

NEURAL NETWORK-BASED CLASSIFICATION OF SINGLE-
PHASE DISTRIBUTION TRANSFORMER FAULT DATA

A Senior Honors Thesis

by

XUJIA ZHANG

Submitted to the Office of Honors Programs
& Academic Scholarships
Texas A&M University
In partial fulfillment of the requirements of the

UNIVERSITY UNDERGRADUATE
RESEARCH FELLOWS

April 2006

Major: Electrical Engineering

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April 2006

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ABSTRACT

Neural Network-Based Classification of Single-Phase Distribution
Transformer Fault Data (April 2006)

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Department of Electrical Engineering

The ultimate goal of this research is to develop an online, non-destructive, incipient fault detection system that is able to detect incipient faults in transformers and other electric equipment before the faults become catastrophic. With the condition assessment capability of the detection system, operators are equipped with better information during their decision-making process. Corrective actions are taken prior to transformer and equipment failures to prevent down-time and reduce operating and maintenance costs.

Diagnosis of data associated with incipient failures is essential to develop an efficient, non-destructive, and online system. Field testing data were collected from controlled experiment and simulation data from mathematical models are studied. This thesis presents a data-mining approach to analyze field recorded and simulation data to characterize incipient fault data and study its properties.

A supervised classifier using neural network (NN) toolbox in Matlab provides an efficient and accurate classification method to separate monitoring signal data into clusters base on their properties. However, raw data collected from the field and simulations will create too many dimensions and inputs to the neural network and make it a complex and over-generalized classification. Therefore, features are extracted from the data set, and these features are formed into feature clusters in order to identify patterns in signals as they are related to various physical behaviors of the system. The similarity between recognized patterns and patterns shown in future monitoring signals will trigger the warning of initializing or developing faults in transformers or equipment.

This thesis demonstrates how different features were extracted from the raw data using various analysis techniques in both time domain and time-frequency domain, and the design and implementation of a neural network-based classification method. The

classifier outputs are classes of data being separated into groups based on their characteristics and behaviors. Meaning of different classes is also explained in this thesis.

DEDICATION

To my parents Wen and Dongxing for their love.

ACKNOWLEDGEMENTS

I would like to thank my undergraduate research advisor, Dr. Karen Butler-Purry for her patience, guidance, directions, constructive critiques, kindness and caring heart. It was she who introduced me into the world of research when I became a sophomore research assistant of the NSF REU program in the summer of 2004. With her encouragement and inspirational ideas, I continued to research in the Power System Automation Lab (PSAL) and had an opportunity to work closely with graduate students and faculty members. Through this hands-on experience, I gained insights into graduate studies, observed and experienced how research is conducted. The informative and detailed guidance from her broad knowledge in power systems, signal processing, and control theories helped me get through challenges and successfully complete research tasks. I thank her for believing in my abilities and being there whenever I needed her.

I would also like to thank my friends and colleagues working in PSAL: Mir, LT, Fabian, Hector, and Tanja for their friendship. We shared a lot and bonded together when we worked side by side and faced difficult times together.

Last but certainly not least, I thank Ms. Raisor and Ms. Veracruz in the honors office for their help and support throughout my senior year as a research fellow.

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INTRODUCTION¹

Overview of Electric Power Systems

A power system is consisted of power generation plants, transmission lines, distribution network, and substations. Transformers are an essential part of the electric power system because it has the ability to change voltage and current levels, which enables the transformers to generate electric power, to transmit and distribute electric power and utilize power at an economical and suitable level [1].

As shown in Figure 1, voltage of electricity generated at the power plant will be increased to a higher level with step-up transformers. A higher voltage will reduce the energy lost during the transmission process of the electricity. After electricity has been transmitted to various end points of the power grid, voltage of the electricity will be reduced to a useable level with step-down transformers for industrial customers and residential customers. Transformers are a vital component of the electric power system, and they are extensively used to help meet the growing energy needs of the U.S. and the rest of the world [30].

¹ This thesis follows the style and format of *IEEE Transactions on Power Systems*.

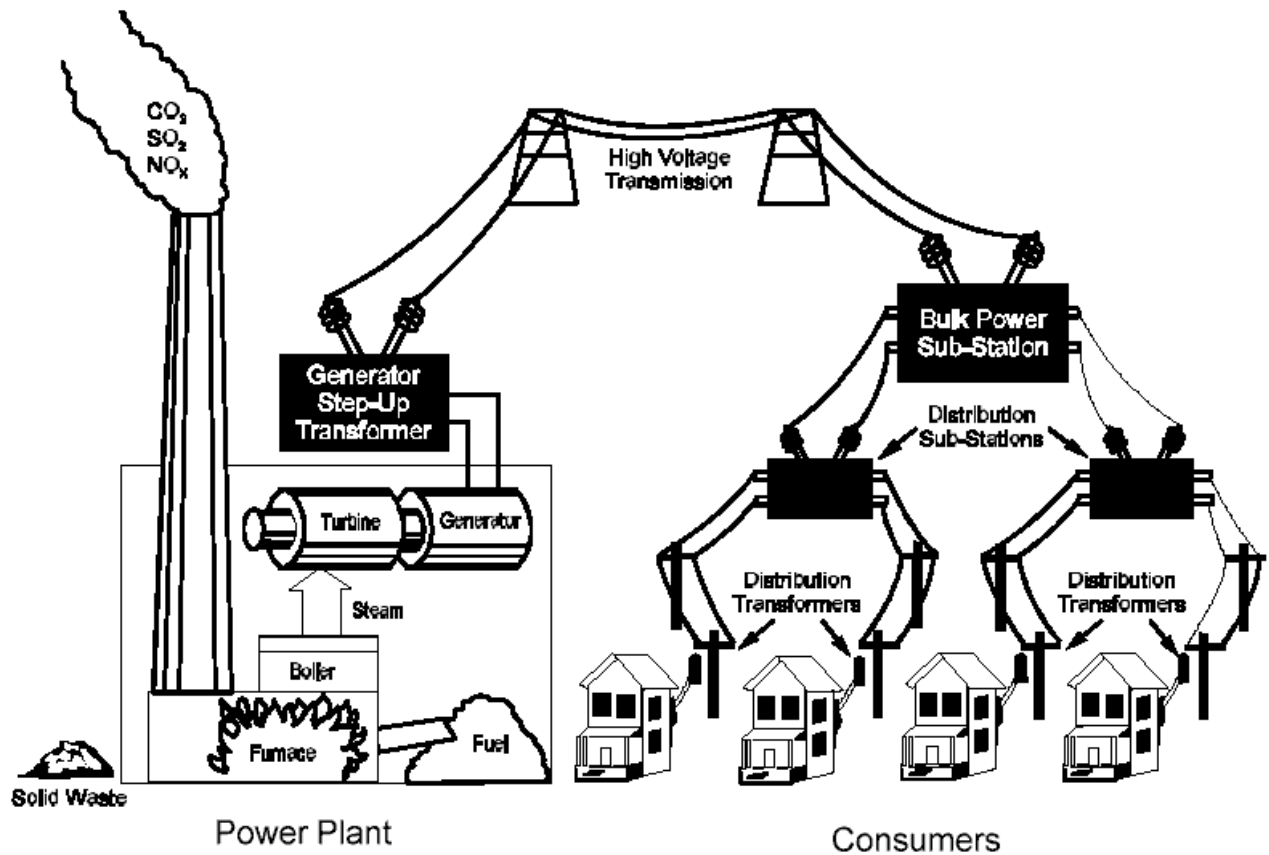


Figure 1 [1]: The structure of an electric power transmission and distribution system

Rising Problem

Energy Market and Power Industry

The trend toward a deregulated global electricity market has created a competitive environment for the power industry. The U.S. Department of Energy predicts the U.S. electric power industry must increase capacity 45% to meet increasing

electric power demand by year 2020 [2]. Reducing operational cost, optimizing usage of electrical assets, and improving reliability and customer service are significant factors to succeed. Detection of incipient faults in electric equipment will allow corrective actions to prevent unplanned outages and reduce down time and maintenance cost. Therefore, utilities are demanding online monitoring and onsite diagnostic systems [44]. Transformers are one of the most expensive and essential components of a power system. High capital investment is made to ensure proper operation and prevent transformer failures [48]. Success in complex equipment such as transformers will allow potential adoption of this methodology to be applied to protection of general electric equipment in power systems. Research findings will contribute to reliable power, satisfactory customer service, and safe operation [24]. The monitoring parameters include only terminal voltages and currents, which can make this detection technique an affordable solution to reliable power in the United States as well as undeveloped countries.

Motivation for an Online, Non-destructive, Fault Detection System

Due to the challenging and competitive energy market, utilities tend to operate the transformers harder, longer, and closer to their capabilities in order to reduce cost and generate the most amount of profit. Transformers are more likely to fail under such a stress besides regular aging and insulation deteriorating processes. Therefore, utilities are calling for an economical yet reliable fault detection system to help with the maintaining and extending the life of their existing assets and equipment to provide affordable and reliable electric power [21]. The detection systems and diagnosis methods developed previously either require the transformers to be taken out of service, which means more operational cost to the utility, or are expensive to implement [5]. Therefore, a low-cost, on-line, non-destructive fault diagnosis and detection system is highly demanded to provide immediate and accurate assessment of the conditions of the equipment in the field.

Contribution of Research

About 70% to 80% of transformer failures in recent years are caused by internal winding faults [31]. There are two types of internal winding faults: internal short circuit

faults and internal incipient faults. Incipient faults are caused by gradual deterioration of insulation materials [25], it is an early stage of the short circuit fault, however, no turns were connected and a short circuit has not been formed yet [26]. The major contributions of this thesis are in two areas. First, a systematic study was designed and implemented to characterize single-phase distribution transformers incipient faults through various analyses in time domain and time-frequency domain to analyze collected data of the project [15]. This characterization is vital to the diagnosis of incipient faults because it reveals the properties of incipient faults. Secondly, an accurate and efficient classification procedure has been established to utilize neural network to create a supervised classifier that is able to classify a data set into different clusters with different characteristics [18]. The classification of data is the basis for pattern recognition technique, which is the key to fault detection [19][20].

LITERATURE REVIEW AND PROBLEM FORMATION

Introduction

In this section of the thesis, a literature review of different fault types of transformers, transformer types and structures, and existing transformer fault diagnosis and detection techniques is presented. In addition, the problem statement of the entire project and also the problem statement of my part of the research are clearly given, respectively.

Incipient Faults

Under stresses from high voltage, current bypasses the conductor through insulators as gradual deterioration of insulation progresses, thus a short circuit was created and the transformer failed [25]. Whenever an incipient fault presents, abnormalities in voltage, current and other electrical parameters will be detected. Therefore, characteristics that uniquely identify abnormal behaviors in transformers can be determined from analyzing collected data, and they serve as a prediction method for incipient failures [14].

Transformer Types

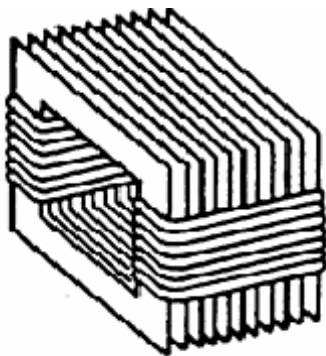
There are many different types of transformers. For instance, power and distribution transformers are used in electrical power systems to generate electrical power, transmit, distribute, and utilize power at a safe and economical voltage level. Isolating transformers can be used to electrically isolate circuits from each other or block signals between circuits. Instrument transformers can be used to measure high voltages and high currents [22]. In addition, based on the core construction, transformers are classified into shell-form or core-form [22].

Internal Structures of Transformers

Field experiments were performed at Conductor Test Facility which is located at Texas A&M University Riverside Campus [31] by previous researcher in PSAL. A single-phase, 7200V/240V/120V custom-built transformer with a power rating of 25kVA and operating frequency of 60Hz was used for test purposes [31]. This distribution transformer was connected to a resistive load bank and an overhead distribution power line, which has a RMS value of 7200V line to neutral voltage supply [44].

Figure 2 shows the basic structure of a transformer. This is a core type structure.

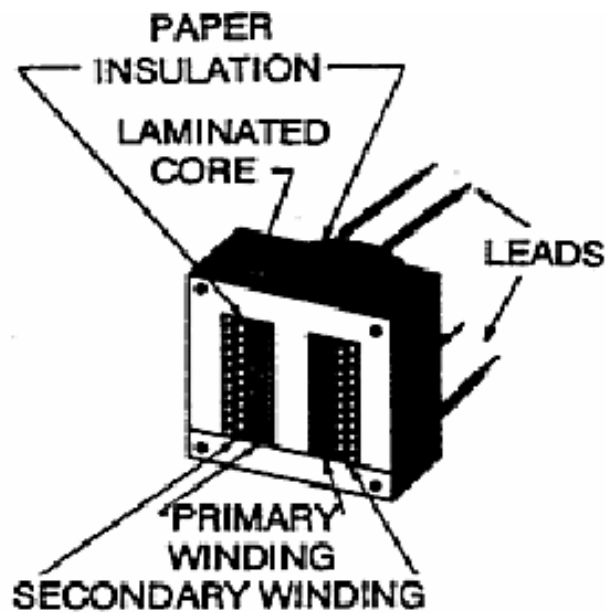
The iron is built in the shape of two cores, and each of the cores is wrapped with coils around them. The number of turns of the coils will determine the voltage change from one side to the other [22].



**Windings Wrapped Around
Laminations.**

Figure 2 [22]: Windings of the transformer

Figure 3 shows a shell type of transformer structure. The coils are usually rectangular in shape, and the iron is built through the opening and around the outside of the coils to form a shell around the coils. Each lamination of the iron forms a rectangle with two windows for the coils to pass through [22].



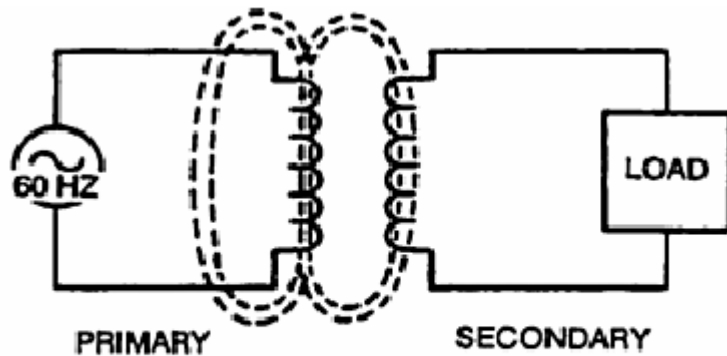
**Cutaway View of Shell-Type Core
With Windings.**

Figure 3 [22]: Insulation and winding structure of transformer

Figure 3 also shows the insulation of the transformer, which is mainly comprised with paper insulation around each winding [34]. As the transformer ages and goes through high voltage and over-current stresses, the insulating material will start to deteriorate gradually [4][25].

Figure 4 shows the basic operating principle of a transformer. The input coil of the transformer is called the primary winding, and the output coil is the secondary

winding [15]. The voltage induced in the secondary is determined by the turns ratio and the primary-side voltage [15] as shown in equation 1.



