substation environment.

For the experimental setup used in this thesis, the data analysis node will use the neuro-fuzzy engine described in Chapter 3. The function of the neuro-fuzzy network was implemented in MATLAB for experimental purposes. However, the code for the neuro-fuzzy network was also implemented in C, for implementation in all PCs at any substation. Figure 4.9 shows the steps that are taken to go from DAQ through the PC104 and on to the artificial neural network (ANN) located on the PC in the substation house.

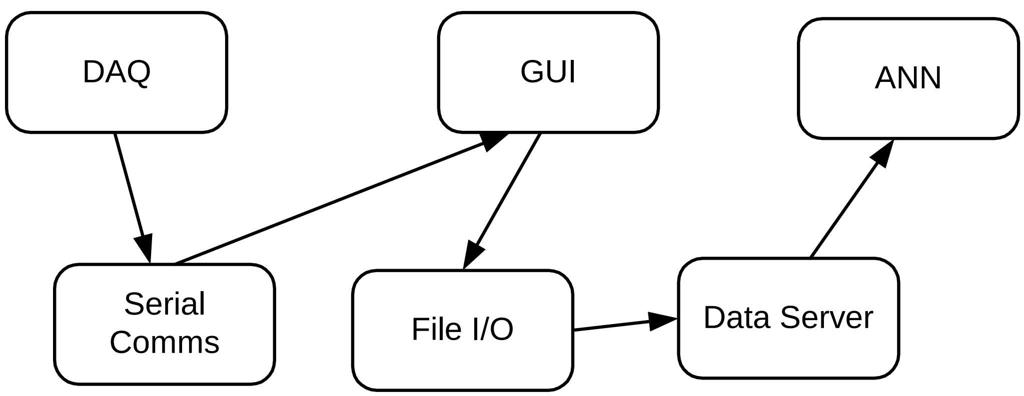


Figure 4.9: Steps taken to transfer sensor data to PC with ANN

For the purposes of the experimental setup, there was the needed addition of communication between the substation computer and the computer in our research lab, which hosts the neural network. A dial-up modem downloaded the data from the field and transferred it to the host computer. RealVNC was utilized to be able to access the substation computer's desktop from the lab, so needed adjustments and corrections could be made remotely.

4.6 Interface Node

To fully realize the benefits of the proposed distributed diagnostic system, each major equipment in the substation, e.g. transformers and circuit breakers, will be equipped with the TNFIN non-linear observer and failure detector. Once the neural network has analyzed the data, potential failures are detected and the health of the equipment estimated, there is still one more node in the distributed system. The useful warnings and

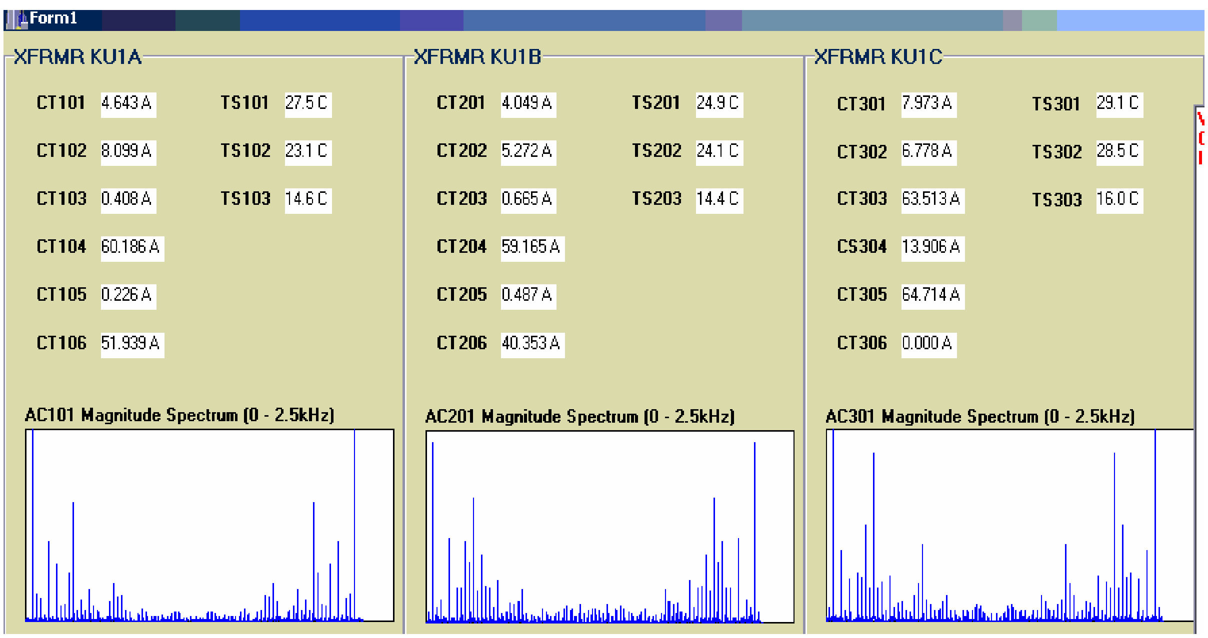


Figure 4.10: Sample GUI interface on substation computer

health diagnosis must be sent to a graphical user interface (GUI) to be displayed to the user (maintenance crew of the substation), so that they can take the appropriate action based on the output of the neural network. By using the distributed architecture, large volumes of sensor data can be converted into a small amount of easy to understand information about the health of the equipment. A sample of the GUI that we have already developed showing the temperature, current, and frequency information obtained from the sensors is shown in Figure 4.10.

4.7 Field Implementation

For the experimental setup, a location was needed to test large power transformers. During the feasibility analysis of this concept, small 10 kVA distribution transformers were used. Though this verified the feasibility of the proposed techniques and provided useful, the distributed system described above needed to be installed on large transformers if the system was to be validated for substation diagnostics. For the purpose of the experiment, three single-phase, 166 MVA transformers at the Ault Substation from Western Area Power Administration (WAPA) in northern Colorado were

Figure 4.11: Three single-phase 166 MVA transformers used in experiment

used (see Figure 4.11). These three transformers served as the test bed for the experiment. Three prototypes of the portable diagnostic module described in the earlier sections of this chapter were assembled and used to monitor these three transformers. The neuro-fuzzy network analyzed the data obtained from the Ault transformers, and the experimental results are discussed in Chapter 6. In addition, this preliminary field testing provided much needed data to serve as a baseline for future transformer diagnostic studies.

5. Foundation for Future Transformer Expert System

The types of diagnostic hardware that were described in the previous chapter simply provide data that can be helpful for diagnostic purposes. There are two ways to use this data and deduce useful information about the health of the transformer. One method is to use modeling or artificial intelligence techniques to identify the system, observe them, and detect faults in the system once undesired patterns are observed, as described in Chapter 3. The other method is to utilize the expertise of individuals who have worked with transformers to determine thresholds for making decisions based on different sensor values. For example, a certain temperature above an expected level or a certain gas level (in ppm) exceeding a threshold would set off a warning to the service crew. In this chapter, commonly used and accepted rule-based thresholds for the different sensors will be described. These thresholds could then be used to implement a transformer expert system. This actual implementation is saved for future research

5.1 Background

As is the case with most real-life situations, operator experience is very valuable. The area of transformer diagnostics is no different. It is the transformer experts who can best identify whether a transformer is operating abnormally. They have worked and maintained them for years. Slowly but surely, expert systems have gained greater acceptance as a viable option to diagnosing a failure in a transformer (Tomsovic, 1993). These expert systems use the information formulated from years of experience in dealing with transformers to form heuristic rules. The progress in computer hardware and software has made expert systems more feasible (Kezunovic, 1998). The Electric Power Research Institute (EPRI) has even developed a transformer expert system, known as Xvisor (Ward, 2001b). Though not 100% full proof, thresholds can serve as useful tools for identifying when a fault is developing or may be imminent. Thresholds have been formed for almost all types of sensors used in transformer diagnostics. The most commonly accepted thresholds are given below.

5.2 Dissolved Gas Analysis Thresholds

As was noted in Section 2.1.1, there are several different key gases that can be used as indicators for the development of potential failures starting in a transformer. These gases include, but are not limited to, hydrogen, methane, ethane, acetylene, ethylene, ethane, carbon dioxide, and carbon monoxide. Through much experience in the field, various gases have been determined to indicate the different operating conditions. These conditions range from normal operating conditions to severe ones. Table 5.1 (Traub, 2001) shows the limits for the key gas concentrations in parts per million (ppm). The table is divided into four alarm levels. **Normal** indicates acceptable concentration for normal operating conditions. **Moderate** indicates higher than normal concentrations and suggests that some analysis should be done. **High** indicates a high level of decomposition and that numerous tests should be run on the oil to establish a trend of gas generation. From this trend, gas ratio analysis (mentioned in Section 2.1.1) can be applied for diagnosis. Finally, **severe** indicates the transformer has excessive decomposition and further operation could result in the failure of the transformer.

As described in Section 2.1.1, often the ratio of gases and the trend in gas generation is more important than the absolute concentrations of any given gas. For example, limits have been formed on the hydrogen content in the oil. These limits are used to indicate insulation deterioration. Unlike the absolute limits given in Table 5.1, these limits also take into account the rate of generation of a specific gas ratio. For hydrogen, a warning is given when there is an increasing trend after 200 ppm of hydrogen is present and while the hydrogen to methane ratio is 5:1 or greater. This high ratio indicates partial discharge and substantiates the hydrogen contents indication of insulation deterioration. One can see 200 ppm of hydrogen is only a moderate condition in Table 5.1; however, when in coordination with the high ratio, it causes a concern.

Table 5.1: Concentration (ppm) for dissolved key gases

Danger Level	Hydrogen	Methane	Acetylene	Ethylene	Ethane	Carbon Monoxide	Carbon Dioxide
Normal	100	120	35	50	65	350	2500
Moderate	101 to 700	121 to 400	36 to 50	51 to 100	66 to 100	351 to 570	2500 to 4000
High	701 to 1800	401 to 1000	51 to 80	101 to 200	101 to 150	571 to 1400	4001 to 10000
Severe	>1800	>1000	>80	>200	>150	>1400	>10000

5.3 Moisture Analysis Limits

Just as the dissolved gas in the oil can indicate insulation deterioration, the moisture in the oil can prove to be just as helpful. A common limit on the moisture content in the oil has been 15ppm. The amount of oil is also dependant of the primary voltage rating of the transformer and the temperature. For this reason, different limits have been placed based on the voltage. For less than 345kV at 75°C, 20ppm is the limit on the moisture in the oil. On the other hand, for 345 kV or higher at 75°C, the limit is only 10ppm. This limit criterion for moisture content is almost universally used to indicate insulation deterioration, oil leaks, and overheating of the transformer.

5.4 Top Oil Temperature Thresholds

Thresholds and limits are most commonly used with temperature measurements, especially of the top oil. Main tank, top oil, bottom oil, and hot spot temperatures are all common temperature measurements that are taken. Overheating is a sure sign of insulation and oil deterioration. Experts commonly use a green, yellow, red system to indicate the condition of the transformer. Green indicates normal operating conditions. Yellow indicates reason for further analysis to be performed. Red indicates impending failure if the transformer remains in operation. Table 5.2 shows the limit criteria for the top oil temperature and the related categorization.

Table 5.2: Warning categories for top oil temperature

Warning Level	Temperature Range
Green	T<90°C
Yellow	90°C<T<100°C
Red	T>100°C

Many times instead of an absolute value for a temperature limit, temperatures above a reference are used to determine when a transformer is in danger of failing. The normal temperature reference is determined by the age and type of transformer being monitored. In this case, the warning categories used differ from the levels given in Table 5.2. The temperature categories for oil temperature above a reference is given in Table 5.3.

Table 5.3: Warning categories for top oil temperature above reference

Warning Category	Temperature above Reference
Minor	T<10°C
Intermediate	10°C<T<29°C
Serious	30°C<T<50°C
Critical	T>50°C

5.5 Vibration Levels

Though not as commonly used, various warning levels have also been developed for vibration readings. While the frequency spectra of the vibration often proves more valuable, excessive vibrations on the shell of a transformer can often be an indication of some malfunction of the transformer. The pumps or fans may no longer be operating properly. The coils or magnetic core may have been jarred loose. All of these malfunctions may ultimately lead to a transformer failure. For this reason, the magnitude of the vibration on the shell of the transformer can be an indicator of a failing transformer or one that needs to be examined or serviced. Table 5.4 provides the warning levels that have been formed for vibration measurements in order to warn of problems with the transformer.

