Transducer Design and Neural Signature Analysis for Diagnosis of Energized Transmission Lines

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Abstract

A new sensor technology based on Electromagnetic Acoustic Transducers (EMAT) for nondestructive testing is developed and used for real-time fault recognition of energized overhead transmission lines. The fault detection is achieved by analysis of the reflected signatures from broken strands on the transmission line. Reflected waves received by the EMAT are analyzed using an artificial neural network (ANN) technique for failure detection and signature identification. From the field tests done at two towers of live transmission lines, this EMAT system shows prospective potential for fault detection in electric transmission lines.

1 Introduction

Transmission line inspection and maintenance are the most elaborate and challenging functions in supporting stable electric power transmission and distribution. This infrastructure is the backbone of the national grid. Transmission lines are normally exposed and operated at a wide range of meteorological conditions for a long period of time. This necessitates a regular inspection of the transmission lines to assure their health and normal operation against damage caused by undamped vibration from wind, corrosion, large temperature variations, ice loading and mechanical stresses due to high tension. While operation and maintenance are major expense that has to be contained, electric power reliability is directly affected by the quality of maintenance.

Typically, visual inspection has been the common method used for transmission lines. Other inspection methods include: distance, current differential, phase comparison and directional comparison protection schemes. Unfortunately, these methods are rarely used in the field. The aluminum strands, which form the outmost layer and inner layers near the conductor surface of a transmission line, can be overtime fatigued and worn during normal operation. Because there is no reliable method to detect wear and broken strands of a conductor without disassembly of the hanging mechanisms at the towers, the damage may occur internally or underneath the mounting hardware is not possible to visually inspect. To answer this major monitoring need, we have developed a new transducer and automatic failure detection technique based on both ANN and EMAT technology. The resulting monitoring system would not require de-energizing electric transmission lines and disassembling of the mounting gear at the towers.

Several types of non-destructive monitoring techniques have been developed based on the principles of radiography, ultrasonics, magnetic particles, optics, thermal imaging, liquid penetrants, leak testing, acoustic emissions, and electromagnetics. Blitz [1], Migliori and Sarrao [2], and Maldague [3] discuss many of these methods in details. Magnetic flux leakage applies a magnetic field to the specimen under test and any changes in the flux are observed. In [1], this method is analyzed with several geometries of metals. This technique can only be used on ferromagnetic materials and the magnetic field must cross the discontinuities at close to right angles to measure the amount of divergent flux. Also in [1] several eddy current methods are described. In this technique, a coil is placed near the surface of the test specimen and an impedance measurement of the material is made. Since this method only tests specimen placed directly under the coil, it requires access to the entire specimen. In [2], ultrasonic transducers are used to find the resonant frequencies of test specimens. This method of testing can take into account microscopic and macroscopic properties of test specimens. Properties such as elastic module and ultrasonic attenuation can be measured with this technique. A band of frequency is swept, using a transducer, and the mechanical response of the test specimen is measured. A particular resonant mode in a test specimen corresponds to a certain resonant frequency that may be measured using ultrasonic technique. Infrared methodologies used for non-destructive evaluation are presented in [3]. These techniques use thermal radiation from the test specimen to create an infrared signature. This signature can highlight flaws in a specimen. The shortcoming of this method is its robustness. Namely, signatures can be corrupted by the presence of thermal insulation between the specimen and the surrounding material.

In this research, a new monitoring system based on the principle of EMAT has been developed to assess the conductor's mechanical integrity in terms of connectivity, corrosion, wear, loss of cross-sectional area, and broken strands. This technology is applied to a typical transmission line conductor, commonly known as Aluminum Conductor Steel Reinforced (ACSR) to monitor and diagnose potential failures. ACSR is the most common type of conductor presently used by the electric utility industry. The monitoring system using an EMAT technology will sense the state of the conductor and through applications of ANN techniques would identify potential failures.