Basic Transformer Action.

Figure 4 [22]: Primary and secondary windings of transformer

$$\frac{\text{Primary Voltage}}{\text{Secondary Voltage}} = \frac{\text{\# of Primary Turns}}{\text{\# of Secondary Turns}} \quad (1)$$

In order to help with the magnetic coupling between primary and secondary windings, the coils are wrapped around a metal core. This core is laminated so that the primary side will induce eddy currents, thus power, on the secondary side of the core [22]. The core is made up of metal sheets that are insulated from each other [34].

Transformer Failures

Manufacture fault, short circuit faults, abnormal transient fault, premature insulation fault, and aging of the insulation materials are major causes of transformer failures [24]. There are two major classes of transformer failures: internal faults and external faults [3]. Internal faults could be faults between two adjacent turns, between a segment of turns, parts of coils, or between a turn and a grouped part of the transformer. External faults include overloads, over-current, over-voltage, reduced system frequency, and external short circuits such as a short circuit created on the secondary windings [2][5]. Recent record suggests about 70% to 80% of transformer failures are due to internal winding faults [31], therefore, internal faults are the focus of this research. These faults occur rapidly and require immediate actions by system protection devices and operators to isolate the fault and disconnect the transformer from the fault [7].

Existing Transformer Fault Detection Techniques

Most existing transformer fault diagnostic and detection techniques such as dissolved gas analysis (DGA) [8], degree of polymerization (DPA) [5], partial discharge analysis (PDA) [9], frequency response analysis (FRA) [5], and transformer function

measurement use parameters other than electrical or require the transformers be taken out of service [5]. These methods are suitable for large scale power transformers and are expensive to implement, therefore, a new method with low cost and on-line detecting capability is demanded [20].

Problem Statement of the Entire Project

Among internal faults, incipient fault is caused by gradual deterioration of insulating materials, so they develop slowly, and they require a relative long time for the incipient behaviors to develop into a short circuit which will lead to a catastrophic failure [25]. Unlike short circuit faults, incipient faults cannot be detected by traditional system protection devices [3], therefore, this research focuses on the development of an online detection system for the incipient faults.

Incipient faults in internal coil windings are the primary cause of transformer failures [5]. Detecting faults caused by a failing component is a fairly immature technology [14]. The research hypothesis is that a non-destructive and online system using neural network-based pattern recognition technique can be used to characterize and detect incipient faults in transformers [6]. With future development, this

methodology also could protect general electric equipment. Incipient faults constitute a dominant subcategory of equipment faults from inception to completion before leading to a catastrophic failure. From a macroscopic perspective, incipient faults refer to the abnormalities associated with any type of deterioration phenomena manifested in the electrical signals [14].

Problem Statement of My Part of the Research

In order to successfully use pattern recognition techniques to detect and predict incipient faults in transformers, the characteristics and properties of the data under healthy and faulty operational conditions must be studied. The terminal monitoring signals are composed of terminal voltage and current signals [31], and the data of these signals are simply collected and stored as one set of data.

These recorded signal data can be classified into different classes. Each class of the data represents a different behavior of the physical system. Therefore, it is necessary to characterize the data and cluster the data set into different classes based on their different characteristics.

OVERALL SOLUTIONS AND METHODOLOGIES OF THE ENTIRE PROJECT

Data-Mining Approach

Figure 2 shows a data mining approach of information extraction and feature analysis of monitoring voltage and current data [14]. M. Mousavi [14] used this approach to analyze and characterize incipient fault data from undergraduate cables, and it has been proven to be an efficient tool to extract information from an unknown set of data and study the properties and characteristics of the data. Although underground cables and single-phase distribution transformers are very different in structures, fault diagnosis techniques, and even monitored signals, it is still beneficial to adopt his data mining approach and apply it to the current transformer project. Collected data will be classified based on selected features to show patterns. Patterns are associated with actual physical conditions of the system. Therefore, certain patterns shown in monitoring signals from the data being studied will indicate incipient faults.

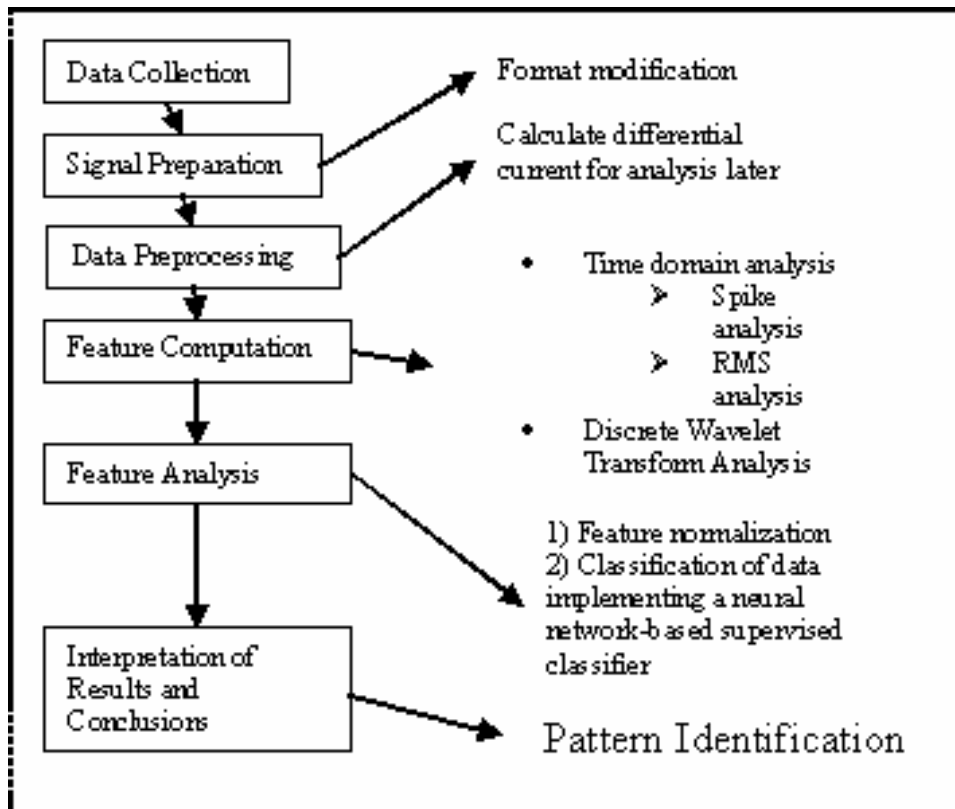


Figure 5 [14]: Data-mining approach to characterize a given set of data

Data collection and preprocessing

Two sets of data from previous research work will be analyzed. Controlled-experiment data are voltage and current signals recorded before and after fault occurrence when fault scenarios were purposely introduced to the transformer during field testing. Simulation data were generated with models built in Maxwell that represent short-circuit and incipient faults to complement limited field testing [15][16]. Usually, the DC component and noise will be filtered out with low-pass and high-pass filters in

the data preprocessing phase to protect low-frequency and high-frequency signals [15]. However, this particular research project does not require the DC removal and de-noising of the original signal.

Feature computation with analysis modules

Time domain analysis will show variations of signals and abnormalities with respect to time. Abnormalities can be seen as presence of spikes and load changes [14]. Therefore, spike analysis including studies of number and magnitude of spikes will convey information about the system abnormalities. Moreover, Root Mean Square analysis can provide a way to measure the step change in the current signals when there is a load change [30]. In addition, Fourier analysis will obtain the frequency information about the signal. Wavelet analysis, which contains information in both time and frequency domain, will also be used [44]. Because the Discrete Time Wavelet Transform provides an amount of decomposition coefficients that are manageable, and the original signal is examined in both time and frequency domain, so a Discrete Time Wavelet analysis is performed instead of Fourier analysis [17].

Feature Analysis and Anticipated Results

A feature is a characteristic used to distinguish data groups formed by similar attributes [14]. For instance, features could be the degree of arcing, severity of spikes, magnitude, standard deviation, and other characteristics of the signal. Once necessary features are computed with proposed analysis methods, data are grouped into clusters. Neural Network-based clustering is a toolbox in Matlab to analyze data. It is also a self-learning intelligent organizer that takes input in numeric vector form and produces output as groups on a map [14]. Each group shows a unique behavior. On the map, the relationship between data points is represented by the depth of color, and these color regions are grouped into clusters. Every cluster represents a physical state of the system. Some clusters indicate systems with fault or abnormal behaviors, and some clusters represent healthy systems [17]. Patterns in clusters of monitoring signal data will predict future actions of the system. Therefore, incipient faults in electric equipment can be detected by appearance of certain patterns in monitoring voltage and current signals.

SOLUTIONS AND METHODOLOGIES OF MY PART OF THE RESEARCH

Neural Network-Based Supervised Classification

A supervised classification method is suitable in this case because normal and faulty data groups are already clearly labeled. Also because the output classes of the Neural Network-based classifier are already known, a supervised classification fits the purpose better. With supervised classification, problems such as putting different clusters into one same cluster or creating too many classes within one single cluster that are associated with unsupervised classification can be avoided [16]. There are five steps to perform this classification [14]:

1. Determine features that will be used
2. Implement Feature Extractor
3. Implement the Neural Network Classifier
4. Train neural network with training data
5. Do studies with test data and determine the accuracy of the classifier

First of all, the entire data set will be arbitrarily separated into two different data sets: training set and test set. The training set takes a lot of data input [38][13], and therefore, it should be 80% of the entire data files available. The test set should be the remaining 20% data files, and the purpose of the test set is to evaluate the performance of the Neural Network classifier.

Feature Extractors of Neural Network

There are two ways to perform the neural network classification:

Figure 6 shows the first method to perform supervised classification with neural network: raw data such as voltage and current signals are directly feed into the neural network. The decision output is different classes that are desired.

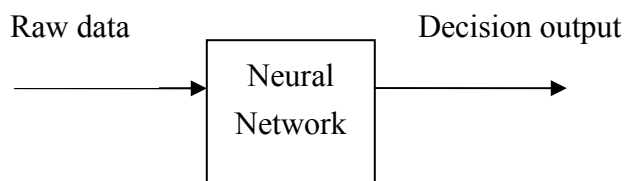


Figure 6: Neural network classifier with raw data

Figure 7 shows the second method to perform supervised classification with neural network: raw data is first converted into feature data, such as Discrete Wavelet

Transform (DWT) of primary and difference current, RMS values of the signal, and spike severity, which are more meaning to the neural network. The patterns in the raw data are harder to find, the dimensions are larger, and the classifier is too complicated to be designed [36]. With these intermediate feature data as input of the network, the number of neurons in the input layer is reduced [35][37]. Therefore, the complexity of the network architecture is also significantly reduced.

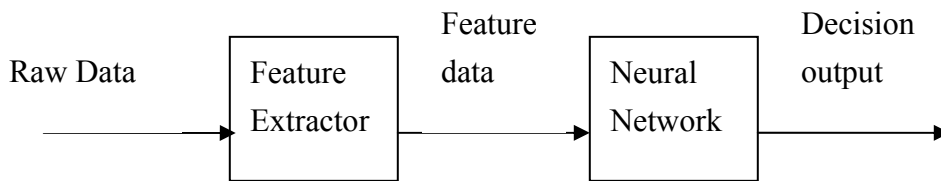


Figure 7: Neural network classifier with feature extractor

Feature Extractor

Different analysis in time domain and time-frequency domain has been performed to provide feature files that are necessary to perform classification and detection operations later on.

Time Domain Analysis

Spike Analysis

The spike analysis is performed to capture the incipient abnormalities that can be characterized by the spikes and not identified through other modules. This analysis uses a detection algorithm based on the theory of outliers to identify the spikes in the entire recording [10][14]. It uses the computed robust estimate of the standard deviation of the first differences of the signal. If a spike is detected that is not accompanied by a simultaneous change in the low frequency current signals, the input signal is flagged as an incipient abnormality. In this analysis standard deviation, mean and median, skewness, and kurtosis of the signal are calculated [14].

RMS Analysis

The RMS analysis is used to characterize captured data. It utilizes an RMS template-matching algorithm to find the best matching template from a given library of templates. Among the identified shapes, four templates capture the data most likely conveying incipient abnormalities. These input data are classified into incipient classes and further analyzed through secondary classifiers. The RMS shape analysis uses the

voltage and low frequency current signals to categorize the data in terms of the shape of the RMS signal calculated over one power cycle for one-second recording. Max RMS step size, percentage of change, max step duration, min step duration, mean RMS value, max RMS value, min RMS value, Standard Deviation of RMS are all calculated with this analysis [14]. The different calculation fields above are different features used in neural network classification [14].

Time-Frequency Domain Analysis

Time-frequency domain analysis methods not only extract the information of the signal in the time domain, but information in frequency domain is obtained as well. This provides a very informative method to extract information from a given set of data. Wavelet analysis is one of the most important and efficient time-frequency domain analysis methods. However, the continuous wavelet analysis generates too many wavelet coefficients [10], and this causes a great degree of redundancy and creates data management issues. Therefore, the Discrete Wavelet Transform is used to only generate wavelet coefficient at the points where power of 2 present, and data redundancy problem is solved with Discrete Wavelet Transform [10].

Application of Discrete Wavelet Transform

The DWT block is the same as the Dyadic Analysis Filter Bank block in the Multi-rate Filters library, but with different default settings [12]. The wavelet analysis is a toolbox within Matlab, and it is a mathematical tool that reveals the time-frequency domain information about the signal with proper chosen time-shifting and time-dilation parameters [42][43].

A wavelet is a waveform with limited duration and an average of zero. It is defined with a wavelet function:

$$\int_{-\infty}^{+\infty} \Psi(t) dt = 0$$

From a basic mother wavelet, a set or a variety of signals can be derived by changing the time-shifting and time-dilation constants [39]. Wavelet transforms are realized with these derived signals. A continuous wavelet transform is defined as “the sum over all time of the signal multiplied by scaled shifted versions of the wavelet function [6]”.

$$C(a, b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{+\infty} x(t) \Psi\left(\frac{t-b}{a}\right) dt$$

In this equation, a is the scale, b is the position along the time axis, and $x(t)$ is the signal function, and $C(a,b)$ is the wavelet coefficient. With wavelet coefficients, which are functions of a and b , the original signal can be reconstructed with proper scaling and shifting parameters [28].