Table 5.4: Warning categories for shell vibration readings

Warning Category	Vibration Reading (in/s)
Minor	$0.10<V<0.25$
Intermediate	$0.25<V<0.50$
Serious	$0.50<V<1.00$
Critical	$V>1.00$

5.6 Bushing Thermal Thresholds

As noted in Section 2.1.7, the temperature of transformer bushings increases dramatically before they fail. Unlike the case with LTCs, bushing temperatures are often compared with the other bushings' temperatures rather than the main tank temperature. In the case of bushings, there are essentially two operating conditions. One, the bushing are operating normally. Two, bushings need to be investigated for leaks, loss of seal or bad connections. The common criteria used is the temperature differential between bushings. If one bushing's temperature is greater than the other two by 5°C or more, the bushing should be investigated.

Many bushing sensors also measure oil level in addition to temperature. In this case, an oil level below a minimum threshold indicates that the bushing should be investigated. The manufacturer determines the minimum oil level for proper operation.

5.7 LTC Thermal Thresholds

Similar to bushing monitoring, the temperature differential between the load tap changer (LTC) and the main tank temperature is a reliable indicator of an impending failure in the LTC as well. As with the main tank, thresholds can be placed on the degree of temperature differential in order to get an idea of the severity of the problem.

In the case of LTCs, the procedure and thresholds used varies with the type of load tap changers. Through much experience in the field with Westinghouse and Federal Pacific UTT-A and UTT-B LTCs, it has been found that if the temperature differential between the main tank and the LTC is less than 15°C, the LTC is operating normally. When the temperature differential rises above 15°C, measures should be taken to investigate the health of the LTC, using knowledge of the highest and lowest tap settings in the past 60 days. It is important to consider the abruptness of the rise in the temperature differential. If the LTC has not passed through neutral since last reset, the contacts should be wiped and DGA monitoring should be performed. If this is not the case and the slope to the temperature differential over the past few days is greater than zero, a severe condition exists and the LTC should be taken offline and inspected internally to determine the problem. For Waukesha type LTCs, the procedure and tests are the same except for the temperature differential indicating a possible problem is 5°C instead of 15°C. Series of other if/then statements have been formed for other types of LTCs as well but shall not be discussed here.

The above thresholds and levels for different transformer diagnostic sensors have been developed based on the knowledge and best judgment of experts in the field. These limits are by no means a guarantee. A transformer may fail when all indicators point to normal. Likewise, a transformer may be able to operate properly for years after a warning has been given. In addition, expert systems have the drawback that they require a wide knowledge base for diagnosis. Often, this knowledge base is not sufficient to translate the appropriate rules. The expert system knowledge base can never be perfect (Xu, 1997). For this reason, people have sought alternate ways to diagnose a transform using sensor data.

5.8 Fusion into Expert System

The various thresholds described above do not qualify as an expert system in themselves. In creating the expert system, a series of IF/THEN statements must serve to connect the various sensor measurements. For example, it is known that a rise in the acetylene concentration with respect to the ethylene concentration indicates arcing occurring in the transformer. Arcing will also cause a rise in the top oil temperature. To validate the arcing hypothesis, the temperature over reference measurement should also be checked. There is always the possibility of sensor failure, which could set off a warning but not be indicative of a developing failure.

The goal of monitoring substation equipment is to prevent catastrophic failures, but also eliminate unnecessary maintenance. By creating an expert system, the idea is to prevent incorrect diagnosis by coordinating the thresholds from several different, but related, measurements. Through this coordination, incorrect warnings based on one threshold can be validated using other measurements as well. Below is an example of coordinated statements incorporated into an expert system in order to detect transformer overheating.

```
IF  (Temperature Above Reference) > 20°C
THEN
    IF  (Fan Bank Current) > 0.5 A
    THEN
        IF (Ethylene Concentration) > 100 ppm
        THEN
            IF (Moisture Concentration) > 15 ppm
            THEN
                Transformer Overheating, Take 0ff-line to Service
            ELSE
                Check DGA and Moisture Analyzer for Proper Functioning
        ELSE
```

Check Thermocouple Sensor
ELSE
Fan Bank not Operating Properly, Have Serviced

ELSE
Transformers Operating Normally

From the example, it can be observed how several sensor measurements and their respective thresholds are utilized to make a diagnosis. First, the temperature sensor is checked to see if there is any overheating. If there is an abnormal reading, the current to the fan banks are checked. If the fans are running, the ethylene, which indicates high temperature oil deterioration, is checked to make sure the level is high. If the ethylene level is above normal, the moisture in the oil is checked. If at any point, a sensor does not confirm the diagnosis of a previous sensor; the proper functioning of the sensor is checked. In this piecewise method, it is possible to deduce if a failure is occurring or if sensors are simply malfunctioning.

In many cases, all the sensor measurements may not be available. It is not necessary to have numerous sensors indicating the same information. The chances of two different sensors failing at the same time and producing an incorrect warning signal is highly improbable. It should be noted that the sensor order to be used is dependent on the type of failure being detected. To detect an arcing failure, the ratio of acetylene to ethylene should probably be the predominant measurement.

Every expert system that is created will consist of numerous set of IF/THEN possibilities like the one given above. The design of each expert system will be different depending on the sensor measurements available and the type of failures being detected. The key to a successful expert system is to utilize all knowledge known about the system and to provide for checks in the system, so that no one measurement is used to diagnose the health of the equipment.

5.9 Proposed Hybrid Diagnostic System

In the previous section, the method for creating an expert system from common sensor thresholds was discussed. There are many problems with simply using an expert system to diagnose the health of a transformer. There are still many types of failures for which thresholds have not been established. There are also many failures that are only indicated by a particular sensor measurement. Therefore, there is no way to validate the expert system diagnosis with another sensor measurement. In Chapter 3, an artificial intelligent technique for transformer diagnostics was described. This neuro-fuzzy fault detector creates its own rule-base using simply input-output data. However, the system would need a database detailing all types of faults to provide full-proof diagnosis. There is always need for additional information to incorporate into its "neurons."

The shortcomings to both the expert system and the neuro-fuzzy network can be overcome by creating a diagnostic system that combines the two techniques. The neuro-fuzzy network can set alarms when the system begins to behave abnormally. At the same time, the expert system thresholds can be applied to determine what may be the failure responsible for this abnormality. Likewise, a warning detected by the expert can be used to indicate when the neural network may be lacking experience. In this way, the expert system can highlight events where the neuro-fuzzy network needs to be trained. Much like the expert system, this hybrid diagnostic system would use the two techniques to combine the best of human and artificial intelligence. A block diagram of this approach is shown in Figure 5.1.

The full potential of this hybrid diagnostic system will not be achieved until the neuro-fuzzy network has witnessed many different failures and a more complete human knowledge base is formed for the various failure modes. Due to the lack of dissolved gas or moisture analyzers in the diagnostic module designed in this thesis, only the foundation for a hybrid diagnostic system is given here. The experimental results for the neuro-fuzzy fault detector are presented in the next chapter.

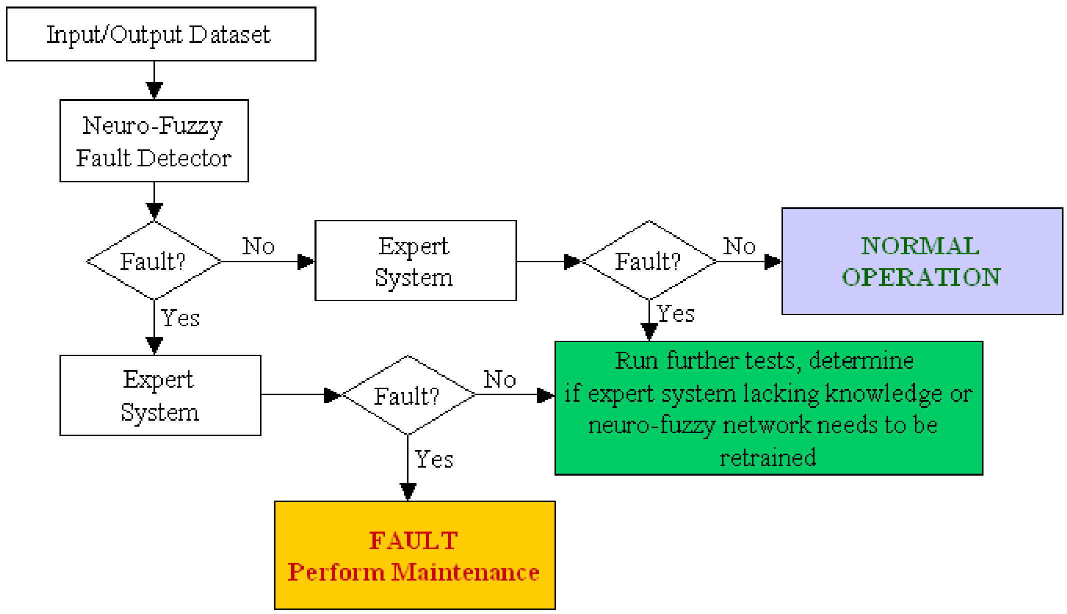


Figure 5.1: Block diagram of hybrid diagnostic approach

6. Experimental Analysis

As mentioned in Chapter 4, the monitoring system designed and developed in this research is being tested on three single-phase 166 MVA transformers at WAPA's Ault substation located in northern Colorado. This chapter focuses on the result of applying the neuro-fuzzy fault detection engine to analyze the data that is obtained by the diagnostic monitoring system of Chapter 4. A detailed look into the results of the system identification, output estimation, and fault detection for the three transformers is given in this chapter.

6.1 Off-line Fault Detection Analysis

As described in Chapter 4, the diagnostic module designed for monitoring transformers is able to collect, manipulate, and send temperature, current, and vibration data to the substation computer. Then a dial-up modem can be used to acquire the data for off-line data analysis by the neuro-fuzzy fault detection engine. For the purposes of experimental analysis, this off-line method is used as opposed to the on-line method. It is also possible to use the monitoring system in coordination with the fault detector for on-line analysis. In this case, the MATLAB or C coding for the system can be installed on the substation computer to analyze the data as it is collected and transmitted by the diagnostic module.

The neural network must be trained to the system before the on-line fault detection can be performed. For the experimental analysis done in this research, the data from the diagnostic module was collected for several weeks before it was transferred to the computer at Colorado School of Mines. The neuro-fuzzy engine implemented in MATLAB could then analyze the data. In the preliminary stages, different sensors were used as the inputs and outputs to determine which configuration yielded the best system identification and observation. Off-line monitoring was utilized for this reason.

6.2 Non-linear System Identification

Once the data had been collected and transferred to the computer at Mines for analysis by the neural network, the problem then became determining which sensor measurements should be used as inputs and outputs for system identification. The robustness of the system identification can vary greatly depending on the number and type of measurements used. The ability of the neural network to locate the global minimum is very sensitive. For this reason, many different combinations of sensor inputs and outputs were tried. The different combinations had a relatively large effect on the mean squared error of the training. The natural choice was to make the transformer currents (primary, secondary, and tertiary) as well as the pump and fan bank currents inputs to the system. In addition to these current measurements, the ambient temperature and top tank temperature were used as inputs. The ambient temperature provided information to the external conditions, while the top tank temperature provided a measure of transformer operation. The main tank temperature was the temperature output. Due to the importance of the lower odd harmonics in determining coil loosening as mentioned in Chapter 2, these frequencies were also used as inputs and outputs. The seventh and ninth harmonics were used as inputs, while the third and fifth harmonics were the outputs. This combination provided the best results for the training sets.

Table 6.1 gives a list of the sensor measurements used for system identification given the transformer data provided by the diagnostic module. The model structure for the chosen set of input and output measurements is given in Equation (6.1).