One of the essential steps for developing effective fault detection is the pre-processing of raw data to extract useful and appropriate information and features. Since the raw data is often too voluminous to be used directly as an input to a classifier, reducing the number of variables embedded within the data can significantly impact the classification process. The process of mapping the original raw data (time domain measurements) into fewer and descriptive features is called feature extraction. Feature extraction method makes it possible to reduce data dimensionality, improve the generalization ability of classifiers, and decrease the computational requirements of pattern classification. Because of these reasons, feature extraction has received considerable attention for the past twenty years [4]. Recently, many artificial neural networks and learning algorithms have been proposed for feature extraction and data projection [5-7]. In this research, two feature extraction methods are applied using multilayer perceptron (MLP) feature extractor [8-9] and principal component analysis (PCA) [4, 7].

2 Design of The Monitoring System For Fault Detection

In the design of a robust and reliable monitoring system, our investigation considered all key aspects of an automatic fault detection technique, namely, a unique and non-invasive sensory system, design of an effective feature extraction method, and development of a robust classifier.

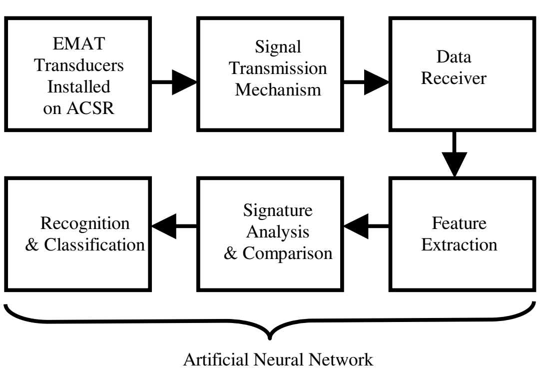

Figure 1: Procedure for Fault Diagnosis in Transmission Lines

Figure 1 summarizes the functional block diagram of the proposed monitoring system. The first three blocks delineate the functions of an EMAT hardware for the monitoring system, and the other blocks describe operations that take place within the software for ANN, embedded within the EMAT monitoring system.

3 Operational Principles of EMAT

An EMAT consists of a transmitter and a receiver. The basic design of these two units is shown in Figure 2. The EMAT couples ultrasonic energy into conductive materials. The simplest form of an EMAT is a wire loop held near a conductive material with a magnet placed above the wire. The transmitter operates based on similar principles as an electric motor, which develops torsional waves. A copper coil is placed as close to the test medium as possible and an alternating current is injected. This current produces a dynamic magnetic field (***H***), which varies in time and space. The resulting eddy current density (***J***) produced in the test medium is given by the Maxwell's equation [10,11].

$$\vec{J} = \vec{\nabla} \times \vec{H} \tag{1}$$

From Maxwell's equations for quasi-static conditions, this eddy current flows in the medium. To create a force in the metal, permanent magnets with high intensity are placed directly over the coil to immerse the medium with magnetic flux. The eddy current interacts with the external magnetic flux density (***B***), to produce a force density given by:

$$\vec{F} = \vec{J} \times \vec{B} \tag{2}$$

Coupled to the lattice of the metal sample, this force is called a Lorentz force and acts in a direction indicated in Figure 2. An elastic disturbance involving particle displacements (***u***) and velocity (***du/dt***) propagates through the test specimen. The receiving EMAT works similar to an electric generator. When the elastic waves pass under the receiver, the surface of the material is displaced in the magnetic field. An electric field (***E***) because of the resultant elastic displacement of the test specimen arises according to the following equation [10]:

$$\vec{E} = \frac{d\vec{u}_{tot}}{dt} \times \vec{B} \tag{3}$$

where du_{tot}/dt is the total particle velocity, which incorporates reflected, as well as incident elastic waves at the surface. With the resulting conduction current density, a related magnetic field ($\boldsymbol{H_R}$) and the resulting electric field (***E***) for a sinusoidal time variations would be generated as described below [11]:

$$\vec{H}_R = \left(\frac{1}{\mu_o}\right)(\vec{\nabla} \times \vec{A}) \tag{4}$$

$$\vec{E} = j\omega\,\vec{A} \tag{5}$$

where $\boldsymbol{A}$ is the vector electric potential outside the test specimen and around the receiver coil, μ_o is the permeability of free space and ω is the frequency of the alternating current.