However, with Discrete Wavelet Transform (DWT), only samples of wavelet coefficients are collected, this way, DWT reduces the redundancy of the continuous wavelet transform [6].

$$DWT_{\Psi} x(m, n) = \int_{-\infty}^{\infty} x(t) \Psi_{m,n}^*(t) dt$$

$$\Psi_{m,n}(t) = |a_0|^{-m/2} \Psi\left(\frac{t - nb_0 a_0^m}{a_0^m}\right)$$

In the two equations above, a_0 and b_0 are constants both greater than 1, m and n are numbers belong to the positive integers. Also, $a = a_0^m$ and $b = nb_0 a_0^m$. Therefore, the DWT function becomes [6]:

$$DWT[m, n] = \frac{1}{\sqrt{a_0^m}} \sum_{k=-\infty}^{+\infty} X[k] \Psi\left(k - \frac{a_0^m nb_0}{a_0^m}\right)$$

$$DWT(m, n) = C(i, j) = \sum_{n=0}^{N-1} x(n) 2^{-j/2} \Psi(2^i n - j)$$

The last function above shows how to use filter bank techniques to implement the DWT in Matlab [10]. Mallat's decomposition algorithm has been extensively used in this procedure. The original signal is decomposed into a low frequency part called approximation and high frequency part called detail [29]. With low-pass and high-pass filters, the original signal is decomposed into two signals. However, the second data point is thrown away to keep the same length of the signal. With an adopted mother wavelet, the DWT performs detail analysis on high-frequency part of the mother wavelet, while approximation analysis is performed on low-frequency part of the mother wavelet [28][29].

Figure 8 shows the decomposition tree of the DWT decomposition. The original signal is down-sampled into two sub-signals with low-frequency part and high-frequency part, respectively. The low-frequency part is further composed into other two sub-signals with different frequency [11]. Based on the structure of the tree, when two new signals are created, one old signal will be discarded, therefore the length of the decomposed signal will stay the same [11].

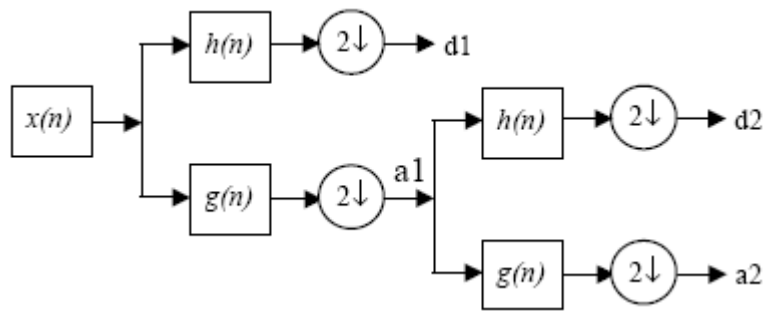


Figure 8 [11]: Wavelet decomposition tree

Figure 9 shows the implementation of DWT in Matlab using Dyadic Analysis Filter Bank. Based on the decomposition tree, the original signal is decomposed into sub-signals with sub-band. The Dyadic Analysis Filter Bank is essentially the same with DWT block, therefore, the DWT procedure is implemented with Dyadic Analysis Filter Bank with Daubechies Db-4 type mother wavelet. The signals were decomposed up to the fourth scale [10].

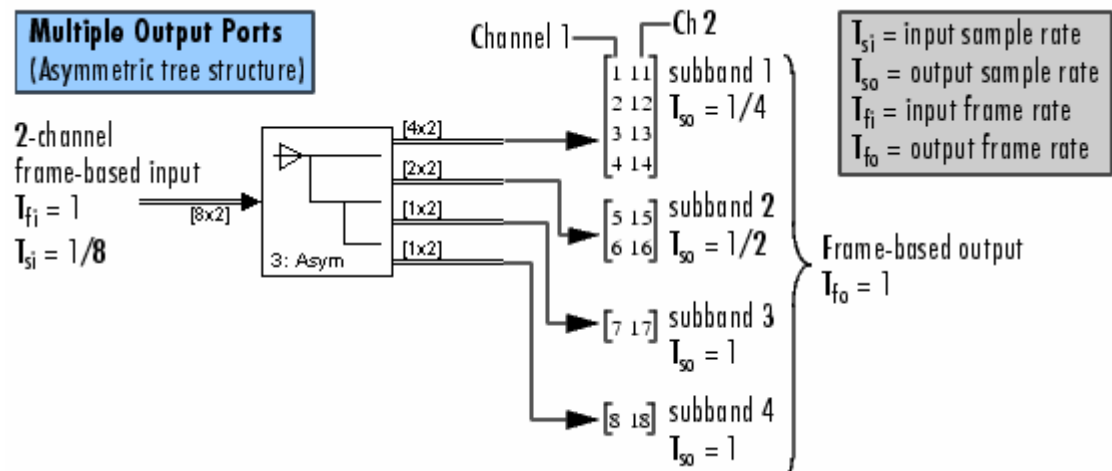


Figure 9 [10]: Implementation of DWT in Matlab

PREVIOUS RESEARCHERS' WORK ON THIS PROJECT

A number of previous researchers have contributed their findings and research results to the advancements of the current project. It difficult to talk about what I did for the project without talking about what has been done by other researchers for the project. This way, the work I have accomplished will fit into the big picture of the entire project.

Field Testing

A custom-built single-phase, distribution transformer was used in field testing to collect data from controlled experiments. In these controlled experiments, a great variety of different fault scenarios on both primary side and secondary side of the transformers were intentionally introduced into the transformer [31]. In the mean while, terminal voltage and current data were recorded with a data acquisition system. The field data is significant to the research because it provides actual and practical data that will reflect the most accurate conditions and situations with a real power system. In addition, controlled experiments will generate faulty terminal voltage and current data that are associated with each fault scenario. With these data clearly labeled together with different faults, patterns in these faulty data can be identified. Therefore, if future

monitoring signal data show similar patterns, it means there is a similar fault. Moreover, supervised classification using neural network will be able to be performed because only the clearly labeled faulty data will help to train the neural network [14][44].

Experiment Setup

A custom-built distribution transformer was used for field testing, and a data acquisition system was used to record signals. There are 780 turns of coils on the primary side and 26 turns of windings on the secondary side. A distribution-network branch or lateral is connected to the transformer through a fuse to power the transformer.

In addition, a load bank was connected to the secondary side of the transformer to provide load and reduce the current level [31]. In order to create short circuits between two the turns, transformer taps were installed and connected to busbars that are fixed on the panel board. These taps can be operated externally, and therefore, different scenarios of faults can be created between any two turns of the internal windings [44].

In order to monitor the real-time signals during the field testing, a portable data acquisition system with real-time data-acquisition capability was connected to the

transformer to collect voltage and current signals and record them at a sampling rate of 3840 samples per second [44].

Field Data

The recorded voltage and current signals are collected at 3840 samples per second. In addition, field-measured primary current data was filtered through a 60Hz notch filter and a notch high-pass filter [31]. The outputs of these signals after the filtering process eventually are sampled at 15360 samples per second [30]. Six different signals have been recorded from the field testing [44]:

i1_primary (primary current)

i2_secondary (secondary current)

notch_hp (notch high-pass primary current)

notch_lp (notch low-pass primary current)

v1_primary (voltage of the primary side)

v2_secondary (voltage of the secondary side)

Transformer Modeling

Field testing could be expensive, dangerous, and not practical. It is not realistic to test all possible fault scenarios with a real transformer in field test. Therefore, a transformer model was created in simulation software to continue generate fault data and data when the transformer is under normal operation [44].

A transformer model developed by Bastard et al. was adapted to generate simulation data [44]. This model was targeted at winding faults of three-phase, power transformers to single-phase, distribution transformers. Also, faults between any two turns of the internal windings of the transformer or faults between a turn and a grounded part of transformer can be studied with this model [15][44]. This is a linear model that studies the terminal behaviors of a single-phase, distribution transformer during incipient and short-circuits faults in internal windings [44].

Simulation Setup

A Finite Element Method (FEA) [23] and circuit analysis techniques [5] were implemented by Hang Wang into the simulating model to build an equivalent circuit that accurately and properly represent a transformer with internal faults under real conditions

in real scenarios [30]. This simulating model has been implemented in the software called ANSOFT Maxwell [31].

When the insulation material deteriorates inside the transformer, and it reaches a certain level, an incipient internal winding faults will be created that will cause a transformer failure. The deteriorating phenomena are caused by factors such as thermal stress, electrical stress, mechanical stress, and moisture inside the transformer [25]. The simulation model was successfully built, and it accurately represents the aging and arching behaviors of the transformer with circuit blocks [5]. The electrical behaviors of the dielectric material, natural, and man-made aging effects to the transformer internal windings are properly represented [5].

Simulation Data

Seven different signals have been recorded with the simulating transformer

model [19]:

i1_primary (primary current)

i2_secondary (secondary current)

i_circ (circulating current)

notch_hp (notch high-pass primary current)

notch_lp (notch low-pass primary current)

v1_primary (voltage of the primary winding)

v2_secondary (voltage of the secondary winding)

The circulating current cannot be obtained with the actual transformer test because it requires cutting the transformer into two pieces to measure the circulating current. Therefore, there are seven signals instead of six. All signals are sampled at 3840 samples per second except the notch high-pass primary current, which is sampled at 15360 samples per second [5].

Field Data Match Simulation Data (Accuracy of Simulation)

The field testing data and simulation data exhibit similar behaviors. During normal operation, the signal was a regular sinusoidal wave. However, periodic and random arcing behaviors can be seen from the signal when the insulation material ages [25]. When an incipient fault eventually developed into a short-circuit fault, a dramatic increase in current can be seen from the signal [5]. After examining in the time domain, it is confirmed that the simulation data and field data are both accurate and match with each other.

PRELIMINARY RESULTS AND FINDINGS

A set of preliminary results were obtained when different features were computed with the feature extractor and the neural network classifier was implemented.

In this stage, only two classes exist as the output of the neural network-base classifier: data files with 10% arcing (low severity) and data files with 50% arcing (high severity).

Calculating Difference Current

Previous research findings suggest the usage of primary current and difference current as major signals for pattern recognition purposes because a significant portion of the system behaviors has been captured with these two signals. The difference current is defined as the difference between the primary current and the secondary current.

Figure 10 shows a simple Matlab program that was written to calculate the “difference current” by subtracting the secondary current from the primary current. For each and every single sample point, a difference current data has been calculated. In addition, the new column vector “diff_cur” which stands for difference current is saved together with the other signal data as column vectors in the “.mat” file.

```

%!dir *mat
%dir('*.mat')
%files=dir('*.mat')
%for i = 1:183
files=dir('*.mat')
for i = 1:183
    load(files(i).name)
    diff_cur=i1_primary-i2_secondary;
    save (files(i).name, 'i1_primary','i2_secondary','i_circ',
        |'notch_hp','notch_lp', 'v1_primary','v2_secondary','diff_cur')
end
end

```

Figure 100: Matlab code to calculate difference current

Calculating Differential Current

Dr. M. Bagriyanik [16] suggested that a differential current signal can benefit the classification results. In a transformer, the primary current and the secondary current are related with the following equation [49]:

$$\frac{i_{\text{primary}}}{i_{\text{secondary}}} = \frac{N_2}{N_1} = \frac{V_{\text{secondary}}}{V_{\text{primary}}}$$

In the equation above, N_1 is the number of turns of the windings on primary side of the transformer, and N_2 is the number of turns of the windings on secondary side of the transformer. The differential current is defined as below [49]:

$$\text{differential_current} = \frac{i_{\text{primary}}}{i_{\text{secondary}}}$$

The equation above indicates the differential current is a ratio of the primary current over secondary current. This signal is very useful because it reveals information

on the shorted windings within the transformer. For example, the differential current, or the ratio of primary current over secondary current, is fixed for a healthy transformer that is operating under normal conditions. However, when there is a short circuit occurred inside a transformer, and there are some turns shorted together. This change will cause the differential current, or the ratio, to change to another value. Therefore, the changes in differential current can tell if there are any short circuits faults in the transformer. However, the differential current is not helpful to analyze incipient and arcing behaviors.

Similarly in Figure 11, a short Matlab program was written to calculate the differential current data for each data file. The new column vector “difcurrent” indicates differential current field, and this column vector has been saved together with other vectors inside the same Matlab data file.

```

%!dir *.mat
%dir('*.mat')
clear all, clc
files=dir('*.mat')
for i = 1:80
    load(files(i).name)
    for ii = 1:3840
        a(ii)=(i1_primary(ii))/(i2_secondary(ii));
    end
end

```

```

difcurrent=a';
save (files(i).name, 'i1_primary','i2_secondary','i_circ','notch_hp','notch_lp',
'v1_primary','v2_secondary','difcurrent')
end

```

Figure 111: Matlab code to calculate differential current

Both of the primary current and the secondary current are collected at a sampling rate of 3840 samples per second. In addition, each data file used in this research has one second capture of the monitoring data. Therefore, there are 3840 data points of primary current and differential current in each data file.

Primary and Difference (or Differential) Currents

First of all, the 3840 data points in a time sequence within one second capture are plotted in Figure 18. The plots of primary current and difference current are shown for both the 10% arcing data files and 50% arcing data files. The data came from file named “INCIPIENT_P226_255_Rp1_10_pc_MEASURED_VALUES”, which is labeled as having 10 % arcing severity. The 50% arcing data file selected was named as “INCIPIENT_P280_300_Rp001_50_pc_MEASURED_VALUES”.

Figure 12 shows the plot for primary current in 10% arcing data file, and Figure 13 shows the plot for corresponding primary current in 50% arcing data file. With

Careful examination and comparison of the two plots, it can be noticed that the arcing phenomena occur randomly in the earlier stages in transformer incipient faults. In the early stage, there is a larger time interval between two consecutive arcing peaks. As the fault develops, arcing becomes more often in the plot with smaller and regular time intervals.