Table 6.1: Input output measurements used for transformer models

Sensor	Measurement Point	Type
T1	Main Tank Temperature	Output 1
V1	Vibration of Third Harmonic	Output 2
V2	Vibration of Fifth Harmonic	Output 3
T2	Top Tank Temperature	Input 1
TA	Ambient Temperature	Input 2
C1	Primary Current	Input 3
C2	Secondary Current	Input 4
C3	Tertiary Current	Input 5
CP1	Fan and Pump Bank Current #1	Input 6
CP2	Fan and Pump Bank Current #2	Input 7
V3	Vibration of Seventh Harmonic	Input 8
V4	Vibration of Ninth Harmonic	Input 9

$$\begin{bmatrix} y_{T1}(k+1) \\ y_{V1}(k+1) \\ y_{V2}(k+1) \end{bmatrix} = F(y_{T1}(k), y_{V1}(k), y_{V2}(k), u_{T2}(k), u_{TA}(k), u_{C1}(k), u_{C2}(k), u_{C3}(k), u_{CP1}(k), u_{CP2}(k), u_{V3}(k), u_{V4}(k)) \quad (6.1)$$

For all three transformers, data collected over the same nine-day period was used to train the neural network. Though shorter periods of time can be used for training, it was found that a nine-day period provided a more accurate identification of the system that was more robust. As mentioned in Chapter 3, varying numbers of membership functions can be used during the training and simulation of the TNFIN neural network. A greater number of membership functions will provide a higher accuracy; however, the training time and the memory requirements increase significantly as the number of membership functions increases. One can think of the membership functions as linguistic values, such as low, medium, high. If there are six membership functions, this means there are 6 fuzzy sets for each input. The neural network determines the degree that each input belongs in each set. The amount of membership functions to use is best determined through trial trainings. For the training of all three transformers used in this experiment, four membership functions per input were used. Through experimentation with up to 12 membership functions per input, the improvement in accuracy was not significant enough to justify the use of more than four membership functions, especially given the added memory that is required. The shape of the four membership functions for the top tank temperature (input 1) for the training of Transformer A is given in Figure 6.1. The membership functions are bell-shaped and slightly overlap, as is to be expected. Figures 6.1-6.12 show the inputs and outputs that were used for the training of Transformer A.

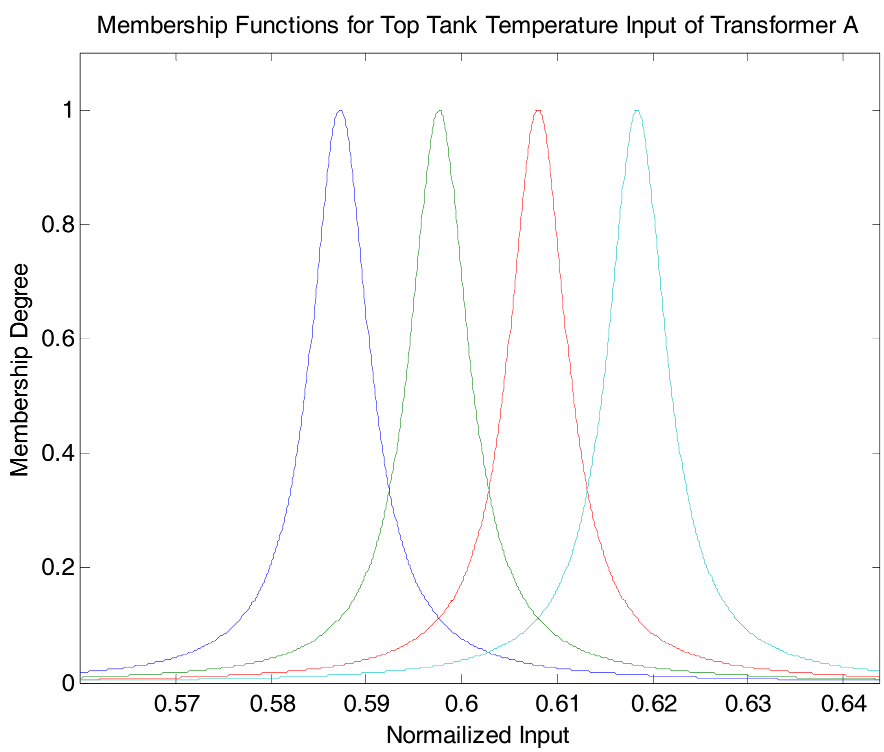


Figure 6.1: Four membership functions of Transformer A's top tank temperature input