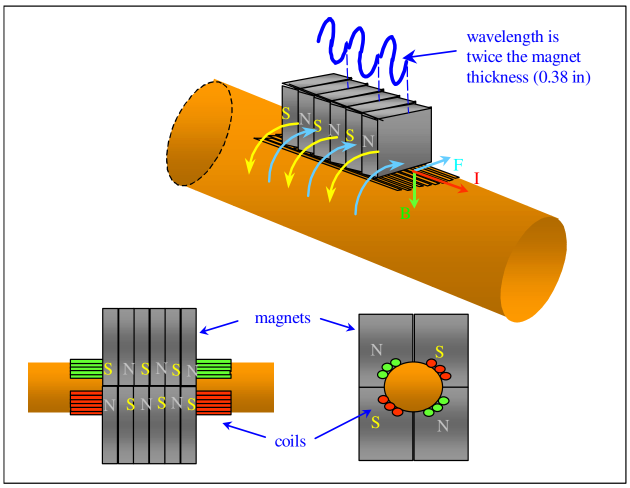

Figure 2: Basic Diagram of EMAT Transducer

A high-amplitude current with high frequency excites the coils of an EMAT transmitter, then an eddy current is induced in the conductor. Combining the eddy current with the magnetic flux created by the magnets, Lorentz force described by Equation (2) is generated. This force causes a small, high frequency localized displacement or acoustic pulse in the conductor. This displacement then propagates down the conductor where the EMAT receiver then detects this wave propagation. The EMAT receiver operates in the same fashion as the transmitter, but instead of producing an eddy current by the coils, the particle displacement along with the magnetic flux of the magnets induces a small voltage in the coils that is translated into the received signal. Since the EMAT system is designed to clamp on to the surface of the conductor, it is considered as a non-invasive monitor and would not require any disassembly of the suspension hardware that holds the conductor in place.

The EMAT system consists of: a microcomputer, which contains necessary software for system operation, fault detection and classification; two transducers; DC/DC converters; batteries; power amplifier, electronics for the operation of the transducers and electric motor for automatic opening and closing mechanism. The EMAT transmitter generates pulses and impinges them onto the conductor through transmitting coils. The EMAT receiver captures the reflected signals and amplifies them. The amplified signal is stored in the memory of microcomputer and is processed through the ANN. The information on EMAT system operation and the result of diagnostics after classification process are displayed on a handset control panel. Figure 3 shows the developed EMAT hardware system and the handset.

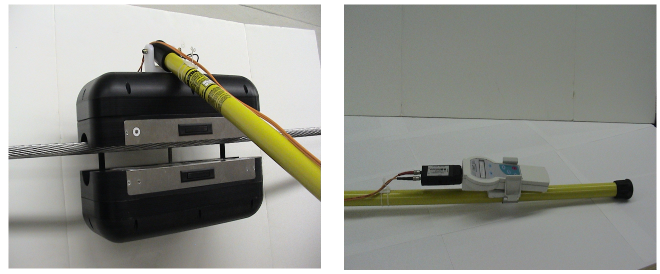

Figure 3: EMAT Hardware System and a Control Handset

4 Feature Extraction and Data Analysis

The raw data is acquired at 5 MHz sampling frequency and the driving frequency range is set to 100 kHz to 200 kHz. The first phase of this signature analysis technique is to mean zero the acquired data. The mean zeroed data sets are overlapped in a time domain and then a 5^{th} order band-pass filter (80 kHz to 250 kHz) is applied to reduce the noise influence. After the filtering, their maximum values are extracted from each row of the data vector and a time domain envelope data file is constructed. Data points representing a driving signal are removed. Finally, a running average filter with summing every 50 data points is applied to get the smooth signature envelope and the envelope is used as the input vector for the feature extractor. Figure 4 illustrates results of the signature envelope extraction steps described.