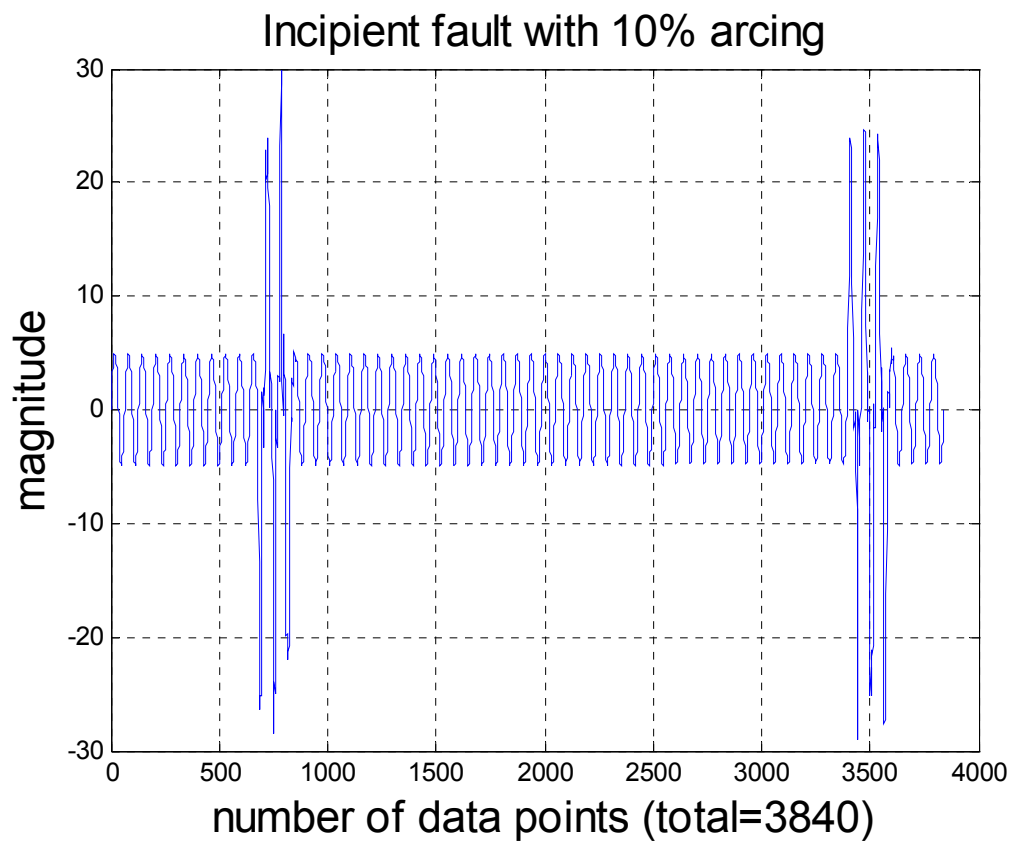


Figure 122: Plot of primary current in time domain with 10% arcing

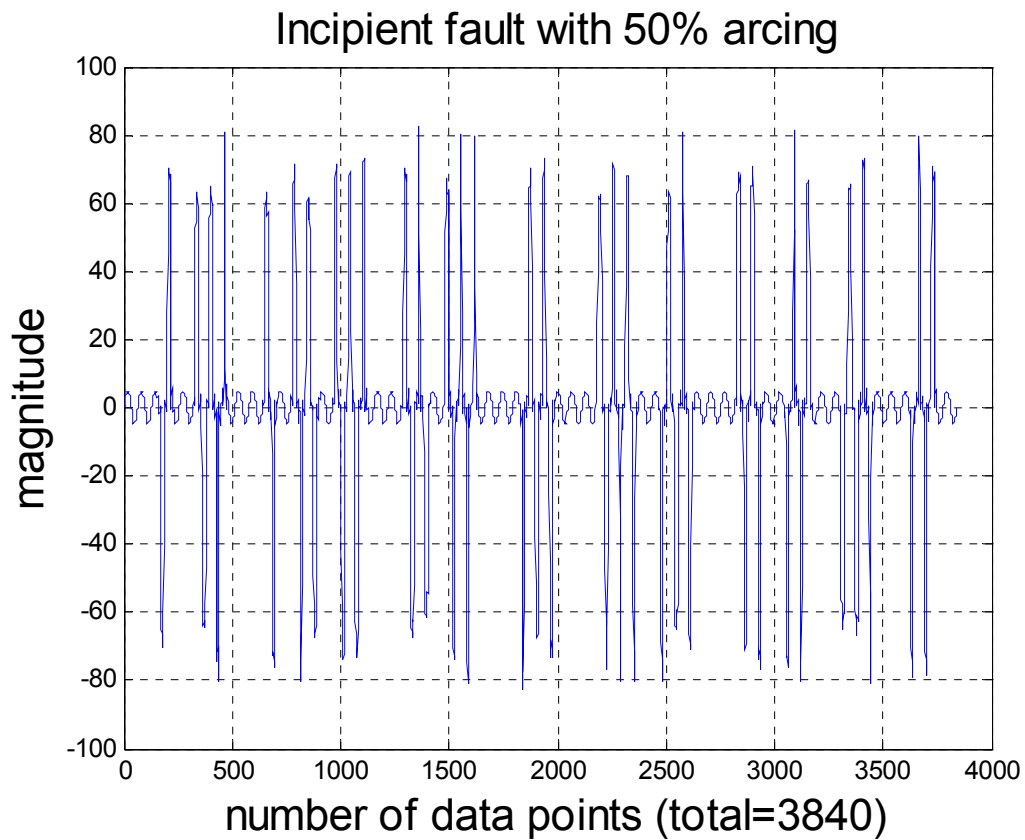


Figure 13: Plot of primary current in time domain with 50% arcing

Similarly, plot of difference current in time domain is obtained and shown in Figure 14 for 10% arcing data file and Figure 15 for 50% arcing data file, respectively. Comparing the two plots in time domain, it can be noticed that the 10% arcing data file has uniformly distributed magnitude of the differential current; on the other hand, the 50% arcing data file has big difference in adjacent difference current points, and therefore has more fluctuation in the difference current magnitude.

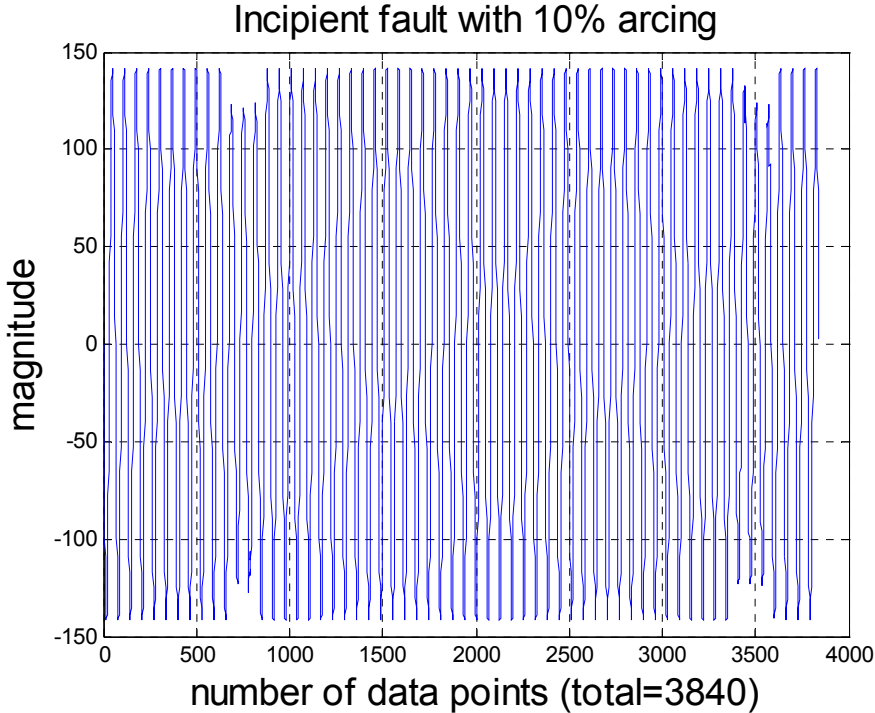


Figure 14: Plot of the difference current in the time domain with 10% arcing

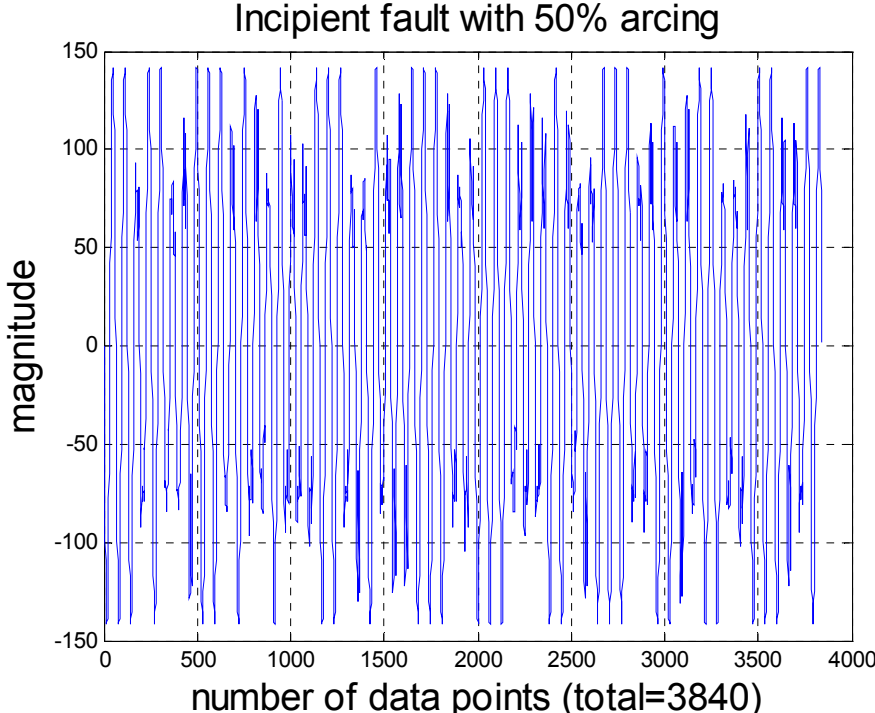


Figure 15: Plot of difference current in time domain with 50% arcing

The plots above proved the importance of both primary current signal and difference current signal because both signals carry a significant portion of the data. It also explains the reason of focusing on these two signals in this research.

Feature Extractor

Features are calculated with the feature extractor. In order to calculate some of the features, different analysis methods are used for feature calculations: statistical analysis, time domain analysis, and time-frequency domain analysis.

Statistical Analysis

The statistical analysis includes the calculations of the maximal value, minimal value, range, mean, median, and standard deviation for both of the primary current and differential current of each of the data file. Thus, there is one value under each feature field for every data file. These values are calculated with built-in Matlab commands:

`Maxp=max(i1_primary) % maxp stands for the maximal value of the primary current`

`Maxdf=max(diff_curr) % maxdf stands for the maximal value of the differential current`

`Minp=min(i1_primary)`

`Mindf=min(diff_cur)`

Rangep=range(i1_primary)

Rangedf=range(diff_cur)

Meanp=mean(i1_primary)

Meandf=mean(diff_cur)

Stdp=std(i1_primary)

Stddf=std(diff_cur)

Madp=mad(i1_primary)

Maddf=mad(diff_cur)

Each of the calculated value above is a feature of the data. There are a total of 12 statistical features.

Time Domain Analysis

In time domain analysis, both RMS shape analysis and spike analysis have been performed. In spike analysis, the skewness and kurtosis of both primary and differential currents are calculated.

Skewness measures the asymmetry of the data around the sample mean, which provides information on the distribution of the data set. If skewness is negative, the data

are spread out more to the left of the mean than to the right. If skewness is positive, the data are spread out more to the right. The skewness of the normal distribution (or any perfectly symmetric distribution) is zero. The skewness of a distribution is defined as [46]:

$$y = \frac{E(x - \mu)^3}{\sigma^3}, \text{ where } \mu \text{ is the mean of } x, \sigma \text{ is the standard deviation of } x, \text{ and } E(t)$$

represents the expected value of the quantity [46].

Kurtosis is used to measure how “outlier-prone” a distribution is [46]. The kurtosis of a normal distribution is 3. Distributions that are more outlier-prone than the normal distribution have kurtosis greater than 3; distributions that are less outlier-prone have kurtosis less than 3 [46]. The kurtosis of a distribution is defined as [46]:

$$k = \frac{E(x - \mu)^4}{\sigma^4}, \text{ where } \mu \text{ is the mean of } x, \sigma \text{ is the standard deviation of } x, \text{ and } E(t)$$

represents the expected value of the quantity t.

The skewness and kurtosis of primary current and differential current are computed with the following commands in Matlab:

Skewp=skewness(i1_primary) %skewp means the skewness of primary current

Skewdf=skewness(diff_cur) %skewdf means the skewness of differential current

```
Kurp=kurtosis(i1_primary)
```

```
Kurtdf=kurtosis(diff_cur)
```

In RMS analysis, the RMS value of the entire signal of primary current and differential current is calculated with a written rms function as shown below in Figure

16:

```
function [rms_signal] = rms(signal,nppc)
% RMS function calculates the rms values of a periodic signal at each cycle
% If the second argument is not provided, the output is the rms value of the whole signal
% Syntax: RMS(input,nppc)
% input is the input signal
% nppc is the number of points per cycle
% nppc = sampling frequency/ signal frequency
% example:
%     x= sin(2*pi*60*[1/1920:1/1920:1]);
%     X = rms(x,1920/60);
% ACTION
if nargin ==1
    rms_signal = sqrt(sum(signal.*signal/length(signal)));
else
    signal = reshape(signal,nppc,length(signal)/nppc);
    rms_signal = sqrt(sum(signal.*signal/nppc));
end
```

Figure 16: Calculating RMS values of primary and difference currents

With this written RMS function in Matlab, the RMS features of the primary current and differential current can simply carried out by inputting:

$RMSp=rms(i1_primary)$ %RMSp stands for RMS value of the primary current signal

$RMSdf=rms(diff_cur)$ %RMSdf stands for the RMS value of the differential current

Therefore, the RMS value of the entire cycle of the period signal is computed for both primary current and secondary current. There are two RMS features obtained.

DWT as a Feature Extractor (Time-Frequency Domain)

The four DWT plots of primary current and differential current below demonstrate the importance of having DWT as the feature extractor of the Neural Network classifier. Through using the features of the DWT extracted from primary current data and differential current data, the DWT can help with the discriminating of different data clusters and groups [27], thus, benefit the predictive and detective system.

Figure 17 shows the plots of the coefficients of the Discrete Wavelet Transform (DWT) of primary current with 10% arcing. Accordingly, Figure 18 shows the plots of the coefficients of DWT of primary current with 50% arcing. It can be easily noticed that the time interval between two adjacent spikes in the plot of DWT coefficients is larger for 10% arcing case. Also, there are fewer spikes that appeared randomly in the plot in the 10% arcing case.