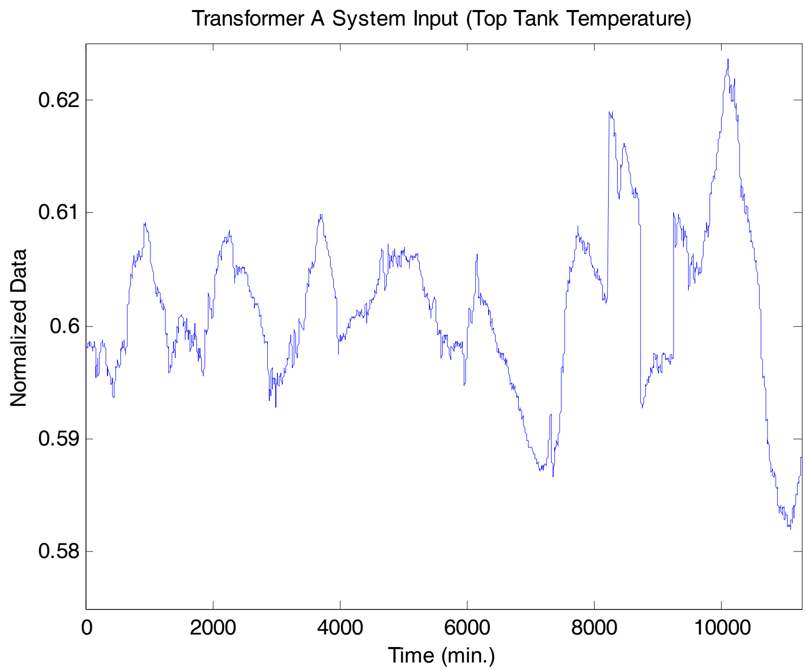


Figure 6.2: Transformer A system input-top tank temperature

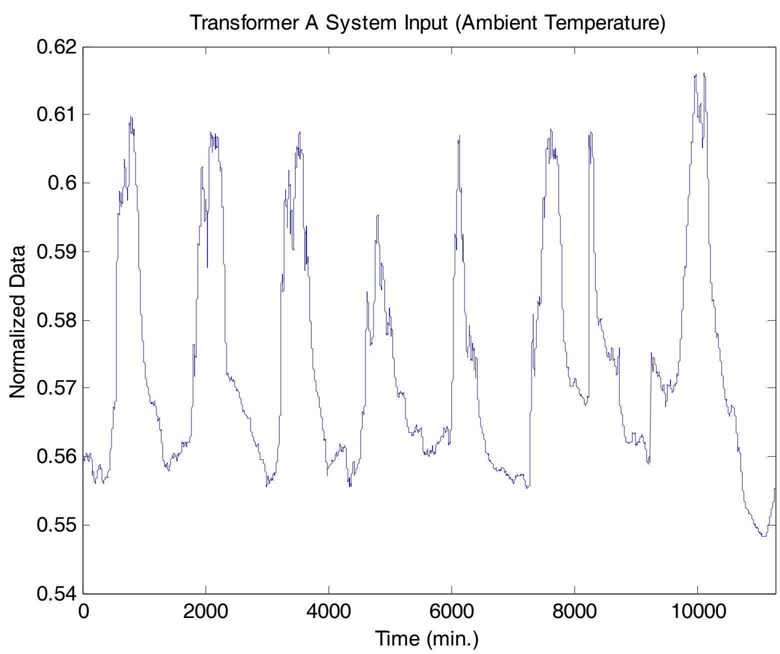


Figure 6.3: Transformer A system input-ambient temperature

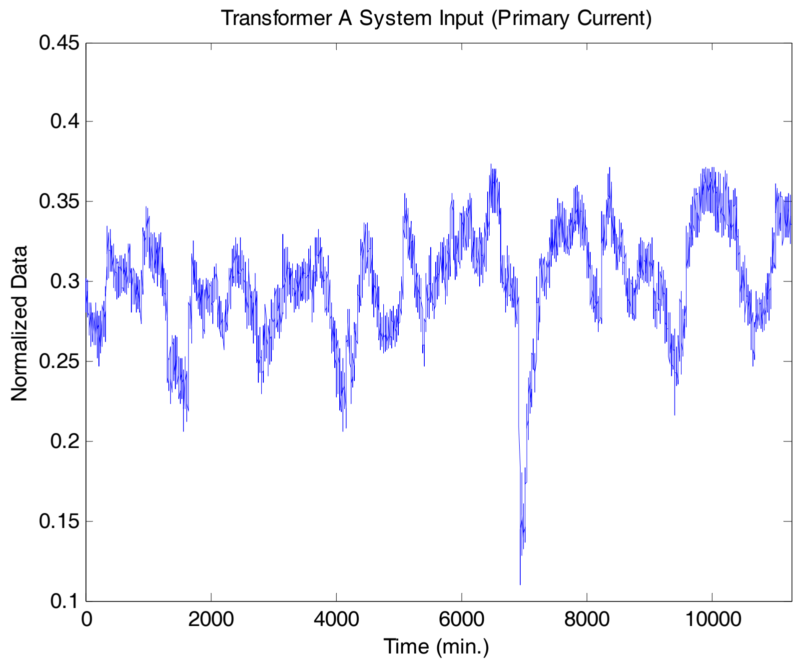


Figure 6.4: Transformer A System Input-Primary Current

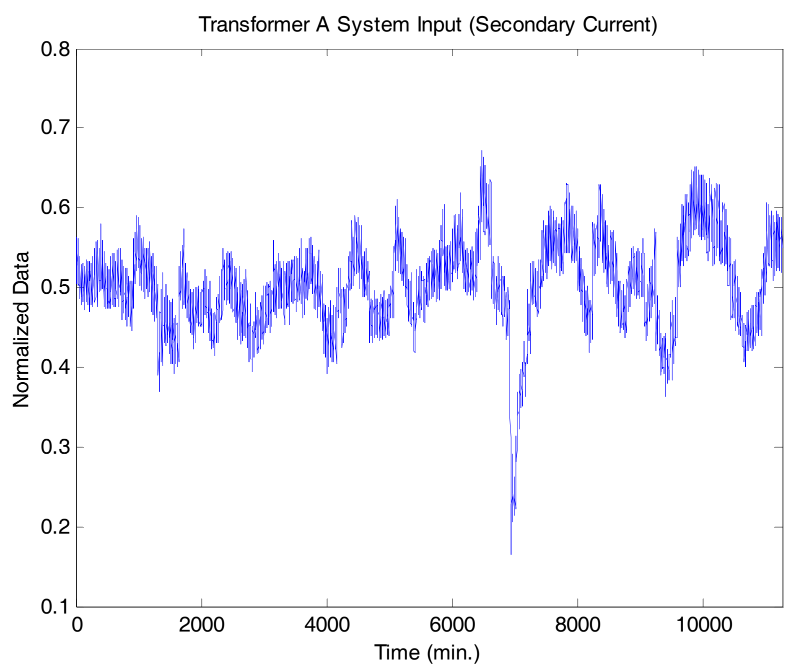


Figure 6.5: Transformer A system input-secondary current

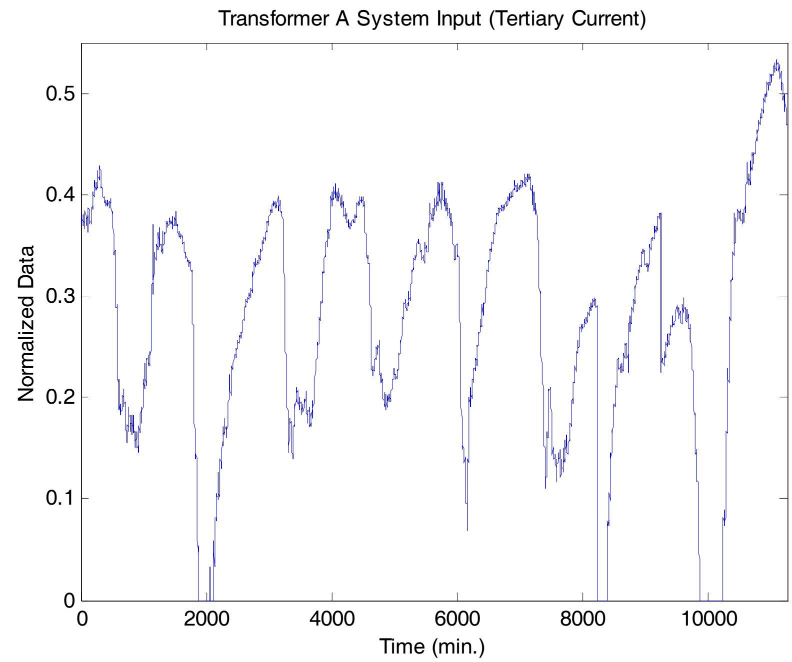


Figure 6.6: Transformer A system input-tertiary current

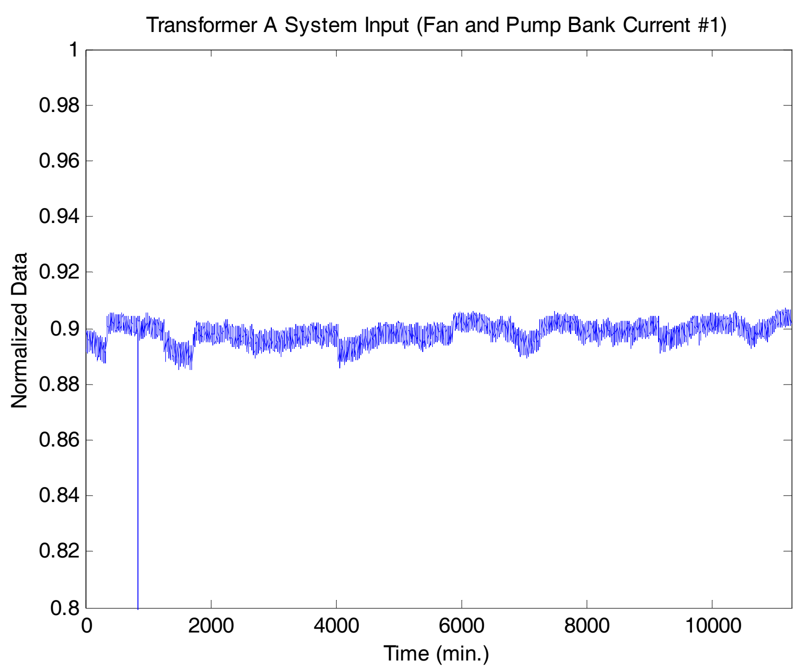


Figure 6.7: Transformer A system input-fan and pump bank current #1

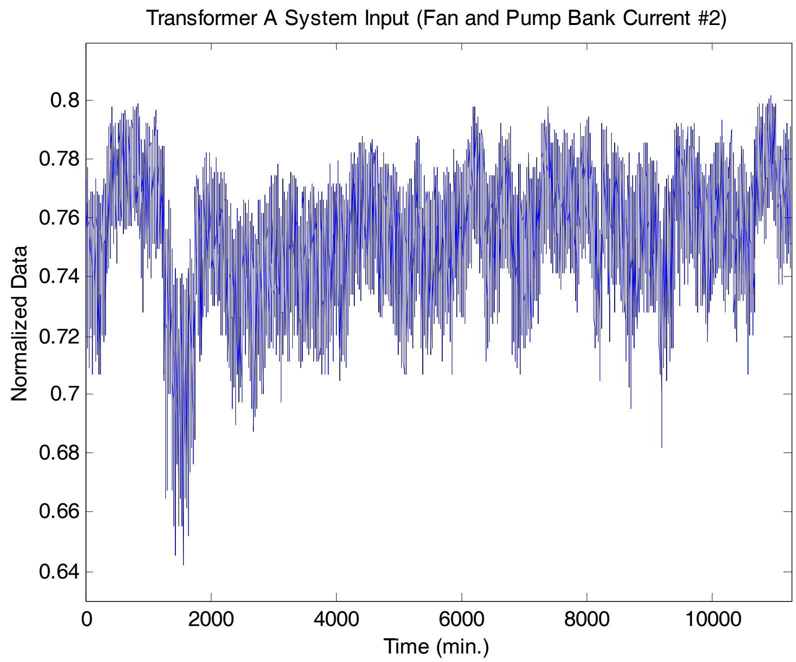


Figure 6.8: Transformer A system input-fan and pump bank current #2

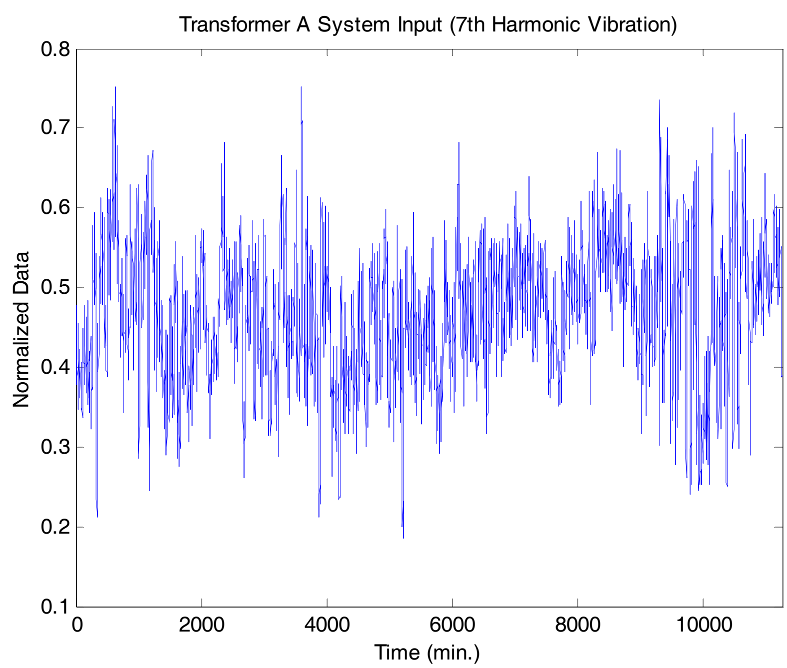


Figure 6.9: Transformer A system input-7th harmonic vibration

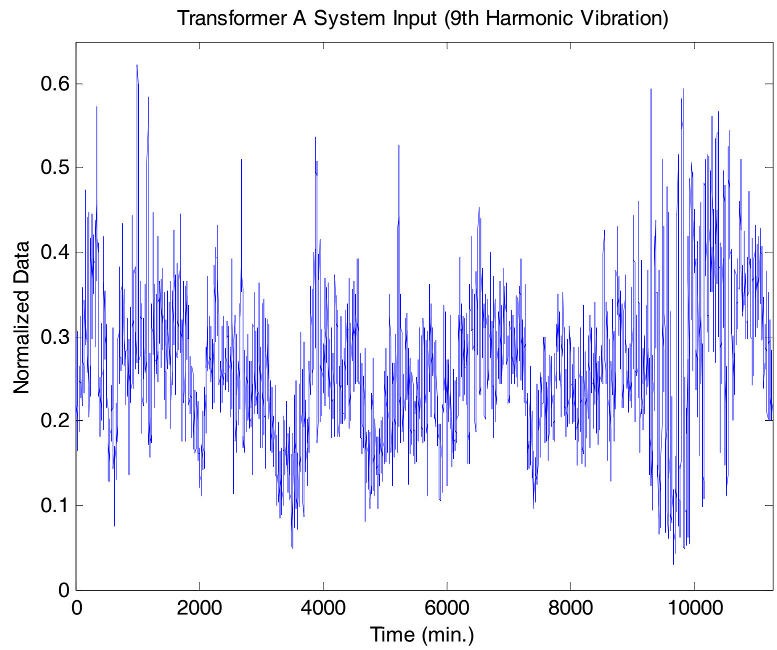


Figure 6.10: Transformer A system input-9th harmonic vibration

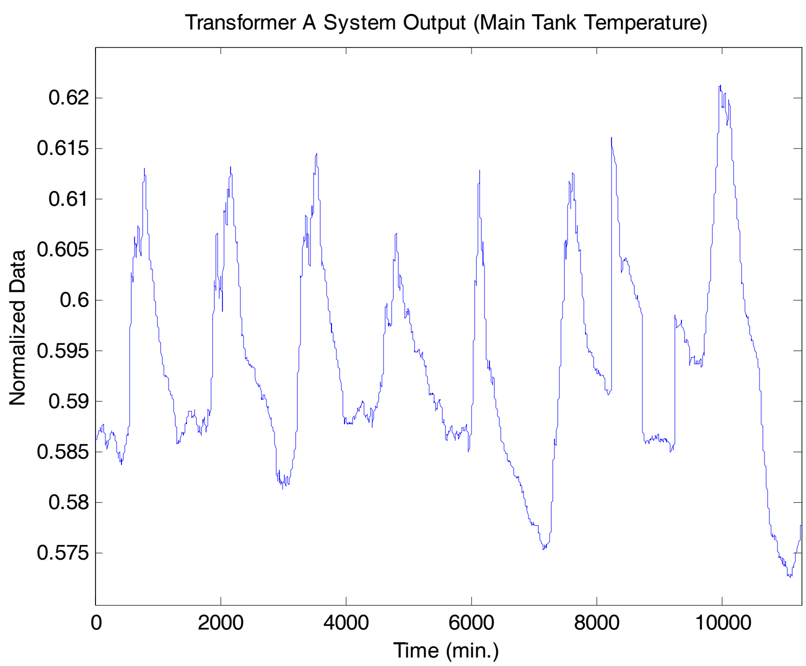


Figure 6.11: Transformer A system output-main tank temperature

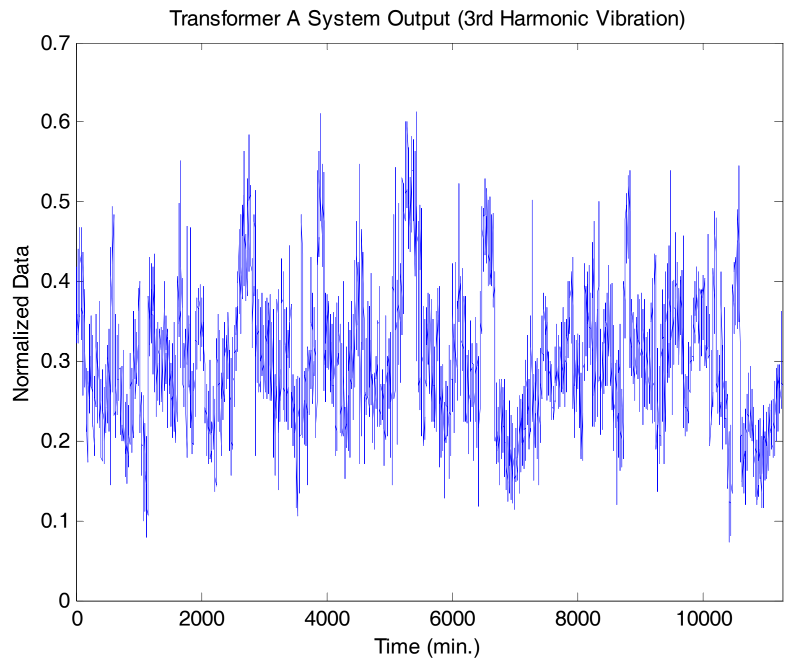


Figure 6.12: Transformer A system output-3rd harmonic vibration

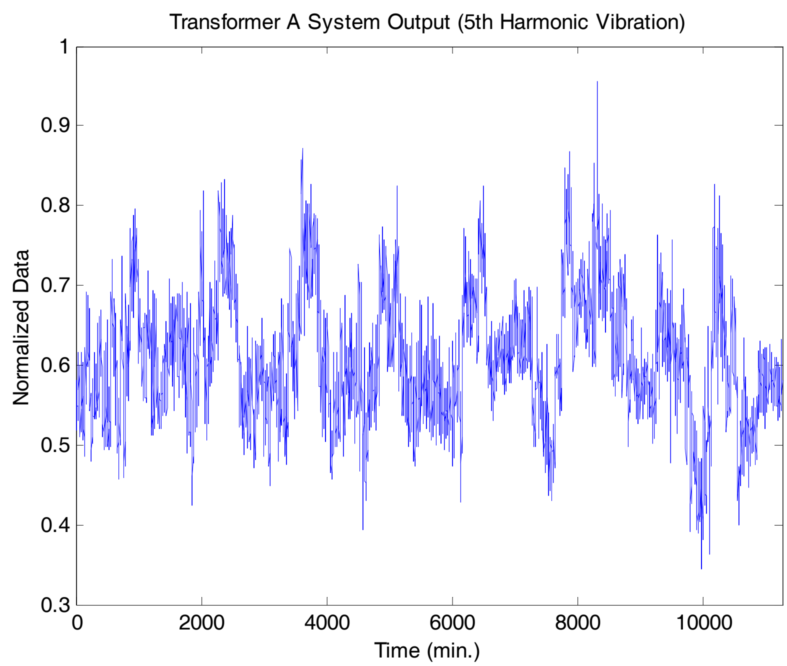


Figure 6.13: Transformer A system output-5th harmonic vibration

From the above graphs, one notices that the inputs and outputs have all been normalized. This was done by finding the maximum value of any given input or output and dividing that input or output by a number about 50% larger than the maximum. This assures that the inputs and outputs will never have a value greater than 1. This is necessary because the TNFIN only accepts inputs and outputs between 0 and 1. The same normalization factor was used for training and simulation so that the parameters (a,b,c,d) determined during training would be appropriate for simulation as well.