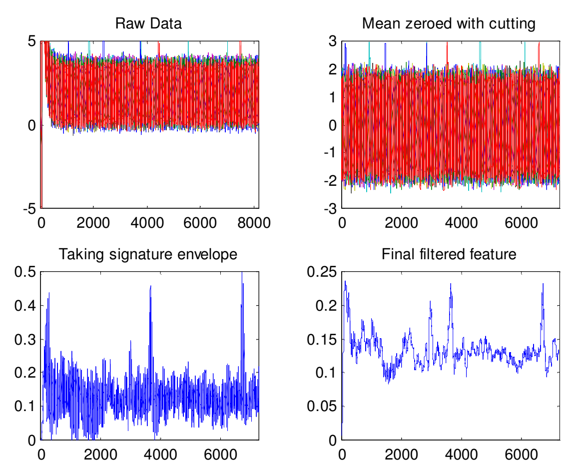

Figure 4: The Process Results of Signature Envelope Extraction

The data shown in Figure 4 is obtained from an actual transmission line in the field. By using the EMAT monitoring system, we have been able to classify this conductor as one with large number of broken strands.

4.1 MLP feature extractor using auto-associative neural network

Multilayer perceptron (MLP) neural network can also be used for feature extraction in an unsupervised mode.

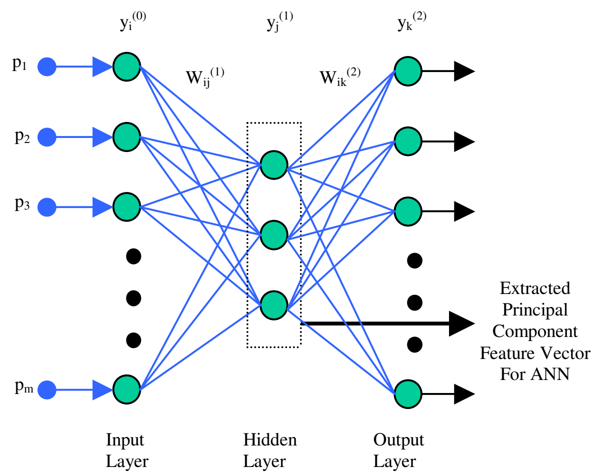

Figure 5: Autoassociative MLP Neural Network

Figure 5 shows the architecture of a network, which is able to find the principal component analysis (PCA) subspace. Instead of nonlinear activation function, the neurons have linear transfer functions. When the number of hidden layer outputs is appropriately selected, the classifier network can easily separate the patterns represented in the projected space, spanned by the hidden layer, and the hidden layer may simultaneously supply means of data projection. This network has m inputs and m outputs, where m is the given number of features. The inputs are also used as targets, forcing the output layer to reconstruct the input space using only one hidden layer. For a given EMAT system data, 17 principal component feature vectors are selected. If two more layers with nonlinear activation functions (sigmoid function) are also included in this network, then we can obtain nonlinear subspace features in the middle layer (so-called the bottleneck layer).

4.2 Principal Component Analysis

Principal component analysis (PCA) is a well-known statistical method for feature extraction, data compression, and multivariate data projection and has been widely used in communication, signal and image processing, pattern recognition, and data analysis [4,7]. PCA is a linear orthogonal transformation from an m-dimensional input space to a d-dimensional space, $d \leq m$, such that the coordinates of the data in the new d-dimensional space are not correlated and a maximal amount of variance (information) of the original data is preserved by only a small number of coordinates. After PCA transformation, the original high dimensional vector (m) can be approximated with the least mean square error for a given d-dimensionality.