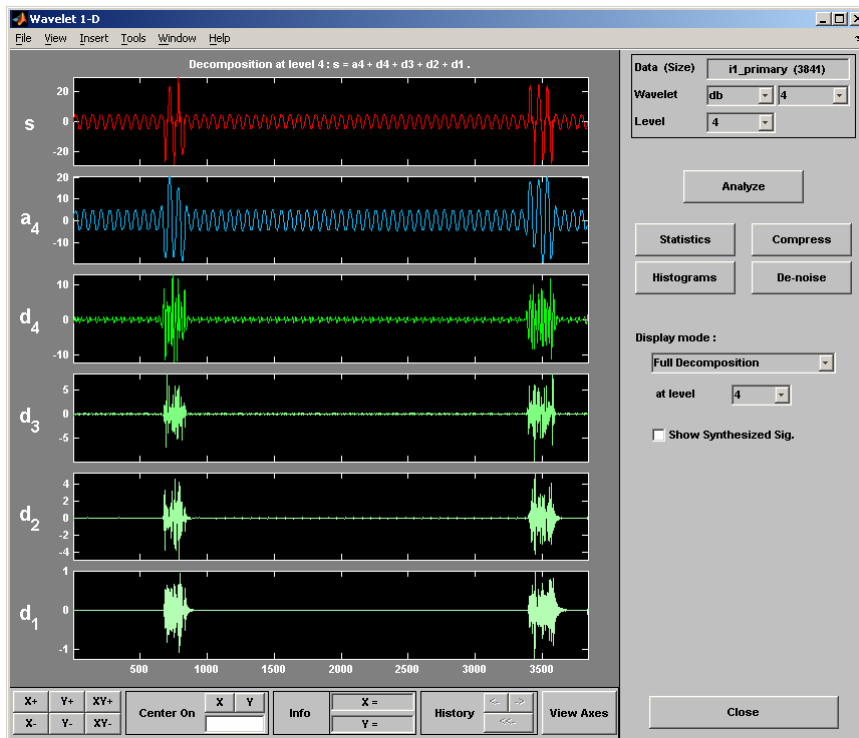


Figure 17 DWT of primary current measured for incipient behavior of 10% arcing

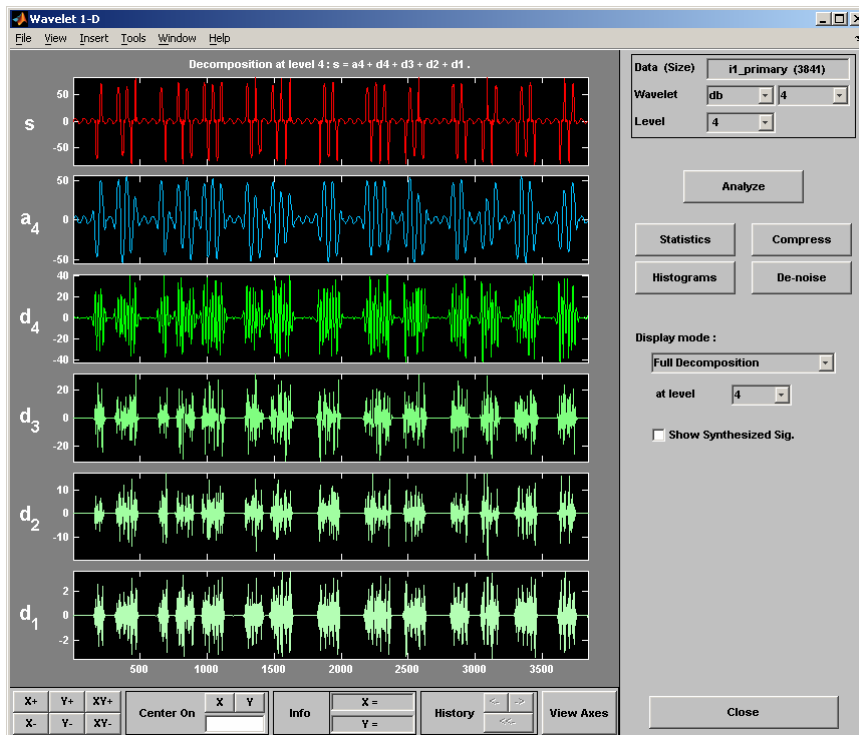


Figure 18: DWT of primary current for incipient behavior of 50% arcing

Figure 19 shows plots of the DWT coefficients of differential current in a 10% arcing data file. Figure 20 shows plots of the DWT coefficients of differential current in a 50% arcing data file. Comparing these two plots, the same conclusion as of last comparison results can be drawn: the plots of DWT coefficients of differential current have random and fewer spikes with larger time intervals can be observed with the 10% arcing data file.

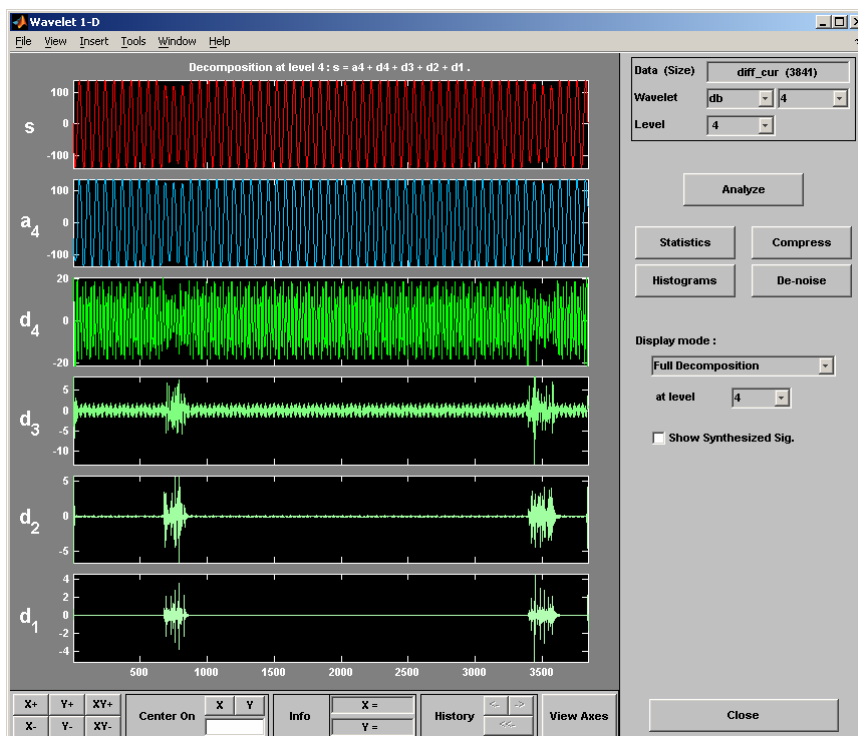


Figure 19 DWT of difference current for incipient behavior (10% arcing)

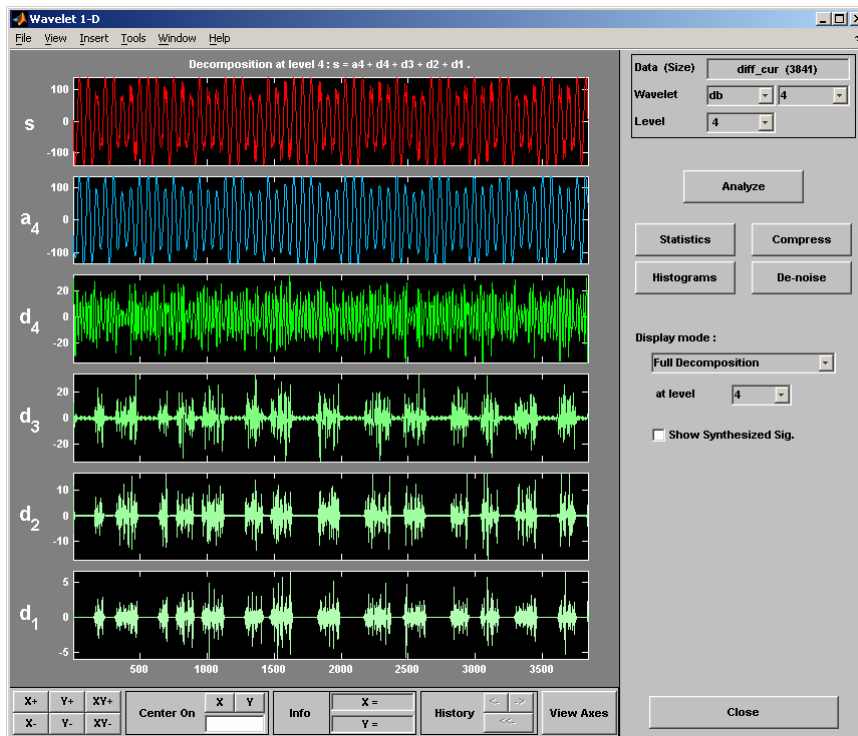


Figure 20 DWT of difference current for incipient behavior of 50%

In general, for internal incipient faults, there are random spikes occurring in the DWT plots of the primary current and differential current. However, the number of spikes and the time interval between adjacent spikes are different in the DWT coefficient plots for different types of data files (various arcing degrees). These plots above illustrated the importance of differential current. More importantly, these plots demonstrated that it is necessary to have DWT as a pre-processor for the neural network-based classifier because it helps to distinguish between two data classes.

Figure 21 shows the process of how different levels of DWT coefficients are obtained. In the panel on the right, the original signal, `i1_primary`, is decomposed into low-frequency and high-frequency parts (approximation `a1` and detail `d1`). Each approximation will be further decomposed into second-level approximations and details (`a2` and `d2`).

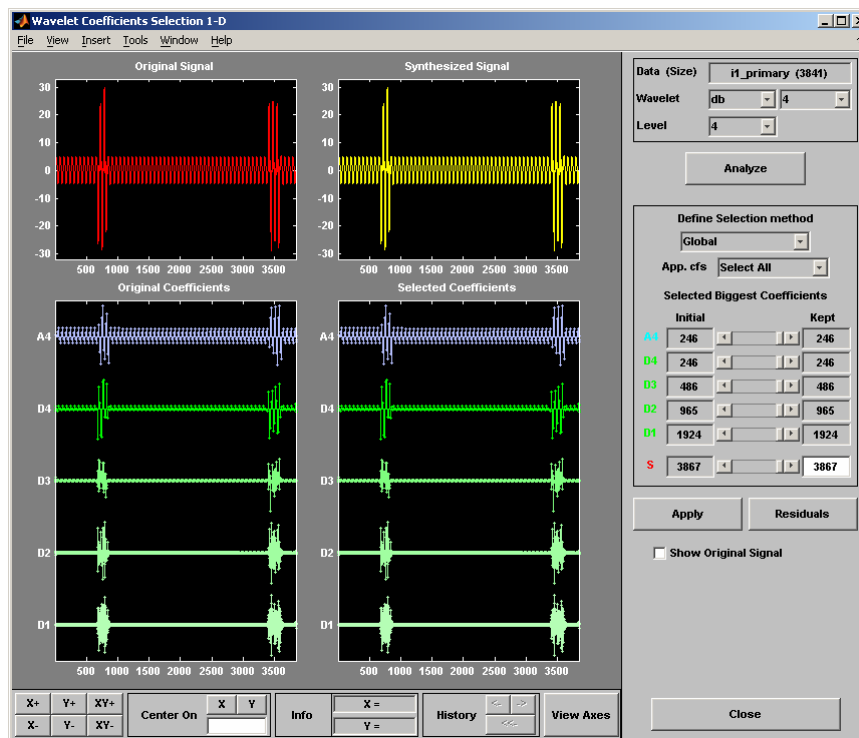


Figure 131: Acquisition of DWT coefficients

Figure 22 demonstrates the decomposition process of the DWT of primary current. On the left, a DWT composition tree is shown. The top right graph shows how

the signal is decomposed, and the lower right graph shows how the original signal can be reconstructed with DWT coefficients.

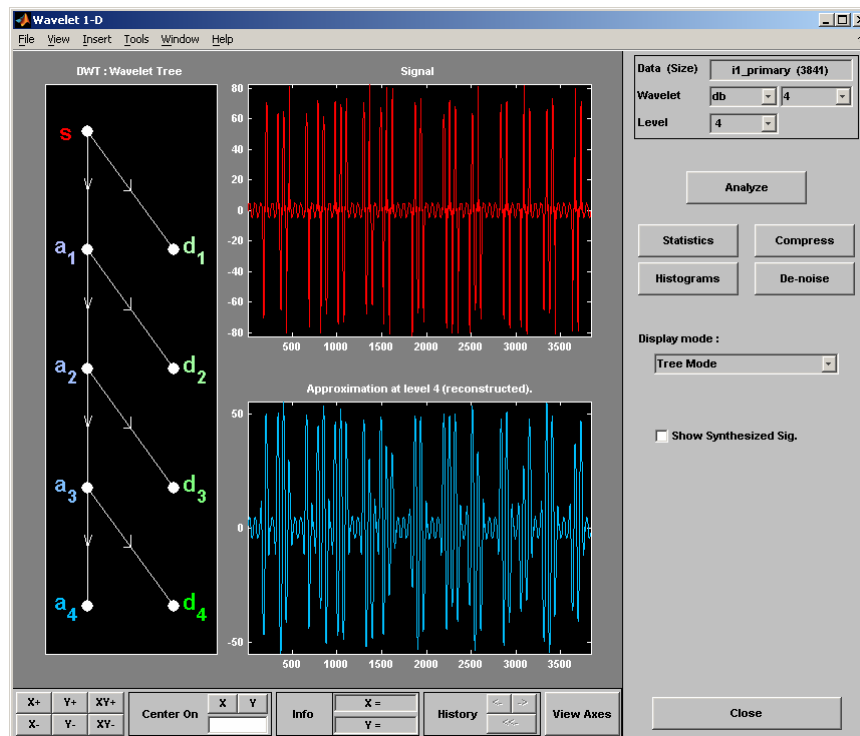


Figure 22: Demonstration of the decomposition tree of DWT

Figure 23 shows some of the statistical measures of the DWT coefficients obtained. For instance, the mean, maximal, minimal, standard deviation, and range can be calculated for these DWT coefficients as well. The total number of the DWT coefficients stays the same due to the nature of the discrete transform process. The mean values of d_1 (first level), d_2 (second level), d_3 (third level), d_4 (fourth level), and a_4

(fourth level) are calculated and stored. Each of the mean value of every single coefficient is also a feature of the data.

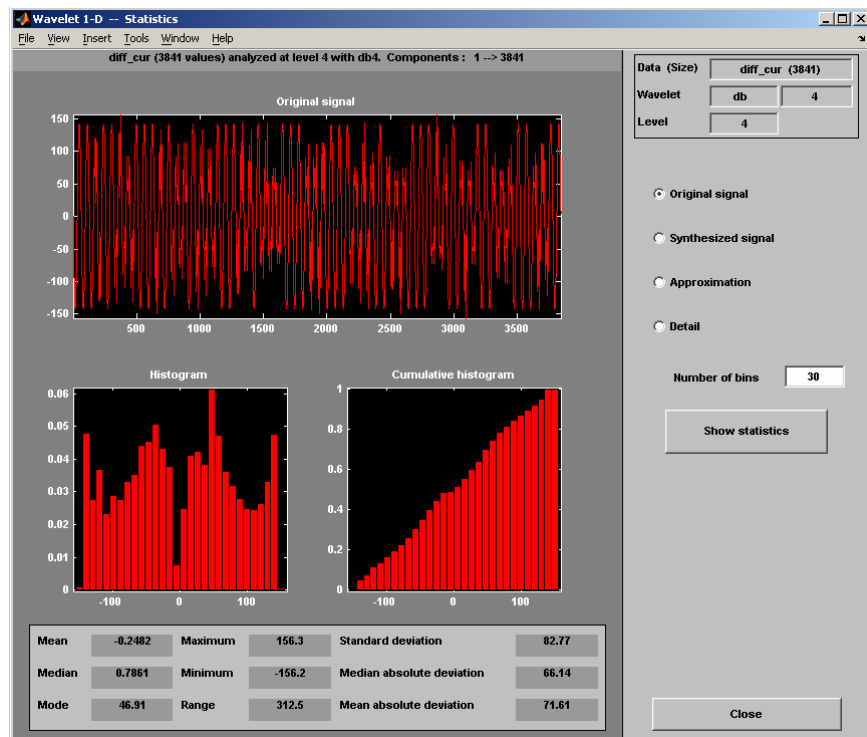


Figure 23: Statistical data of the DWT coefficients

In all DWT processes performed above, the Db-4 type mother wavelet (Daubechies—4) has been used. Also, the decomposition level of the DWT of these signals has been kept at 4. In Matlab, the following commands were used to calculate the mean value of each DWT coefficients:

```

[c1A,c1D]=dwt(i1_primary,'db4');
[c2A,c2D]=dwt(c1A,'db4');
[c3A,c3D]=dwt(c2A,'db4');
[c4A,c4D]=dwt(c3A,'db4');
coed1p=mean(c1D);    % calculating mean value of coefficient d1 for primary
current
coed2p=mean(c2D);    % for d2
coed3p=mean(c3D);
coed4p=mean(c4D);
coea4p=mean(c4A); % for a4
[c1Adf,c1Ddf]=dwt(diff_cur,'db4');
[c2Adf,c2Ddf]=dwt(c1Adf,'db4');
[c3Adf,c3Ddf]=dwt(c2Adf,'db4');
[c4Adf,c4Ddf]=dwt(c3Adf,'db4');
coed1df=mean(c1Ddf); % calculating mean value of coefficient d1 for differential
current
coed2df=mean(c2Ddf);
coed3df=mean(c3Ddf);
coed4df=mean(c4Ddf);
coea4df=mean(c4Adf);

```

Figure 24: Matlab code to calculate mean DWT coefficient values

Creation of Features Structure

Now that all necessary features of the data have been calculated and extracted. It is time to create a structure called “Features” to store all the calculation values and results in this structure.