The results of the TNFIN training are shown in Figure 6.14-6.22. The network did a fairly good job of training. The mean squared error was around .001 for all three phases. Given the noise present in the system and variation in the measurements, this error is more than acceptable for training purposes. The network struggled with identification for the vibration outputs but provided accurate temperature identification. Table 6.2 gives a summary of the training results for the three transformers.

Table 6.2: Summary of training results for three transformers (A-C)

	Transformer A	**Transformer B**	**Transformer C**
Number of Inputs	9	9	9
Number of Outputs	3	3	3
Number TNFIN Nodes	183	183	183
Sample Size	11256	10753	11256
Mean Squared Error (MSE)	.0022	.0012	.00091
Training Time	99.593	95.036	96.028

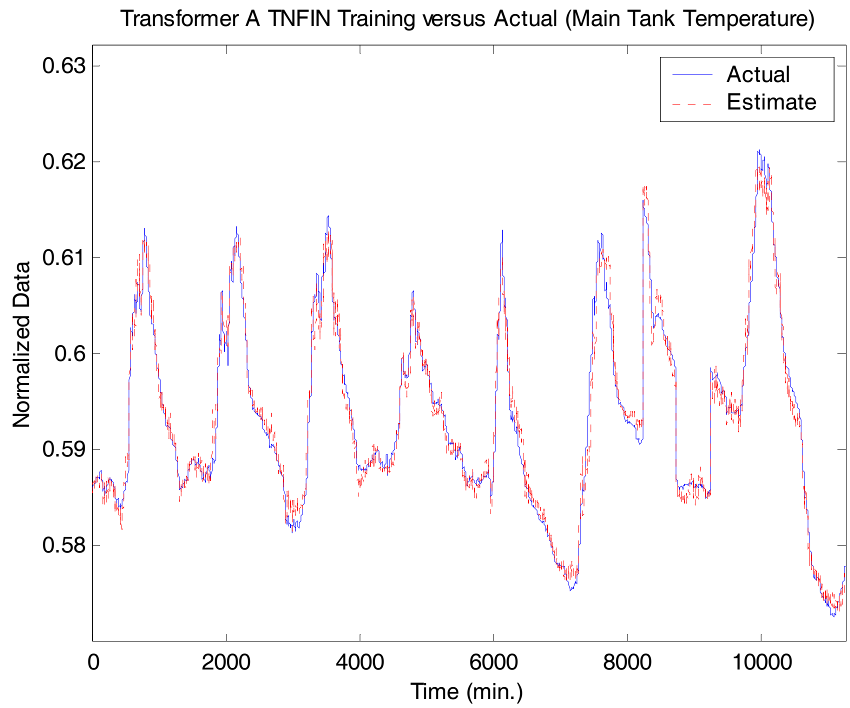


Figure 6.14: Transformer A TNFIN training versus actual-main tank temperature

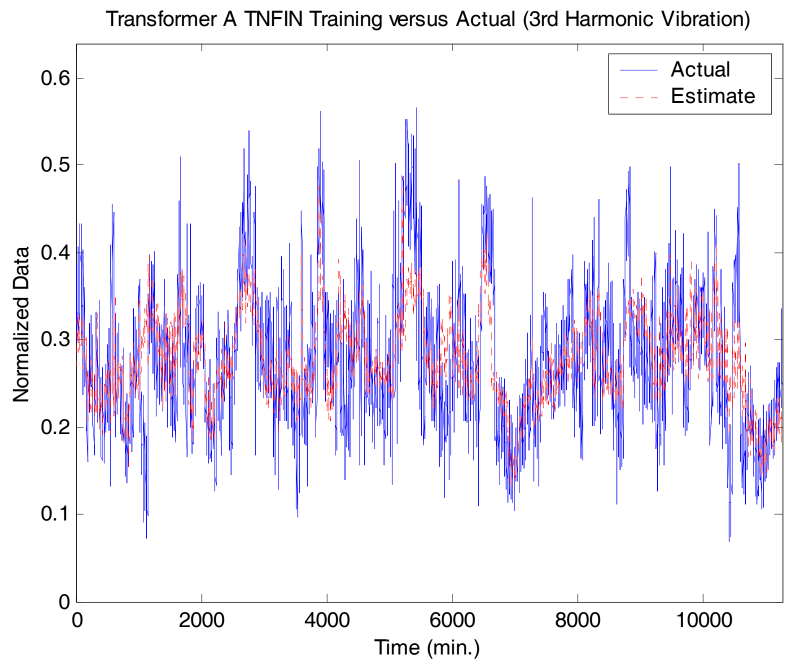


Figure 6.15: Transformer A TNFIN training versus actual-3rd harmonic vibration

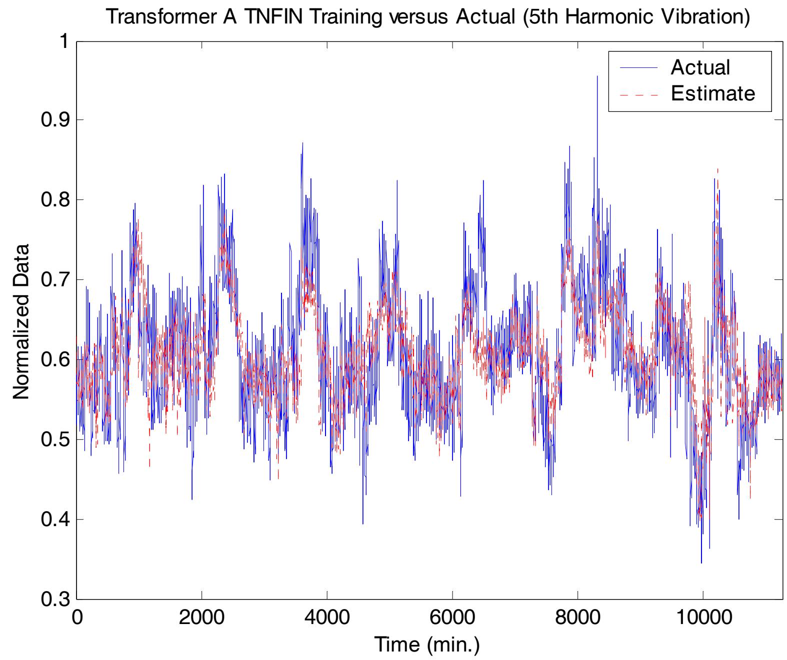


Figure 6.16: Transformer A TNFIN training versus actual-5th harmonic vibration

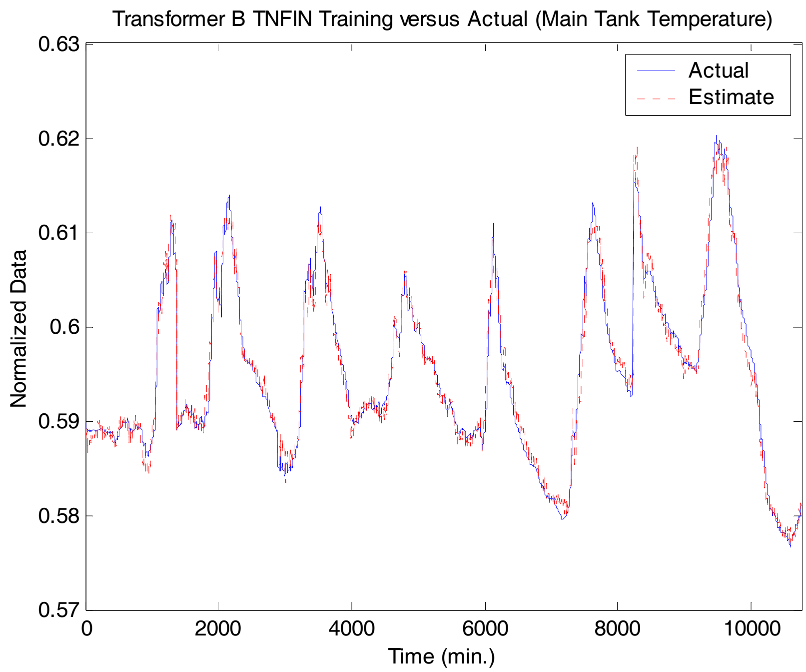


Figure 6.17: Transformer B TNFIN training versus actual-main tank temperature

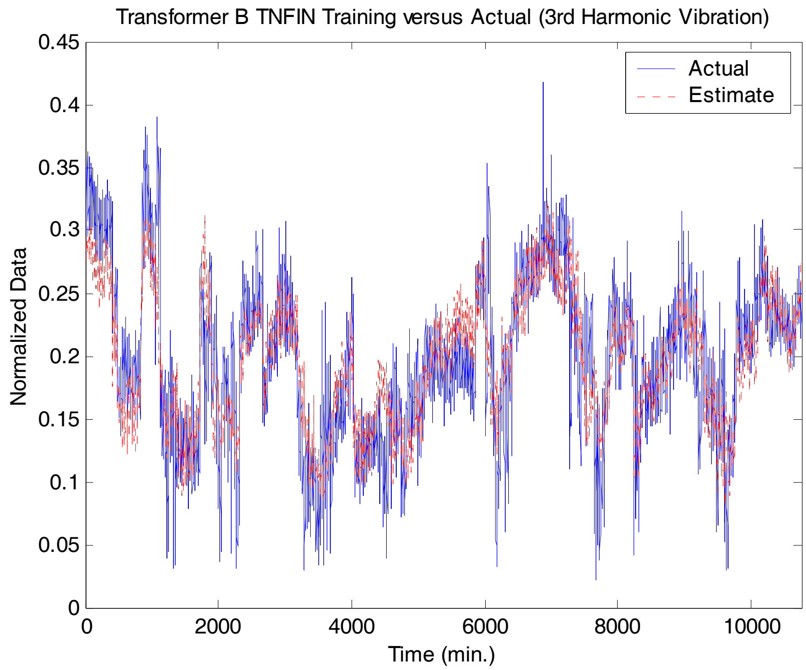


Figure 6.18: Transformer B TNFIN training versus actual-3rd harmonic vibration

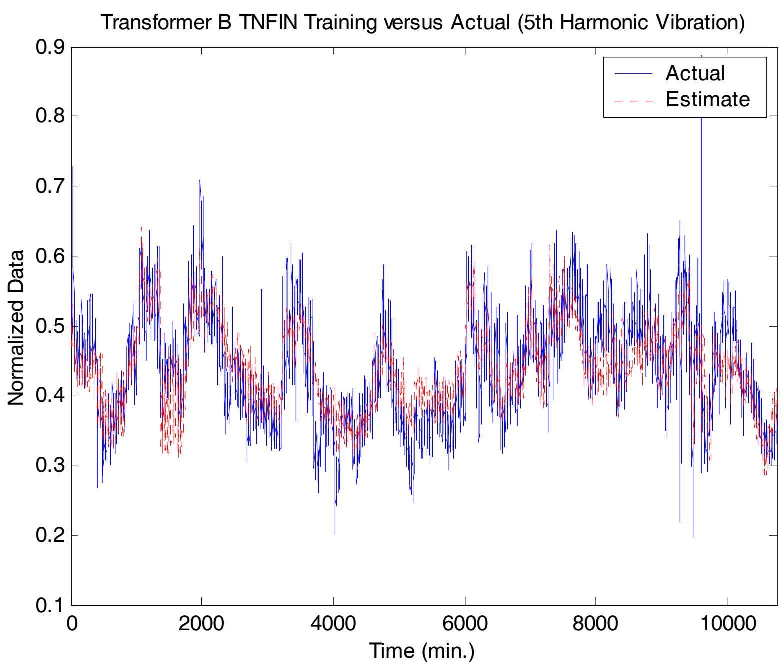


Figure 6.19: Transformer B TNFIN training versus actual-5th harmonic vibration

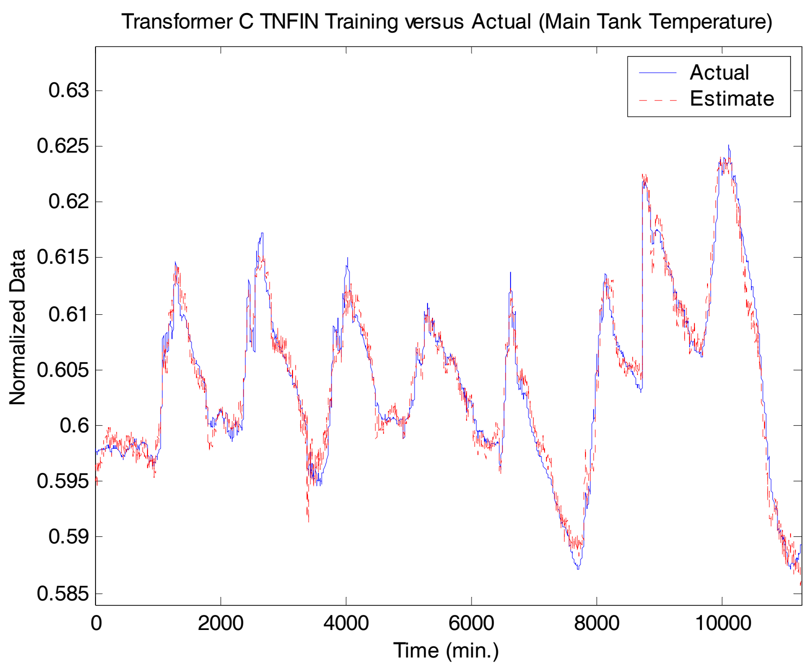


Figure 6.20: Transformer C TNFIN training versus actual-main tank temperature

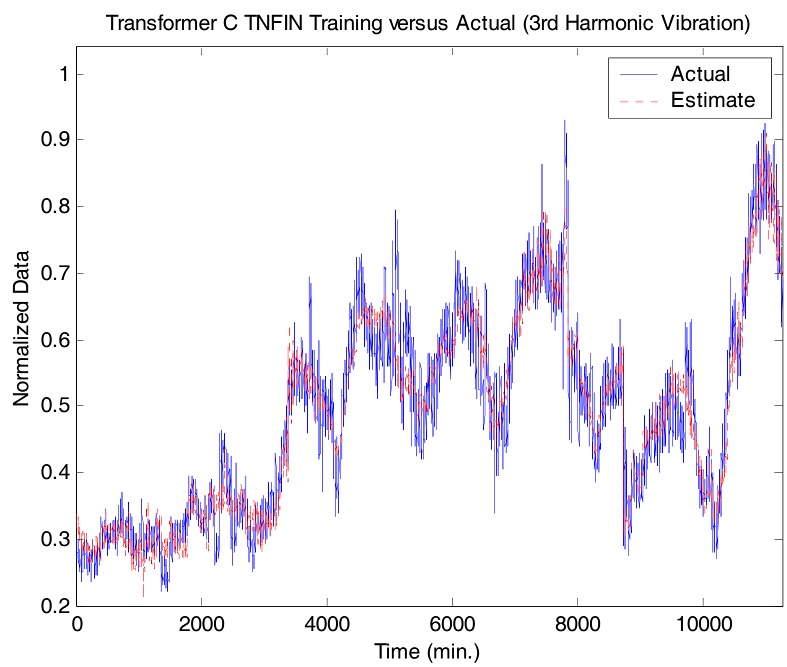


Figure 6.21: Transformer C TNFIN training versus actual-3rd harmonic vibration

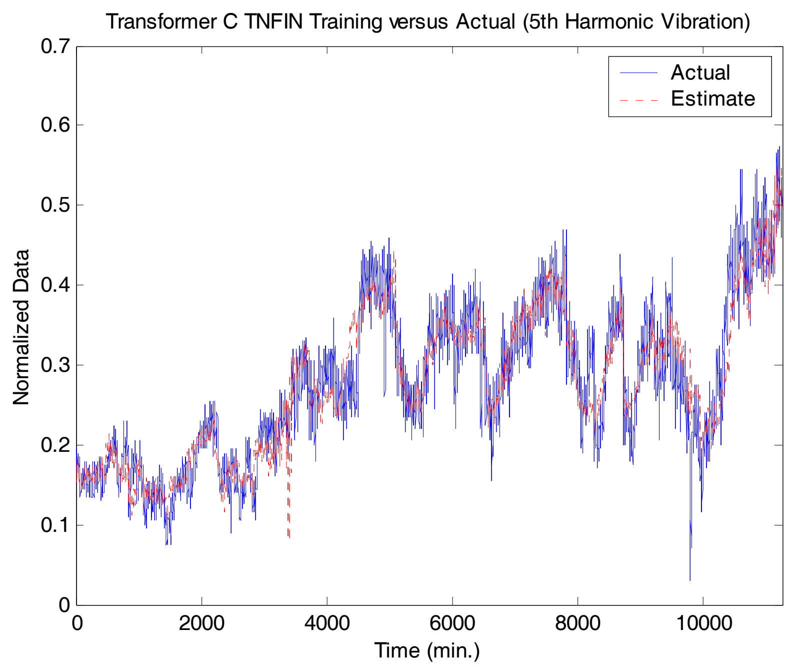


Figure 6.22: Transformer C TNFIN training versus actual-5th harmonic vibration

6.3 Model Validation and Output Estimation