Since PCA method makes the transformed vectors orthogonal and uncorrelated, the collinearity problem between signatures will be removed. The PCA transformation requires the following steps.

- Make a given raw data matrix **Xo** (m by n) mean zeroed **X**
- Calculate covariance matrix of **X, Cov(X)** (m by m)
- Obtain eigenvectors and eigenvalues of covariance matrix of **X**
- Select most important d eigenvalues of **Cov(X)** where, $m > d$
- Obtain eigenvectors (Principal components, PCs) corresponding to selected eigenvalues
- Obtain a reduced dimensional feature vectors through the vector multiplication by PCs, Y = PCs $*$ **X** where Y is a d by n matrix.

5 Classifier

Neural networks have been applied widely for pattern recognition problems. The most popular one is a multilayer perceptron (MLP) classifier based on the back-propagation learning rule (BP algorithm). In this study, three different types of neural network have been constructed and employed. Since the main issue in classification is robustness to variances of general test sets, we have attempted to find the most appropriate neural network for the transmission line fault detection. This study has resulted in the use of an Adaptive Resonant Theory (ART) neural network for the classification.

5.1 Adaptive Resonance Theory Neural Network

The ART network was introduced to resolve the instability of feedforward instar-outstar systems [12]. The ART is designed not only to be stable enough for the significant past learning, but also to be adaptable enough to incorporate new information whenever it may appear. The ART network is composed of three layers, and in the first layer, the preprocessing for the other layers is accomplished. Usually, the input pattern preprocessing includes noise reduction, contrast enhancement, normalization, and input transformation.

At the second layer, the preprocessed input feature is compared to each of the existing prototypes saved in the third layer. Among the prototypes, only one prototype, which is most similar to the input, becomes the "winner". If the similarity between the winner and input exceeds the vigilance number (ρ), learning is enabled and the winner is modified to more closely reflect the input. If the similarity between the winner and input is less than the vigilance number, the current winner is disabled and the search process is repeated. If none of the successive winners exhibit adequate similarity, learning is enabled to form a prototype similar to the input. The subsystem, including the second and the third layers, is called the attentional subsystem. That subsystem incorporates a dimensionless vigilance number to decide if the match is satisfactory. In updating the weight matrix, the ART network uses the Kohonen learning rule.

6 Implementation and Verification Through Field Tests

In order to investigate the operation and performance of this monitoring system, the EMAT unit was deployed in the field. Within the experimental setup in the laboratory, EMAT displayed a very satisfactory performance in the simulated testbed [13]. The field test took place in Kearney, Nebraska. The conductor cable under investigation was a Linnet 336 ACSR cable, and was energized at 115 kV. The conductor has four layers of stranded cable with 26 aluminum strands (outer layer) and 7 of the core steel strands. As verified by the sponsor utility, the first conductor to be tested does not have any failures. Thus, it is considered as the normal conductor. In the second tower, the Phase I conductor has nine broken strands and the Phase III conductor has four broken strands. For the convenience, we call Phase I conductor major abnormal one and Phase III minor abnormal one. Figure 6 shows a schematic diagram of the tower under investigation. Figure 7 shows the EMAT system operated by linemen at the tower in the field test.

For the collection of comparative data sets, the EMAT system (transmitter and receiver) is mounted and clamped at the end of armor rod of the conductor during data acquisition.