Later when the feature input data is input into the neural network based-classifier, the data stored in this structure can be easily input into the classifier by calling the field names within the structure.

In Figure 25, the structure created to store the features is shown. In Figure 26, different fields within one structure are shown. It has different field names such as max, min, mean, STD...etc. Each of the field is filled with a number from a single data file. The way this structure is built will allow convenient calls of the field data to be input into the neural network later.

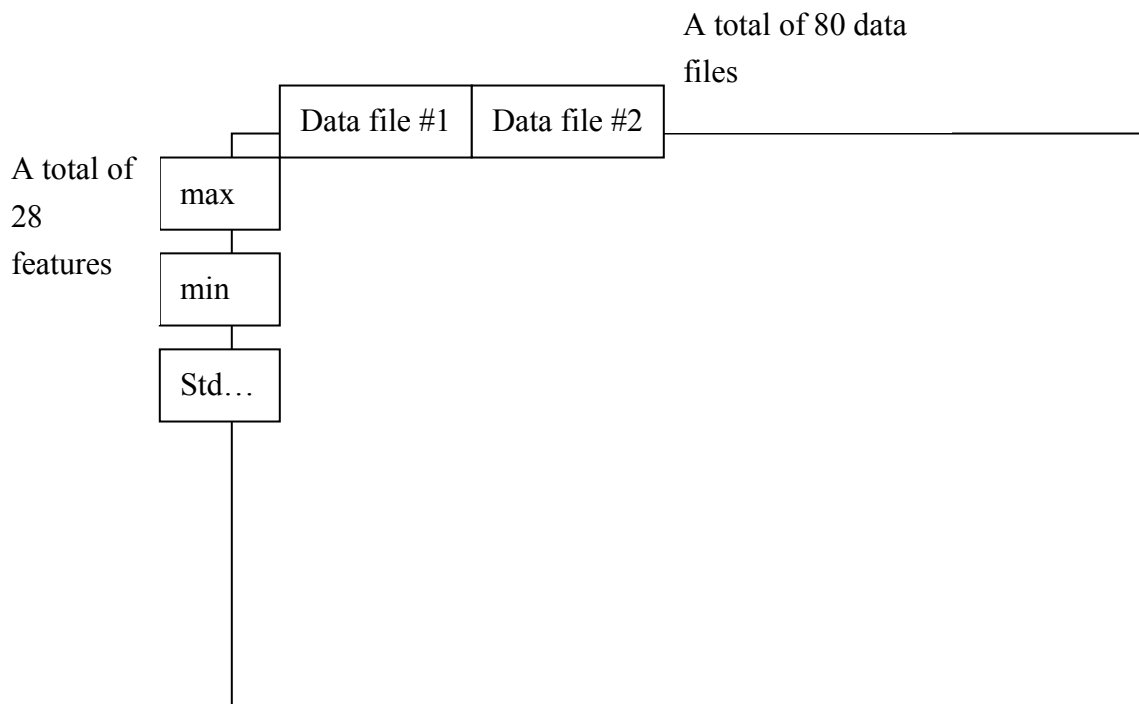


Figure 25: Creation of a structure for features

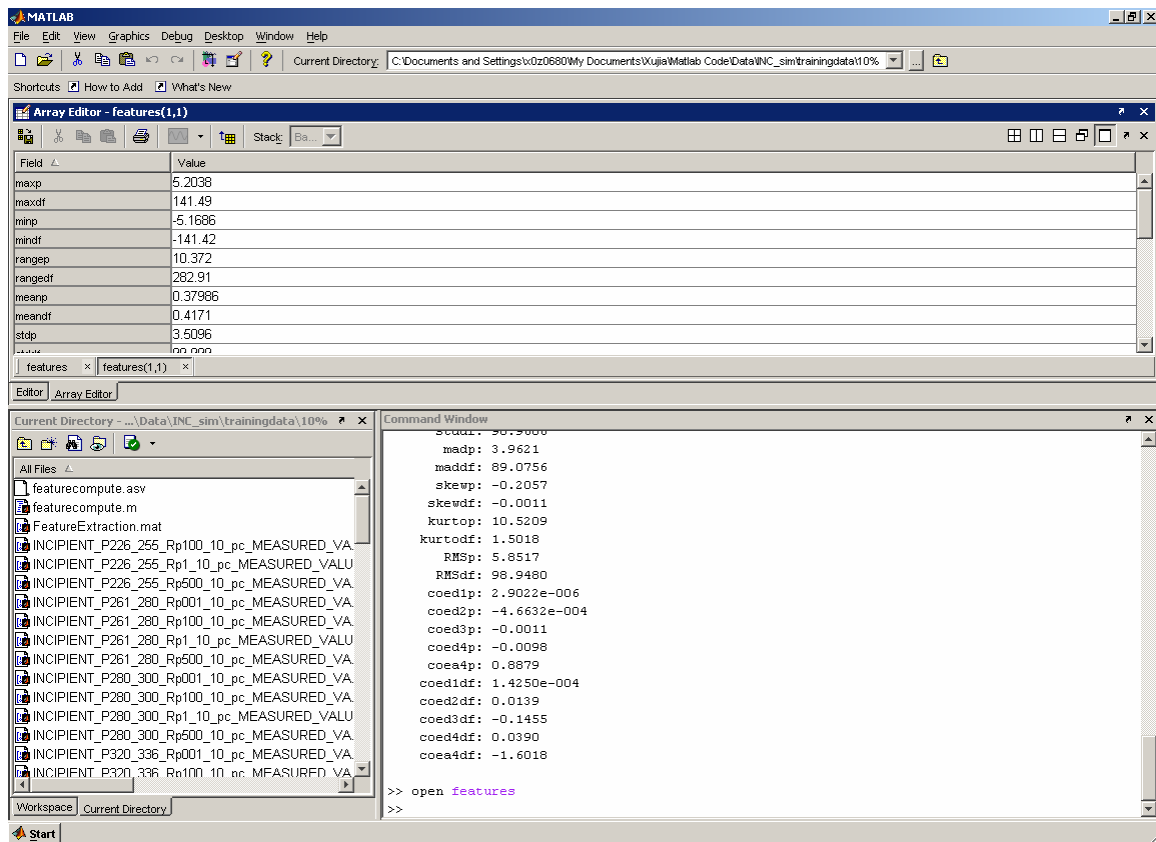


Figure 26: Structure created for features

Normalization

In general, features are normalized before being input into the neural network. Feature data points are normalized to be a value between 0 and 1. This data is normalized before inputting it into the neural network model.

In order to achieve a value between 0 and 1, the normalized value is calculated with the following equation [18]:

$$\text{NormalizedValue} = \frac{\text{ActualValue} - \text{MinValue}}{\text{MaxValue} - \text{MinValue}}$$

Choice of Neural Network

A probabilistic neural network is good for classification problems [13]. When an input is feed into the classifier, the first layer will be able to compute the distance between the input vector and the training input vectors, and produce a vector whose elements show the closeness between the input data points and the training vector points [47]. The second layer will sum up “contributions for each class of inputs to produce as its net output a vector of probabilities [47].” As the last step, a transfer function called “compete [47]” will pick the maximum of the probabilities on the second layer, and it will also provide a one for that class and a zero for the other classes [47].

Figure 27 shows the two different layers of the neural network, and it also shows how the input to the neural network is processed, and how output classes are formed on the competitive layer. The probabilistic neural network used in this research belongs to a type of neural network called Radial Basis Networks [13][47].

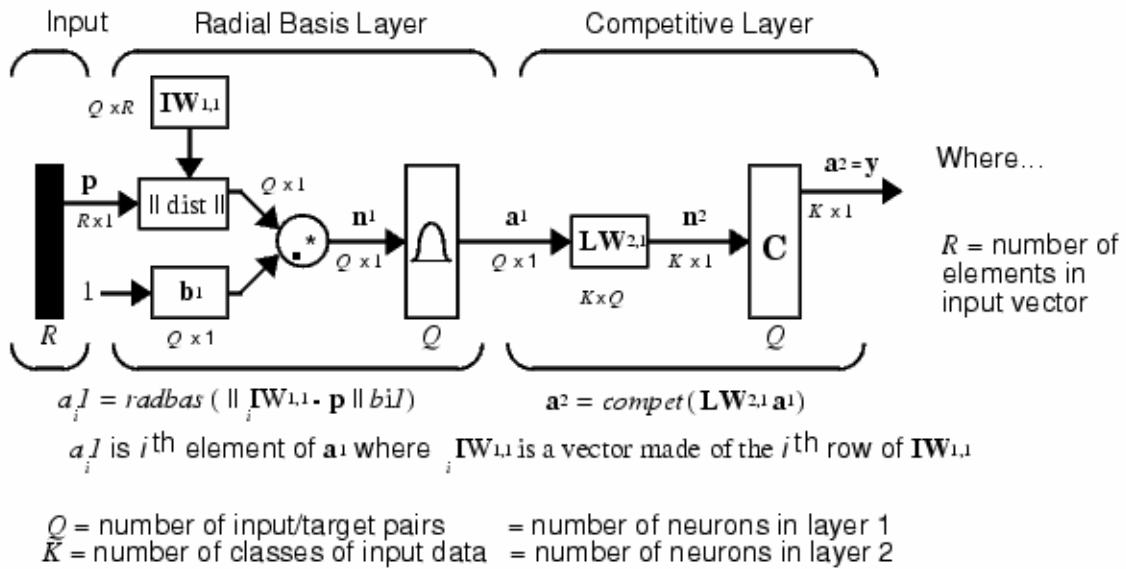


Figure 27 [47]: How probabilistic Neural Network works

Supervised Neural Network Classifier

A neural network is ideal for fault identification because it has the ability to recognize the hidden and complex relationships between the fault status and symptoms and predict fault based on future monitoring signals from previous knowledge [32]-[34]. An improved Back-Propagation Neural Network Classifier is implemented for classification of the recorded field and simulation data. The given data set is divided into two subsets: training set and test set [40]. The training data set is used to train the neural network to estimate the structure and assess the performance of various candidate model structures and thereby select a good model structure that will provide a minimum output

error of that network for the testing subset [41]. The testing data set is used to evaluate the performance of the network and measure the generalization performance of the well-trained network.

Four Different Studies: an Overview

In this thesis, four different types of studies have been conducted to design a Neural Network-based classifier with different input and output scenarios. With different input and output and their different combinations of the classifier, the performance of the classifier can vary dramatically. Therefore, it is important to implement and study the classifier performance under each study. The following is the list of the four different studies:

Study 1: Neural Network-Based Classifier with Primary Current and Difference Current as Input Signals and Two Output Classes

Study 2: Neural Network-Based Classifier with Primary Current and Differential Current as Input Signals and Two Output Classes

Study 3: Neural Network-Based Classifier with Primary Current and Difference Current as Input Signals and Four Output Classes

Study 4: Neural Network-Based Classifier with Primary Current and Differential Current as Input Signals and Four Output Classes

As stated in the study descriptions, study 1 and 2 will have only two output classes:

10% arcing incipient behavior class (low severity incipient fault)

50% arcing incipient behavior class (high severity incipient fault)

The difference between study 1 and study 2 is that study one uses primary and difference currents as inputs while study two uses primary and differential currents as inputs.

Similarly, study 3 and study 4 have the common point that both of them have four output classes:

Normal Operation

Short Circuit Faults

Incipient Fault with 10% Arcing Severity

Incipient Fault with 50% Arcing Severity

However, study 3 uses primary and difference currents as inputs, and study 4 uses primary and differential currents as inputs. The different input and output selection

combinations will change the performance of the classifier, and therefore, each study is conducted. The descriptions and distinctions between four studies are summarized in the table below:

Table 1: Summary of Four Types of Studies Using NN-based Classifier

	Classifier Inputs	Decision/Classification Outputs
Study 1	Primary Current	10% Arcing Incipient Behavior (Low Severity)
	Difference Current	50% Arcing Incipient Behavior (High Severity)
Study 2	Primary Current	10% Arcing Incipient Behavior (Low Severity)
	Differential Current	50% Arcing Incipient Behavior (High Severity)
Study 3	Primary Current	Normal Operation
		Short Circuit Faults
	Difference Current	10% Arcing Incipient Behavior (Low Severity)
		50% Arcing Incipient Behavior (High Severity)
Study 4	Primary Current	Normal Operation
		Short Circuit Faults
	Differential Current	10% Arcing Incipient Behavior (Low Severity)
		50% Arcing Incipient Behavior (High Severity)

Classifier Training and Testing Procedure

Generally, the training and testing procedures for the Neural Network-based classifier are similar. Therefore, this thesis will go over the training process and testing part of the classifier design and implementations in details. It is a redundancy to go through the same process with the other three studies, therefore, only results and evaluations of other studies are provided.

Training Process and Theory of the Supervised Neural Network Classifier

Training of the Neural Network-base classifier is similar to teaching a child how to read. First of all, a matrix which is consisted of rows (features and attributes) and columns (individual data files to be classified) is obtained prior to training. In the training process, a classification number is assigned to each individual data file from their known and existing labels. This is similar to showing a child what a new word looks like so that he or she can remember and recognize the same word next time. In another word, Neural Network learns how a class of data looks like so that it will recognize data in that class later when a new set of data is feed into the classifier.

Study 1: Neural Network-Based Classifier with Primary Current and Difference Current as Input Signals and Two Output Classes

As mentioned earlier, only the training and testing process of the classifier is demonstrated in details for study 1, and only results and evaluations are provided for the other studies because they all have similar procedures and steps. The following steps and procedures are specific and applicable to study 1 only without special notes.

Labels and Labeling System of Data Files

The naming system of the simulation data file clearly identifies the parameters used in the simulating and the behaviors of the transformer (health or faulty). For instance:

“INCIPIENT_P55_160_Rp1_10_pc_MEASURED_VALUES” means the fault was between turn 55 and turn 160. The resistance R_p used was 1Ω , and the arcing severity was 10%.