Once the neural network has formed a model based on a training set, the robustness of this model must be validated using sample data not contained within the training set. Often times, the neural network may struggle to give accurate estimates of the system outputs during sample simulations. Therefore, another 9-day data set was used to validate the neural network training. The neural network was found to be fairly robust for the temperature estimates with the error lying below 0.01 (equivalent to several degrees Celsius). The network struggled more with the vibration estimates. Here, the error between actual and estimate are as high as 0.3 at times. This is less alarming given the normalization factor for the vibration was twenty times less than for the temperature. A plot of the error in validation for the three outputs is given in Figures 6.23-6.25.

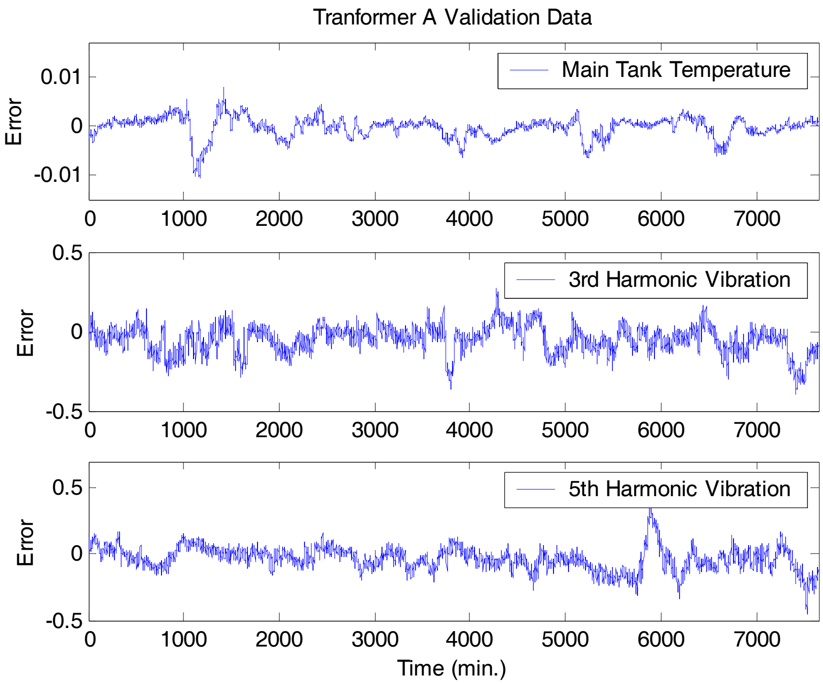


Figure 6.23: Transformer A neural network validation

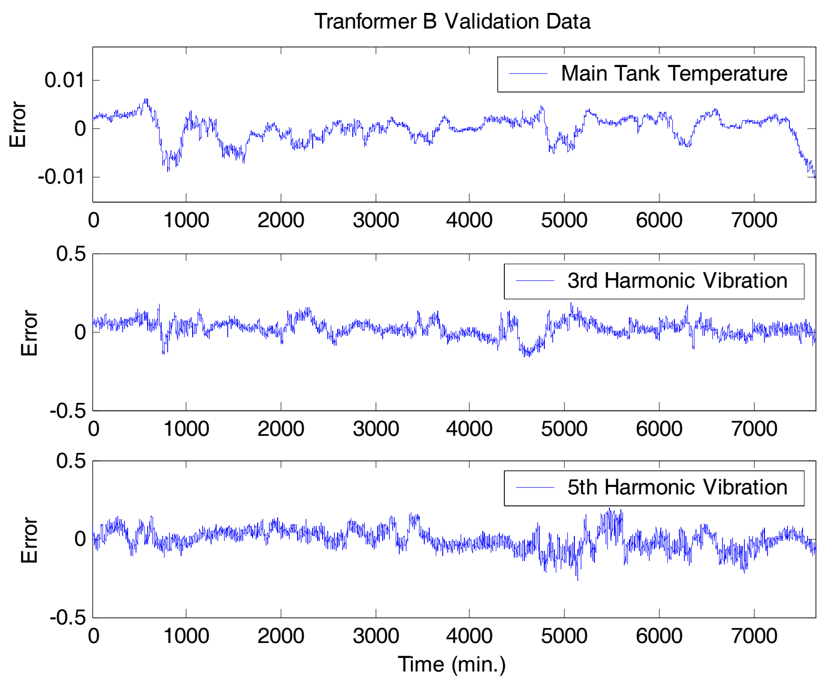


Figure 6.24: Transformer B neural network validation

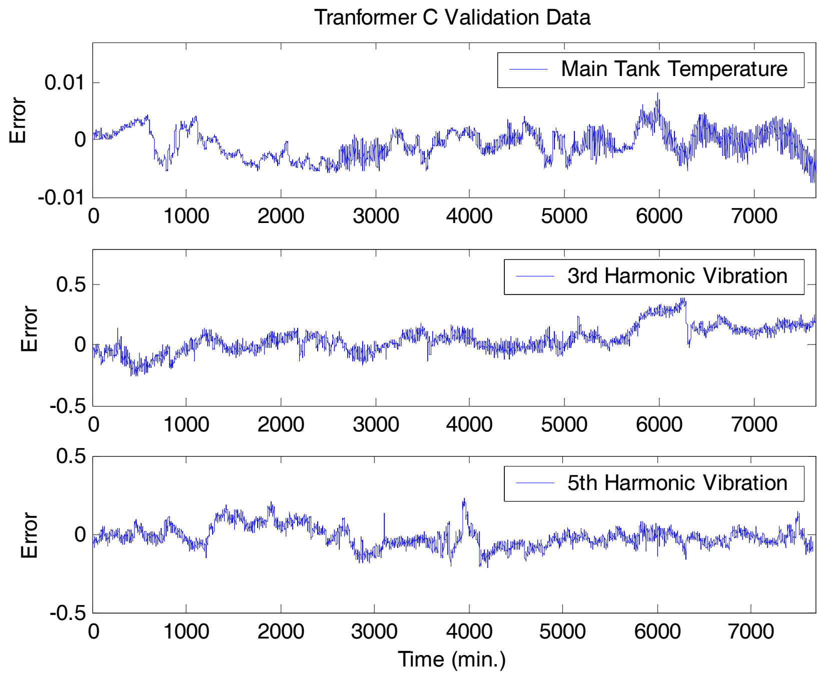


Figure 6.25: Transformer C neural network validation

One must also be aware that the starting point of the neural network can greatly affect the robustness and observability of the outputs. The neural network will often struggle for a period of time before it recognizes a point with which it is familiar. For this reason, it is recommended to overlap the beginning of the sample set with a portion of the training set. However, even when doing this, it will sometimes take the network a period of time before it produces accurate estimates. An example of the recognition time of the neural network is given in Figure 6.26. It took the trained neural network of Transformer A until the 6000th minute before it produced accurate estimates. One should note that this can occur during short periods of time, and that the fault detection engine should not send out a warning unless the error stays above a threshold for a sustained time.