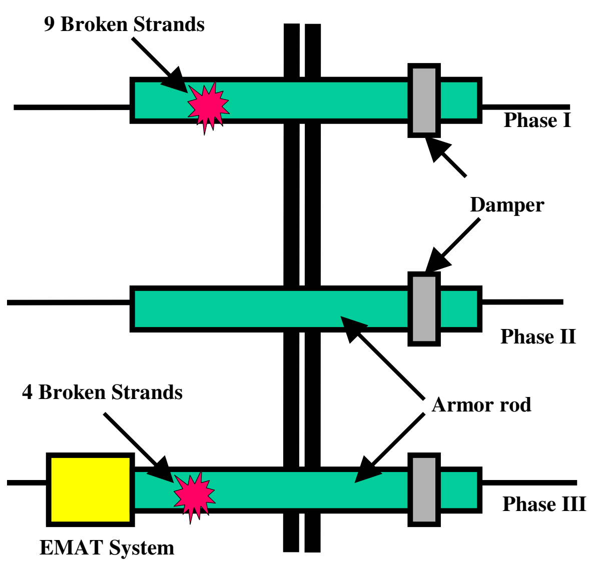

Figure 6: Schematic Diagram of the Tower Under Test

The first 17 data sets (Normal 6, Minor Abnormality 6, Major Abnormality 5) are used to train the classifiers and the other 17 data sets are used for the verification of the classifier (Normal 6, Minor Abnormality 6, Major Abnormality 5).

Figure 7: Operation of EMAT System By Linemen

Each training data set and verification data set are processed according to the described feature extraction methods after pre-processing, and then the extracted feature vector, having much smaller data dimension, is input to the neural networks for classification. Table 1 shows the verification results of classification based on two feature extraction methods (the first column) and the ART classifier. Overall, using PCA feature extractor has shown the better performance. In the major abnormal case, two sets among five test sets were recognized as the minor abnormal case. By this way, we have sixty percentage of correct recognition in the major abnormal case. As shown in Table 1, the MLP feature extractor using a linear activation function is not satisfactory to generate distinctive features for the ART classifier and PCA method shows the better results except for the major abnormal case. Most confusion in major abnormal ones happened because those were recognized as the minor abnormal case. Based on the recognition in the ART classifier, we can say that the recognition performance is more dependent on useful feature extraction. Figure 8 represents typical signatures obtained for each condition.

Table 1. Field Verification Results of the Classifier (Correct recognition %)

Classifier/ Feature Ext.	Cases	ART
MLP	Normal	66.7
	Minor AB	100
	Major AB	60
PCA	Normal	100
	Minor AB	100
	Major AB	60

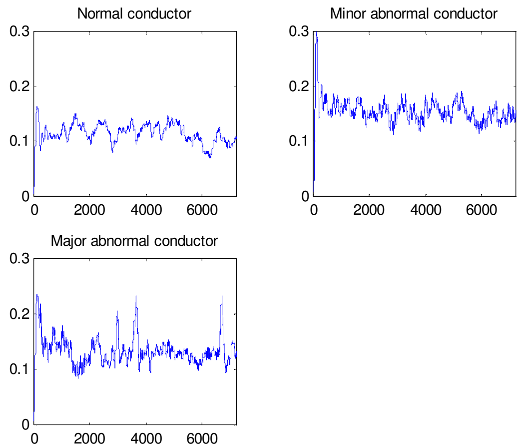

Figure 8: Typical Signatures According To ACSR Conditions

7 Conclusion

Two feature extraction methods (Autoassociative MLP and PCA) and a neural network (ART) for classification have been employed and tested for the field implementation of the EMAT system. The results present better recognition performance using PCA method in classification rather than a MLP feature extractor. Basically, the signals (signatures) obtained in the field test showed highly nonlinear response. Because of this, autoassociative MLP feature extractor using the linear activation function did not show satisfactory results in the classification. Most of the confusion happened between the signatures of minor abnormal and major abnormal conductors. The most efficient feature extractor is the PCA method. This is because PCA extractor has the ability to identify reliable and key features from complex and correlated signatures. Using feature vectors from PCA extractor, the employed classifier displayed meaningful results. This indicates that employing EMAT, proper feature extractor and a robust classifier based on ANN techniques, can result in an effective tool for the health assessment of the energized transmission lines.

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