Similarly, “INCIPIENT_P55_160_Rp10_50_pc_MEASURED_VALUES” means the fault was between turn 55 and turn 160. However, the resistance value used in simulation was 10Ω , and the arcing severity level was 50%, which indicates a pending fault.

The naming and labeling system of the simulation data files significantly contribute to the usage of a supervised neural network-based classifier. Because the behaviors of the transformer were already clearly labeled with the name, training of the supervised neural network would allow neural network to learn patterns inside normal and faulty data. In addition, the testing data of the neural network classifier will obtain

classification results. These results can be compared with the labels to evaluate how accurate performance of the classifier.

Based on the label of the simulation data, two classes can be created as the decision output: low severity degree class, which is a collection of 10% arcing data files and a high severity degree class, which is a collection of 50% arcing data files. 20% of the total simulation data files was categorized as the training set and was used for training; therefore, 36 out of the total 182 files are for training purposes.

After the neural network classifier has been properly trained, the test-set data are input into the neural network classifier, which will classify the data into two output classes as shown in Figure 28: low severity degree class and high severity degree class, 10% arching and 50% arching files, just as it was trained.

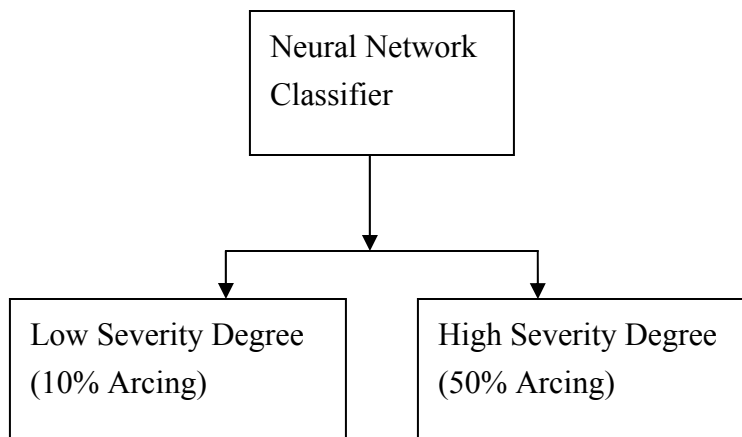
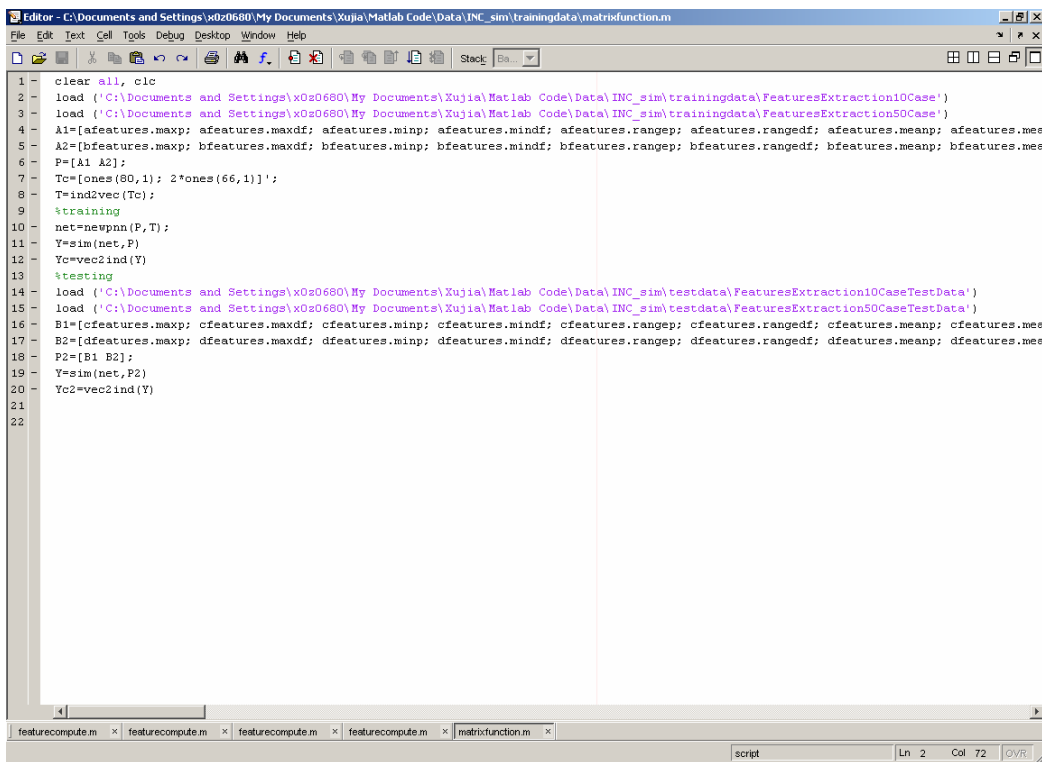


Figure 28: Training of the neural network

Training of the Neural Network

Figure 29 shows the Matlab code that was used to train the neural network and test the neural network with test data. Figure 30 helps to illustrate how this training process works. Each field of the Features structure contains all the information on that field from all data files. Each column in this features structure is input into a matrix, and the label of this column is created with another matrix Tc. If Tc equals one, it means the class that the data file belongs to is 10% class. If Tc equals two, it means the class that the data file belongs to is 50% arcing class.



```

1 - clear all, cloc
2 - load ('C:\Documents and Settings\x020680\My Documents\Xujia\Matlab Code\Data\INC_sim\trainingdata\FeaturesExtraction10Case')
3 - load ('C:\Documents and Settings\x020680\My Documents\Xujia\Matlab Code\Data\INC_sim\trainingdata\FeaturesExtraction50Case')
4 - A1=[afeatures.maxp; afeatures.maxdf; afeatures.minp; afeatures.mindf; afeatures.range; afeatures.rangedf; afeatures.meanp; afeatures.meandf; afeatures.range; afeatures.rangedf; afeatures.meanp; afeatures.meandf];
5 - A2=[bfeatures.maxp; bfeatures.maxdf; bfeatures.minp; bfeatures.mindf; bfeatures.range; bfeatures.rangedf; bfeatures.meanp; bfeatures.meandf];
6 - P=[A1 A2];
7 - T=[ones(80,1); 2*ones(66,1)]';
8 - T=ind2vec(T);
9 - %training
10 - net=newpnn(P,T);
11 - Y=sim(net,P)
12 - Yc=vec2ind(Y)
13 - %testing
14 - load ('C:\Documents and Settings\x020680\My Documents\Xujia\Matlab Code\Data\INC_sim\testdata\FeaturesExtraction10CaseTestData')
15 - load ('C:\Documents and Settings\x020680\My Documents\Xujia\Matlab Code\Data\INC_sim\testdata\FeaturesExtraction50CaseTestData')
16 - B1=[cfeatures.maxp; cfeatures.maxdf; cfeatures.minp; cfeatures.mindf; cfeatures.range; cfeatures.rangedf; cfeatures.meanp; cfeatures.meandf; cfeatures.range; cfeatures.rangedf; cfeatures.meanp; cfeatures.meandf];
17 - B2=[dfeatures.maxp; dfeatures.maxdf; dfeatures.minp; dfeatures.mindf; dfeatures.range; dfeatures.rangedf; dfeatures.meanp; dfeatures.meandf];
18 - P2=[B1 B2];
19 - Y=sim(net,P2)
20 - Yc2=vec2ind(Y)
21
22

```

Figure 29: Matlab code for training and testing of neural network

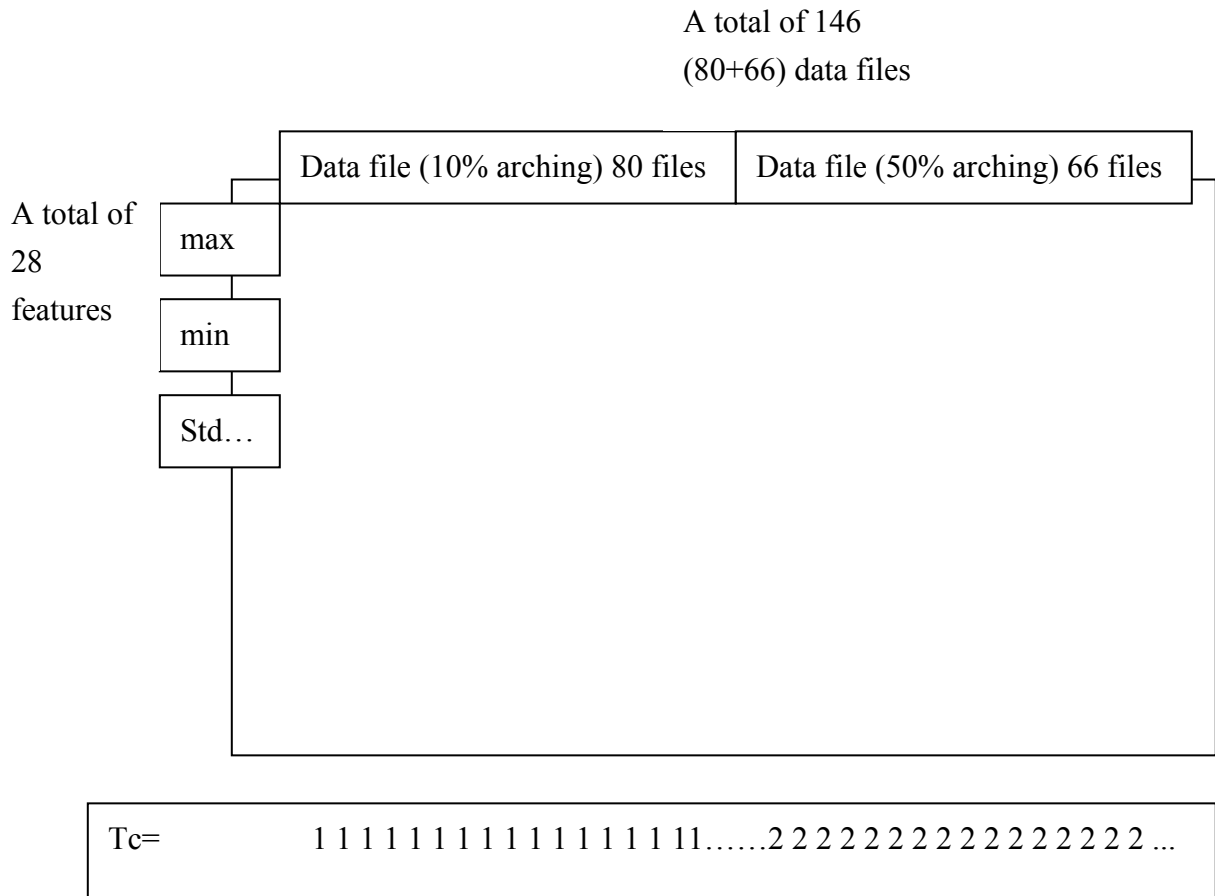


Figure 140: Illustration of how training works

Training Accuracy

The training accuracy is defined as: $\frac{\# \text{ filesCorrectlyAssigned}}{\text{total\#ofFiles}}$, and this number

has been calculated after the training process, which is 100%. It makes sense because the exact same data set is used to test the neural network based-classifier after it has been trained with the same data set.

Testing and Performance Evaluation of the NN Classifier

Generalization

The test set data was feed through the neural network based supervised classifier.

Table 1 shows that the number of data files labeled with 10% arcing is 18 and the number of data files classified with 10% arcing is 25.

Table 5 also shows the number of data files labeled with 50% arcing is 18 and the number of data filed classified with 50% arcing is 11.

The percentage of error is calculated with:

$$\frac{29 \text{CorrectlyAssignedFiles}}{\text{totalof36Files}} * 100\% = 81\%$$

Table 2: Evaluation of the Classifier Performance (Study 1)

Number of Data Files Used for Training	146
Number of Total Data Files for Testing	36
Number of Data Files Labeled with 10% Arcing	18
Number of Data Files Labeled with 50% Arcing	18
Number of Data Files Classified with 10% Arcing	25
Number of Data Files Classified with 50% Arcing	11
Percentage of correctly assigned label	81%

In Figure 38, the output classes (from Matlab code and simulations) are compared with the file labels to compute for the accuracy of the neural network classifier.

Labels = Columns 1 through 15

1 1 1 1 1 1 1 1 1 1 1 1 1 1 1

Columns 16 through 30

1 1 1 2 2 2 2 2 2 2 2 2 2 2 2

Columns 31 through 36

2 2 2 2 2 2

Yc2 = Columns 1 through 15

1 1 1 1 1 1 1 1 1 1 1 1 1 1 1

Columns 16 through 30

1 1 1 1 2 2 2 2 2 1 2 1 1 2 1

Columns 31 through 36

1 2 2 1 2 2

Figure 151: Output Classes for signal selections of primary and difference currents

Study 2: Neural Network-Based Classifier with Primary Current and Differential Current as Input Signals and Two Output Classes

In study 2, the differential current is used instead of difference current together with primary current as inputs. The decision output classifications are still 2 classes.

Figure 39 below shows the Matlab output classes.

Labels = Columns 1 through 15

1 1 1 1 1 1 1 1 1 1 1 1 1 1 1

Columns 16 through 30

1 1 1 2 2 2 2 2 2 2 2 2 2 2 2

Columns 31 through 36

2 2 2 2 2 2

Yc2 = Columns 1 through 15

1 1 1 1 1 1 1 1 1 1 1 1 1 1 2

Columns 16 through 30

1 2 1 1 2 1 1 1 1 1 1 1 1 1 1

Columns 31 through 36

1 2 1 1 1 1

Figure 162: Output class for signal selections of primary and differential current

A summary of the results of study 2 is shown in table 2, and the percentage error is calculated for the classifier performance.

Table 3: Evaluation of the Classifier Performance (Study 2)

Number of Data Files Used for Training	146
Number of Total Data Files for Testing	36
Number of Data Files Labeled with 10% Arcing	18
Number of Data Files Labeled with 50% Arcing	18
Number of Data Files Classified with 10% Arcing	32
Number of Data Files Classified with 50% Arcing	4
Percentage of correctly assigned label	50%

Again, the percentage of error is calculated with the previous equation:

$$\frac{\#CorrectlyAssignedFiles}{total\#ofFiles} * 100\% = percentage_error = \frac{18}{36} = 50\%$$

Study 3: Neural Network-Based Classifier with Primary Current and Difference Current as Input Signals and Four Output Classes

In study 3, the decision output classes of the Neural Network-based classifier have been increased from 2 classes to 4 classes to examine the accuracy and flexibility of the overall performance of the classifier. Figure 31 shows this process.