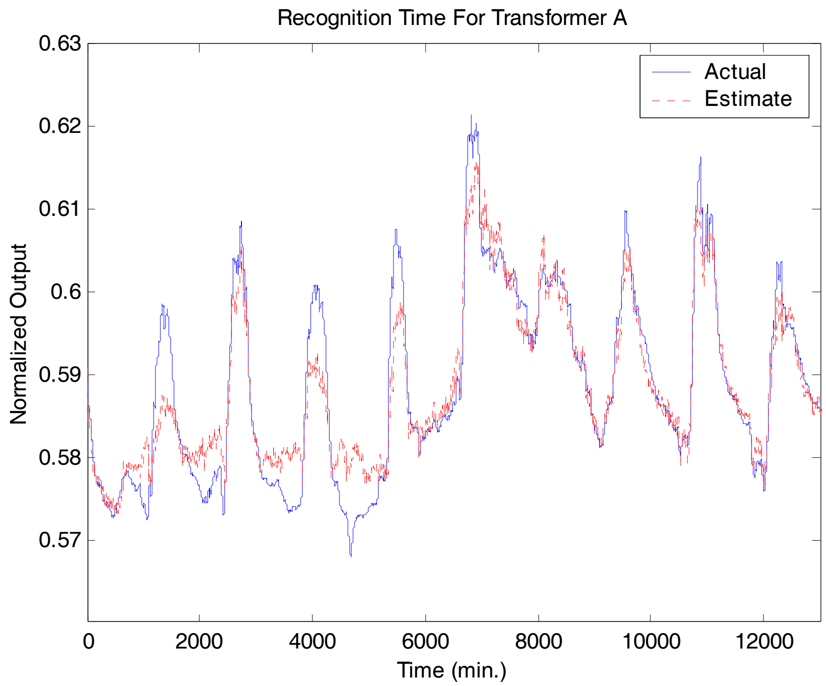


Figure 6.26: Recognition time for neural network training of transformer A

6.4 Fault Detection

As illustrated in Chapter 3, non-linear system identification and output estimation are the two preliminary steps toward fault detection. Now that the non-linear system dynamics have been identified and proven to give robust estimates of the outputs (in particular the temperature), the desired goal of fault detection can be achieved. There are two different types of failures that can occur and be detected by the neuro-fuzzy system. These are actual system failures and hardware (i.e. sensor) failures. The successful detection of these two types of failures is discussed in the next two sections.

6.4.1 System Failure

As might be expected, witnessing an actual fault to occur over a six month period for a transformer, whose average life is around 40 years, is not highly probable. During this research, the statistics held true and no transformer fault was witnessed on any of the three transformers being monitored. For this reason, a fault had to be simulated in the system. To simulate a fault, the top oil temperature was raised by 10% over its observed value. This would represent the type of temperature increase that would occur if extensive arcing, caused by insulation deterioration in the first few turns, was developing. The benefit of the optimization based fault detection used in this research is the ability to use a-priori knowledge, such as sensor error, valid bounds, etc., to adapt the fault detection to the specific application. From Chapter 3, a no-fault condition exists when:

$$\min_{y_l(k)} \| Y^n(k) - \overline{F}^n(u_{l+n+-1}(k+n-1), y_l(k)) \|_W < \varepsilon \qquad (6.2)$$

In the case of the thermal fault being detected here, the weighting factor W would eliminate the vibration outputs, since they are indicative of mechanical failures, not thermal, and were less robust, as shown in the previous section. Therefore, the W used for the thermal fault detection was [1 0 0;0 0 0;0 0 0]. Looking at the errors in Figures 6.23-6.25, the maximum error in temperature is around 0.0075. Therefore, with the given W, the maximum ε under normal operating conditions is 0.0075. For this reason, ε is set at 0.0075, because the norm of the error never exceeds this value for any prolonged time during normal operating conditions.

Using these parameters for the fault detection, the data from all three transformers was analyzed by the neural network. In each case, the neuro-fuzzy system was able to detect the failure, which occurred at the 5000th minute. Figures 6.27-6.29 show the results of the fault detection minimization for each of the three transformers. In these figures, one can see that there are still regions, where the error drops below ε after the fault has occurred. This is not unexpected from a neural network. There will always be local regions where the dynamic model identified by the neural network is less sensitive to fault detection. It is still apparent that the system is experiencing a fault, since there is no prolonged period of time before 5000 minutes where the error is above 0.0075.

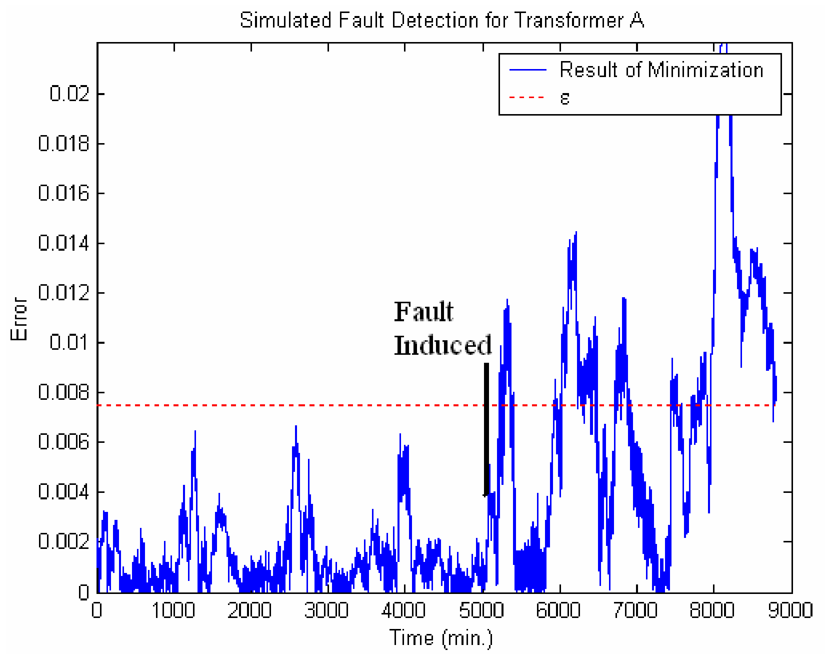


Figure 6.27: Result of fault detection for transformer A

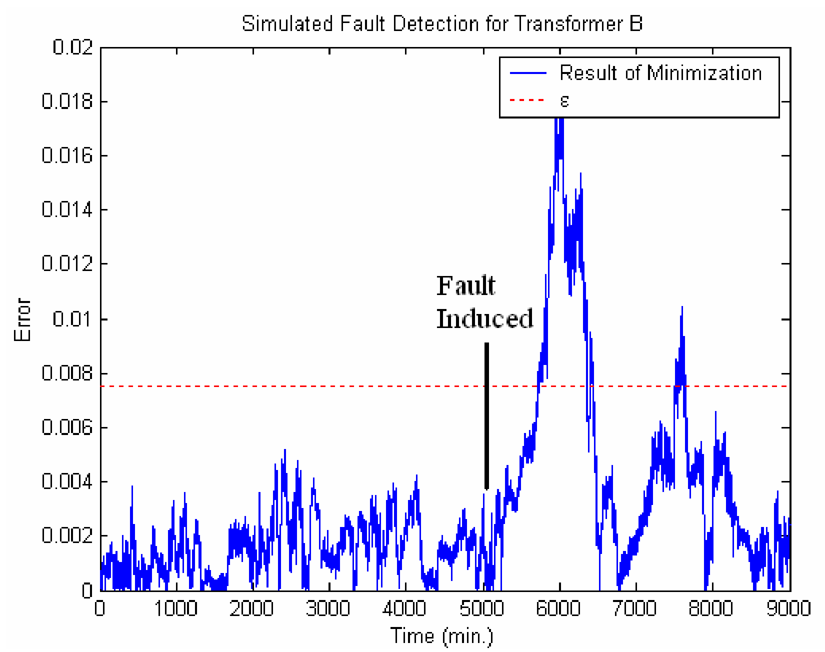


Figure 6.28: Result of fault detection for transformer B

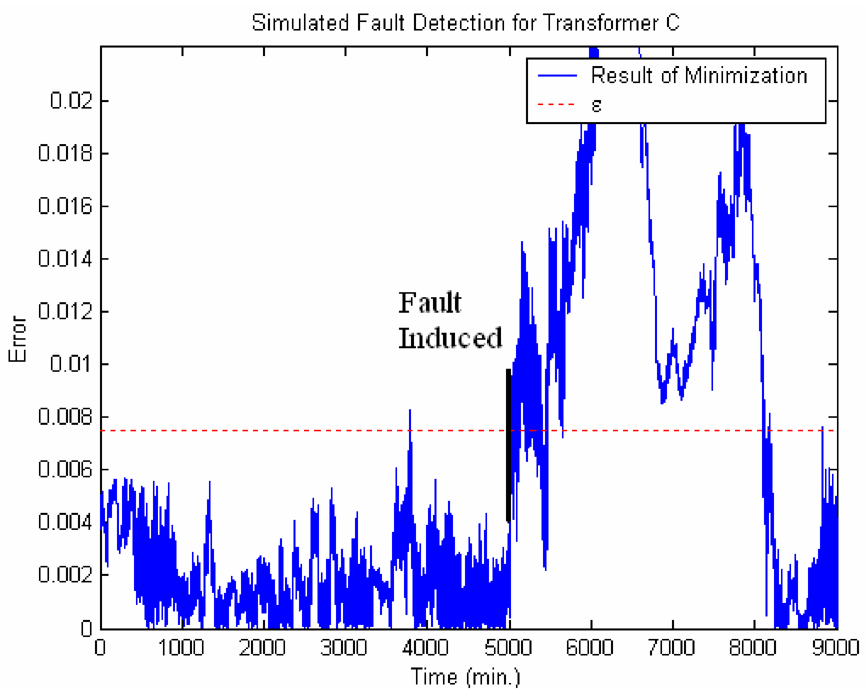


Figure 6.29: Result of fault detection for transformer C

The weighting, W, that is placed on the various outputs when determining the error minimization will be dependant on the fault being detected. A mechanical fault would place more emphasis on the vibration outputs instead of the temperature output, as illustrated in this example.

6.4.2 Sensor Failure

In the previous section, it was seen how a change in the dynamics can be detected using the TNFIN network. This change can be caused by a developing failure in the system, as simulated in the last section, or by a faulty sensor. In order to prevent errant diagnosis of a transformer's health, additional processing is required. A faulty sensor can be detected and isolated by using only some of the outputs when performing the optimized fault detection. In other words, it is assumed that there is no knowledge about one of the outputs. By removing one output sensor at a time, it can be determined if the detected change is caused by a sensor or is actually indicative of a developing fault in the system.

The method for detecting a sensor failure is best illustrated by an example. The sample data from Transformer C is used. All three outputs are used in the error minimization; however, the temperature measurement is weighted ten times more to compensate for the difference in normalization factor. At time (t = 5000), the first vibration sensor fails and begins to produce inaccurate outputs. This failure is induced by eliminating the lowest frequency output of the accelerometer, thus simulating an accelerometer that can no longer detect low frequencies. When all sensors are considered, it is seen that a fault has occurred, since the error exceeds ε. The top-left graph of Figure 6.30 illustrates this fact. One by one a sensor is ignored. A fault is still detected in every case, as shown in Figure 6.30, except when sensor V1 is removed. Therefore, V1 must be a faulty sensor. A more detailed and processing intensive procedure can be utilized to determine an input sensor fault. In this case, the neural network must be retrained to identify the system with one less input and then the same procedure is followed, removing one input sensor at a time. This method may not work for inputs that are critical to accurate system identification.

6.4.3 System and Sensor Failure

There is always the possibility that a sensor may fail at the same time that the system is experiencing a failure. Sometimes a system failure may cause a sensor failure. It is desired that the fault detector be able to detect and isolate both failures. If the failures occur at a different times with the sensor occurring first, it is easy to see how the TNFIN fault detector could detect both faults. By using the approach of the previous section, one could see there would be a shorter period of failure when the faulty sensor was removed, thus indicating that both a sensor and system failure had occurred but at different times. The problem becomes detecting both failures when they occur simultaneously. As an example, the system and sensor faults that were simulated in the past two sections now occur at nearly the same time. Since a thermal fault is being detected, more weight is placed on the temperature output just as in the previous section.