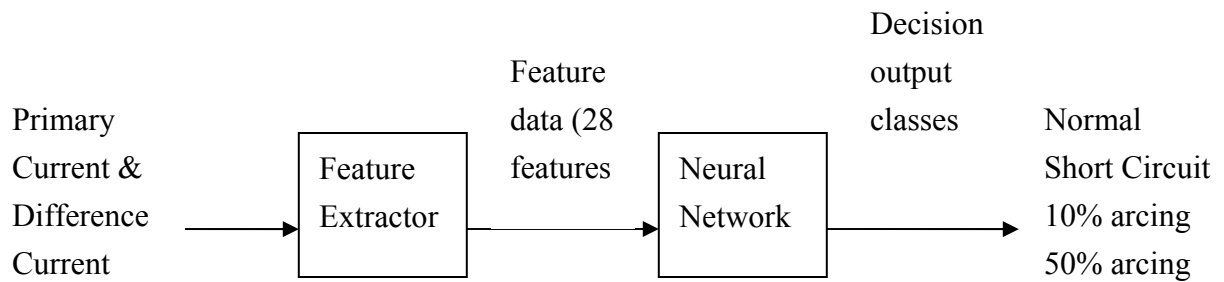


Figure 33: Study 3 Inputs and Outputs

Figure 32 below shows the Matlab output classes of the NN based-classifier.

There are a total of 72 individual data files for testing purposes. Among them, 16 files are labeled with normal class, 20 files are for short circuit fault class, 18 files are for 10% arcing incipient fault class, and the rest of 18 files are of 50% arcing incipient fault class. The classifications are summarized in the plot below.

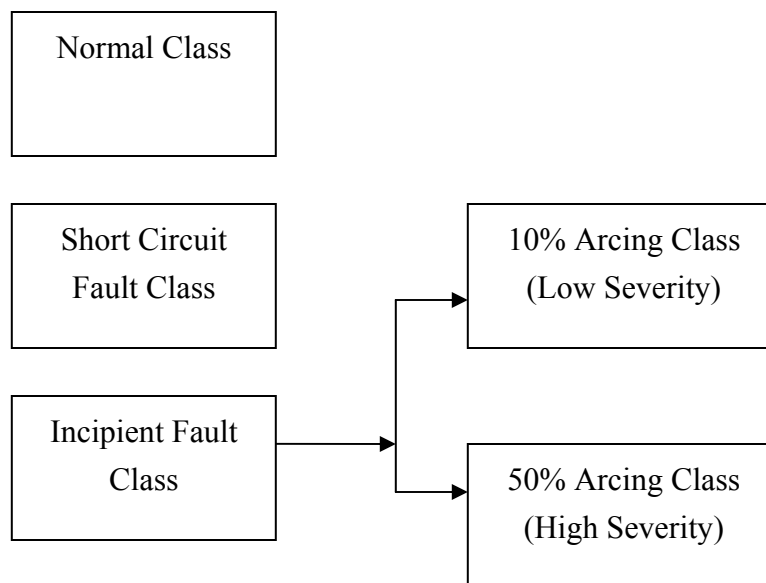


Figure 34: Classes for Study 3 and 4

Figure 33 shows the output classes from Matlab NN classifier simulations. As shown in the labels, the first 18 files are class one, so the first 18 numbers are all ones. The second 18 files are class two, they are labeled with twos. The next 16 files are of class three, they have threes. Finally, the last group of data files are class 4, and they are labeled with fours.

Labels =

Columns 1 through 15

1 1 1 1 1 1 1 1 1 1 1 1 1 1 1

Columns 16 through 30

1 1 1 2 2 2 2 2 2 2 2 2 2 2 2

Columns 31 through 45

2 2 2 2 2 2 3 3 3 3 3 3 3 3 3

Columns 46 through 60

3 3 3 3 3 3 3 4 4 4 4 4 4 4 4

Columns 61 through 72

4 4 4 4 4 4 4 4 4 4 4 4

$Y_{c2} =$

Columns 1 through 15

1 1 1 1 1 1 1 1 1 1 1 1 1 1 1

Columns 16 through 30

1 1 1 1 2 2 2 2 2 1 2 1 1 2 1

Columns 31 through 45

1 2 2 1 2 2 3 3 3 3 3 3 3 3 3

Columns 46 through 60

3 3 3 3 3 3 3 4 1 1 1 1 1 1 1

Columns 61 through 72

1 4 4 1 4 1 1 4 1 1 1 1

Figure 35: Study 3 Class Outputs

Comparing the labels with the output classes, the performance of the Neural Network-based Classifier is once more evaluated, which is summarized in table 4.

Table 4: Evaluation of the Classifier Performance (Study 3)

Number of Data Files Used for Training	385
Number of Total Data Files for Testing	72
Number of Data Files Labeled with 10% Arcing	18
Number of Data Files Labeled with 50% Arcing	18
Number of Data Files Labeled with Normal	16
Number of Data Files Labeled with Short Circuit	20
Number of Data Files Classified with 10% Arcing	40
Number of Data Files Classified with 50% Arcing	11
Number of Data Files Classified with Normal	16
Number of Data Files Classified with Short Circuit	5
Total Number of Correctly Labeled Files	50
Percentage of correctly assigned label	69%

Again, the percentage of error is calculated with the previous equation:

$$\frac{\#CorrectlyAssignedFiles}{total\#ofFiles} * 100\% = percentage_error = \frac{50}{72} = 69\%$$

Problems can be noticed in this set of results. Most of the class 4 data files are misclassified as class 1. However, all 16 class 3 files (normal operation class) have been correctly and successfully identified. It also shows that the Neural Network-Based Classifier is having trouble distinguishing between class 1 (10% arcing incipient fault) and class 4 (short circuit faults) data files. However, it is very successful when it classified class 3 with a perfect accuracy.

Study 4: Neural Network-Based Classifier with Primary Current and Differential Current as Input Signals and Four Output Classes

Similar to the other three studies that have been conducted previously, study 4 looks at the classifier with four different classification outputs. However, the inputs used are primary current and differential current. From discussions presented in the differential current section of the thesis, it was expected that the differential current will help with the distinction between short circuit faults and normal operation data files.

Figure 34 below shows the Matlab NN-based Classifier output classes. The labels of the files are exactly the same as those used in study 3.

Labels =

Columns 1 through 15

1 1 1 1 1 1 1 1 1 1 1 1 1 1 1

Columns 16 through 30

1 1 1 2 2 2 2 2 2 2 2 2 2 2 2

Columns 31 through 45

2 2 2 2 2 2 3 3 3 3 3 3 3 3 3

Columns 46 through 60

3 3 3 3 3 3 3 4 4 4 4 4 4 4 4

Columns 61 through 72

4 4 4 4 4 4 4 4 4 4 4 4

Yc2 =

Columns 1 through 15

1 1 1 1 1 1 1 1 1 1 1 1 1 1 2

Columns 16 through 30

1 2 1 1 2 1 1 1 1 1 1 1 1 1 1

Columns 31 through 45

1 2 1 1 1 1 1 1 1 1 1 1 1 1 1

Columns 46 through 60

1 1 1 1 1 1 1 1 1 1 1 1 1 1 1

Columns 61 through 72

1 4 4 4 4 1 1 4 1 1 1 1

Figure 36: Class Outputs of Study 4 (with differential current)

Results of the performance evaluation of study 4 have been summarized in table

5 below:

Table 5 Evaluation of the Classifier Performance (Study 4)

Number of Data Files Used for Training	385
Number of Total Data Files for Testing	72
Number of Data Files Labeled with 10% Arcing	18
Number of Data Files Labeled with 50% Arcing	18
Number of Data Files Labeled with Normal	16
Number of Data Files Labeled with Short Circuit	20
Number of Data Files Classified with 10% Arcing	63
Number of Data Files Classified with 50% Arcing	4
Number of Data Files Classified with Normal	0
Number of Data Files Classified with Short Circuit	5
Total Number of Correctly Labeled Files	23
Percentage of correctly assigned label	32%

Again, the percentage of error is calculated with the previous equation:

$$\frac{\#CorrectlyAssignedFiles}{total\#ofFiles} * 100\% = percentage_error = \frac{23}{72} = 32\%$$

The performance of this study is poor considering the accuracy of the classifier is in the thirties. The classifier could not separate class 1 (10% arcing) and class 3 (normal operation) data files. In addition, the distinction between class 1 and class 2 (50% arcing) has not been well made. The different degree of incipient fault severity is hard to detect with settings and parameters of the NN-based classifier fixed as in study 4.

Comparison of Study 1, Study 2, Study 3, and Study 4 Results

After careful review and comparison of results from these four different studies performed with Neural Network-Based Classifier, many useful conclusions can be drawn. Table 6 below summarizes the accuracy performance of the four studies.

Table 6: Comparison of Results from 4 Different Studies

Study Type and Description	Accuracy
Study 1: primary and difference current with 2 output classes	81%
Study 2: primary and differential current with 2 output classes	50%
Study 3: primary and difference current with 4 output classes	69%
Study 4: primary and differential current with 4 output classes	32%

First of all, it can be observed that the difference current as input to the Neural Network classifier works better than having a differential current. Secondly, it can be seen that the Neural Network classified designed and implemented in this thesis supports the argument that it works better with less classes, in this case, the accuracy of two output classes is much higher than having a four-class output. In addition, it is proved that the differential current does not help much with the distinction between short circuit faults and 10% arcing incipient fault classes. However, the classifier implemented here works well with normal and incipient fault classes. For instance, all 16 class 3 (normal

operation) data files were correctly and successfully identified from the rest of the data.

SUMMARY AND CONCLUSION

Summary

In summary, because raw data would create complex and inaccurate neural network architectures, feature data was extracted from the raw signals and then feed into the neural network. Because the feature data is meaningful and carries more specific information, the number of neurons in the middle layers will be reduced and only simpler network architecture is needed. As shown in table 6, as part of the time domain analysis, spike analysis and RMS analysis have been performed on the primary current and differential current, which is the difference between the primary current and the secondary current. Also, differential current has been obtained to help distinguish short circuit fault class from other classes. However, performance evaluation of the classifier did not support this argument and did not show an increase in accuracy of classification when differential current has been used. As part of the time-frequency analysis, the DWT analysis is also performed on the primary current and differential current to help the discrimination process of the predictive and detective maintenance method.

Table 7: Analysis Methods and Signals of Study

DOMAIN	ANALYSIS METHOD	SIGNALS
Time Domain Analysis	Spike Analysis	Primary Current
		Differential/Difference current
	RMS Analysis	Primary Current
		Differential/Difference current
Time-Frequency Analysis	DWT Analysis	Primary Current
		Differential/Difference current

The DWT analysis is proven to be an efficient feature extractor for the neural network to generate feature data and provide better classification results. Also, the difference current is calculated by subtracting the primary current by the secondary current. Similarly, the differential current has been proven to carry a significant portion of the signal information and benefit the formations of feature clusters. The DWT plots of the primary and differential current have shown that various types of faults can be distinguished from each other using DWT on these signals.

Finally, the neural network classifier is trained with data files in the training set of the data. Once the Probabilistic Neural Network Classifier has been properly trained, the testing data set can be input into the neural network classifier to classify the data into

clusters. An evaluation of the performance of the Neural Network classifier was also conducted after running the testing data set.

Four different studies have been done to examine the performance of the NN classifier under different combinations of input singles and output decision classes. The results from the four studies show that the differential current does not help with classification of short circuit fault class as predicted. However, the classifications of incipient fault class and normal operation class have been successful. In addition, the 2-class simulation results show much higher accuracy of the classifier than the 4-class simulations do.

Conclusion

In conclusion, a Neural Network-based classifier has been successfully designed and implemented in this research work. Different inputs and output decision classes have been tried under four different studies to provide performance evaluation of the implemented classifier. Spike analysis, RMS analysis, and discrete wavelet transform were proven to be efficient feature extractors of the neural network-based supervised classifier. The primary current and differential (or difference) current are the focus of the research because they carry important information of the signals and provide better feature cluster formations. The Probabilistic Network Classifier has been successfully trained with training data, and the performance evaluation of the classifier from the test data shows that the accuracy of the neural network classification method is acceptable.

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OBJECTIVE	To obtain a full-time Electrical Engineering position starting June 2006	
EDUCATION	Texas A&M University, College Station, TX Bachelor of Science in Electrical Engineering, Anticipated Graduation Date: May 2006 Overall GPA: 3.76 Major GPA: 3.79 <i>Financed 100% of college education</i>	Sept 02 to Present
WORK EXPERIENCE	<p>CenterPoint Energy, Houston, TX <i>Co-op Electrical Engineer, First Co-op Work Term</i></p> <ul style="list-style-type: none"> • Worked in Real Time Operations group at Energy Control Data Center • Ran contingency analysis and performed daily case studies to analyze the stability and reliability of the transmission power system • Analyzed outage feasibility and coordinated with other groups to schedule outages • Maintained an up-to-date modeling system and device information database <p style="text-align: right;">Aug 04 to Jan 05</p> <p><i>Co-op Electrical Engineer, Second Co-op Work Term</i></p> <ul style="list-style-type: none"> • Worked in Electric Distribution Planning group • Produced Electric Distribution Development Plan for Wallisville substation and circuits • Used GIS and Cymdist to study distribution system and maintained system peak-load database <p style="text-align: right;">May 05 to Aug 05</p>	
UNDERGRADUATE RESEARCH	<p>University Undergraduate Research Fellows Program <i>2005-2006 Fellow</i></p> <ul style="list-style-type: none"> • Participate in two semesters of independent research that culminate in a senior honors thesis and a symposium presentation • Conduct research on Pattern Recognition Techniques in Power System Protection Applications <p style="text-align: right;">Sept 05 to May 06</p> <p>Power System Automation Lab, College Station, TX <i>Research Assistant</i></p> <p style="text-align: right;">Jan 05 to May 05</p> <p>Gained knowledge in power flow and stability studies, fault analysis and system protection</p> <p>Research Experience for Undergraduates (REU) funded by NSF</p> <p style="text-align: right;">May 04 to Aug 04</p> <p>Researched in the topic of Detection, Classification and Location of Incipient Faults of Underground Cables</p>	
ACTIVITIES	<p>Student Engineers' Council</p> <p style="text-align: right;">Sept 02 to Present</p> <p>Engineering Career Fair Social Director</p> <p style="text-align: right;">Jan 05 to Present</p> <p>Texas Regional Engineering Conference Project Design Director</p> <p style="text-align: right;">Sept 03 to Aug 04</p> <p>International Week (Director)</p> <p style="text-align: right;">The Big Event</p> <p>IEEE and Toast Master</p> <p style="text-align: right;">Asian American Association</p> <p>Volunteer for International Student Services</p> <p style="text-align: right;">Intramural Indoor Soccer</p>	
HONORS	<p>University Undergraduate Research Fellow</p> <p>University Honors Program</p> <p>Foundation Honors Program</p> <p>Engineering Scholar Program</p> <p>Eta Kappa Nu & Tau Beta Pi</p> <p>Academic Excellence Scholarship</p> <p>College of Engineering Scholarship</p> <p>Bolton Scholars Scholarship</p> <p>Honors Incentive Scholarship</p> <p>Dean's Honor Award</p> <p>Dependent Children of Faculty/Staff Scholarship</p> <p>Improved Teaching Scholarship</p> <p>2nd place in Undergraduate Research Poster Presentation, Student Research Week '05</p>	