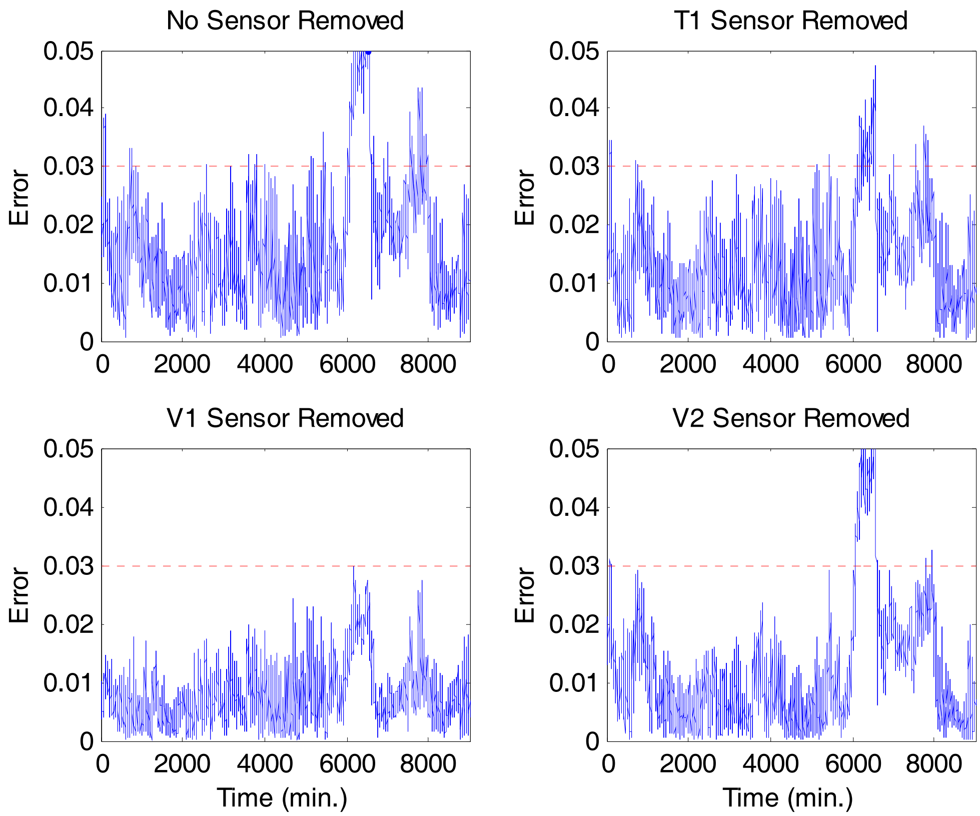


Figure 6.30: V1 sensor failure, detection and isolation of sensor failure

Figure 6.31 shows the results of removing the sensors one at a time and seeing if the faults are still detected. Here, a problem is detected. There are obviously some spikes that are created by the sensor failure at around 6000 minutes. In all three graphs, there is a short period of time where a fault is detected and ε is exceeded, namely at around 5000 minutes. However, much of the information about the system failure has been lost. It is difficult to distinguish if a system failure has occurred or simply a sensor failure. This is one area where the TNFIN fault detector lacks. It is difficult to distinguish between residuals caused by system failures and those caused by sensor failures, if they occur at the same time.

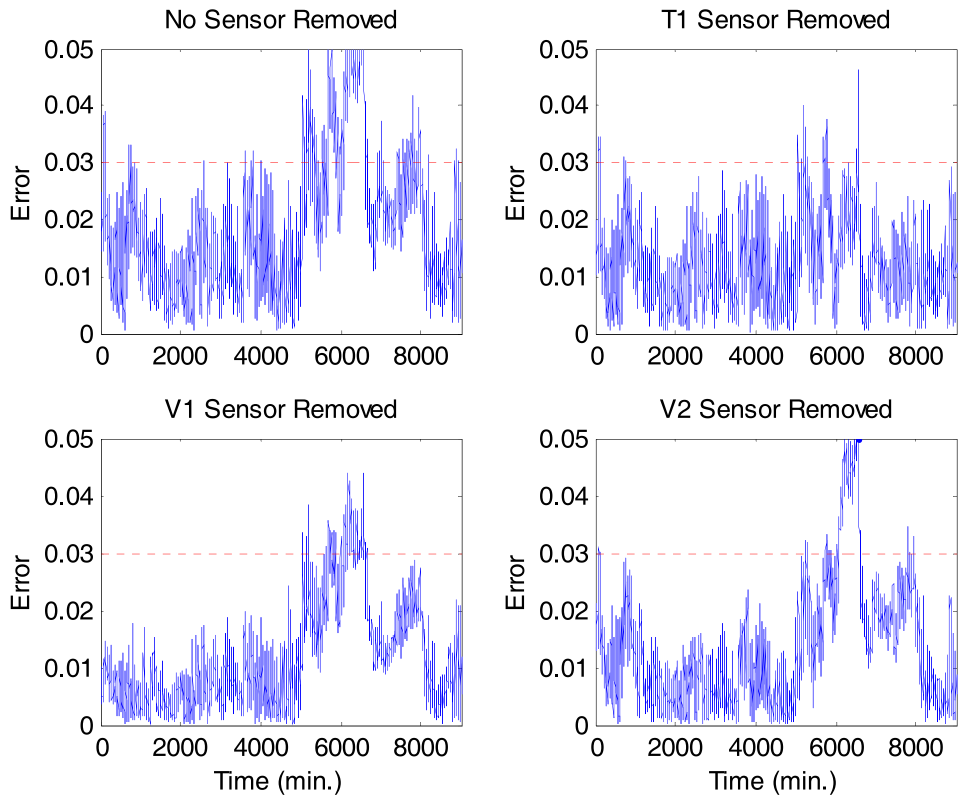


Figure 6.31: Detection and isolation and system and sensor failure

In summary, using the neuro-fuzzy system described in Chapter 3, the non-linear transformer dynamics were identified. Robust output estimates could then be made, which allowed for optimized fault detection. The fault detection method could distinguish between system and sensor failures. The fault detection capability can be improved by training with larger data sets, in order to capture more of the system dynamics and thus form a better model. Actual transformer faults must be witnessed before full validation of the fault detection engine can be verified.

7. Conclusions and Future Work

7.1 Summary

Much important advancement was reached from the research described in this report. A transformer diagnostic system that could be implemented on large scale, field-level equipment was developed and tested. The neuro-fuzzy fault detection engine developed and validated on a small 10kVA distribution transformer was implemented on three large substation transformers. Through this field implementation, valuable information was gained about the diagnostic module needed for monitoring and how the neuro-fuzzy system can be utilized to provide the maximum fault detecting capability. The major contributions of this research are summarized in the following sections.

7.1.1 Diagnostic Hardware Module

- A diagnostic module was designed and three prototypes were manufactured. This diagnostic module included the non-invasive sensors that have been found to indicate developing faults in transformers. The system also included its own power supply, signal conditioner, DAQ card, and PC104 to process the data from the sensors. The module was also equipped with a RS232 to fiber converter to send the data in the noisy substation environment
- The diagnostic module is magnetically mounted to the inside of the transformer cabinet, making the system easily installable and portable. The diagnostic module could be completely installed on a transformer in less than an hour once the AC power connection has been established.
- The three diagnostic module prototypes were placed on three single-phase transformers at the Ault substation. They were placed in the harsh environment starting in the summer

months and continuing into the winter. The modules successfully collected data during these varying weather conditions proving their durability.

7.1.2 Data Manipulation and Communication

- The appropriate software was written in C for both the PC104 located on the diagnostic module and the computer located inside the substation house. The PC104 converted the temperature and current data to their appropriate values and performed an FFT on the accelerometer data.
- Data was sent from the PC104 to the substation computer at one-minute intervals. The substation computer saved the data as strings in date marked files. A GUI was placed on the substation computer to allow maintenance personnel to see the sensor outputs and the FFTs.
- Substation computer connected through modem to CSM computer. The modem did not sacrifice substation security, but allowed for easy access to data. The installation of RealVNC allowed for remote control over the system through the substation desktop.

7.1.3 Non-linear System Identification and Fault Detection

- System identification and fault detection was applied to three large 166 MVA transformers at the Ault substation using the data obtained from the diagnostic module designed in this research. Using current, ambient and top tank temperatures, and certain frequencies as inputs, the main tank temperature as well as certain vibration frequencies were predicted using the TNFIN. The experiments showed that the temperature dynamics could be accurately identified using the TNFIN. The TNFIN struggled more with the vibration dynamics but still provided decent estimates of the highly varying outputs.
- After identifying the system through training, the TNFIN was used to estimate the outputs for a validation data set. The estimates could then be compared with the actual

sensor measurements. The neural network was found to be relatively robust. However, the neural networks estimates were highly sensitive to starting positions and could result in large errors due to poor output observability.

- Fault detection was successfully achieved on the transformer by simulating a thermal fault in the system, which would be representative of internal insulation deterioration.
- The ability of the neuro-fuzzy fault detection engine to distinguish between sensor fault and system fault was also successfully documented through setting the outputs of one sensor to zero, simulating a malfunctioning sensor condition. By eliminating the knowledge of one output sensor at a time, the location of the faulty sensor was found.

7.1.4 Foundation for Hybrid Neuro-fuzzy Expert System

- The framework and preliminary rule-base for a hybrid neuro-fuzzy expert system was presented. The system would combine the most accepted sensor threshold levels with the neuro-fuzzy fault detection engine of this research to provide a reliable transformer health diagnosis. The final architecture of the system will have to be adjusted as the neuro-fuzzy system increases its knowledge base through witnessing and experiencing a variety of failures.

7.2 Future Work

The research presented in this research focused on validation and implementation of the neuro-fuzzy fault detection engine on large substation transformers. This validation was accomplished through the design of a diagnostic module, which could non-invasively collect data that has been shown to provide diagnostic information about the health of transformers. This data was then transferred to the neuro-fuzzy detection engine via a modem. From this point in the research, there are several areas for possible future work. The major areas of study are given below.

- This research focused on the implementation of the diagnostic module on three single-phase transformers of the same age and type. However, in order for the neural network to provide more accurate identification for many different types of transformers, a larger database with data from many different models and years of operation is required. For this reason, one area of possible future research is to implement the system described in this thesis on many more transformers. Through this, it is hoped that the system will actually witness different failures and be able to train itself to different types of behavior, normal and abnormal.
- The work of this thesis focused on transformer diagnostics. However, the diagnostic module and fault detection system can easily be expanded to include circuit breakers and other substation equipment. This research could focus on using the diagnostic system presented in this thesis for fault diagnosis of all substation equipment. This would ultimately lead to the final goal of an intelligent substation.
- Research has focused on diagnostics at the individual substation level. Work can be done to integrate the diagnostics and health information of several substations together into one network. By doing so, the neuro-fizzy system could see more types of failures and train itself to different health conditions. In addition, the network would be able to provide information to the utility about the health of the grid and what areas may be aging and need replacement. The network could send out warnings when one substation is having problems so that other substations could compensate.
- The experimental results obtained in this research only used the neural network for non-linear system identification and fault detection. Future work could utilize the output observer by training with measurements of the dissolved gas content in the oil and then estimating this after training is complete. It is known that DGA data provides valuable diagnostic information; however, on-line DGA analyzers are expensive. By training with the DGA data and then using the observer once the network is trained, it is possible to

achieve both accurate diagnostic capability as well as a more economically feasible diagnostic system.

- The foundation for a hybrid neuro-fuzzy expert system was presented in this report. The most valuable and accepted sensor thresholds were detailed. The implementation of these thresholds into an expert system that could be combined with the neural-fuzzy fault detection engine for more accurate fault detection is a major area for future research endeavors.
- The diagnostic module designed in this research still required a fiber optic connection to the substation house in order to transfer the data. This limits the portability and increases the work needed for installation. An area of future research could focus on the development of hardware and signal processing module that would utilize wireless communication.
- Finally, there is also a great amount of work that can be done in the area of pattern recognition of faults and life expectancy. Once a large database of data has been collected from several different transformers and different types of faults have been witnessed, it will be possible to try to classify behaviors and how they relate to impending failures. In the long term, the pattern classification could lead to life expectancy predictions for the transformer.

Transformer and substation diagnostics is an expanding field of study. The diagnostic module and fault detection system presented in this thesis can be altered and expanded to provide more and more valuable information on the health of substation equipment. The potential of this system is vast and with further investigation, the concept of an Intelligent Substation can be realized.

8. References

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