INTRODUCTION

Natural gas is one of the cheapest forms of energy and is the source of more than 30% of the energy produced in the USA [1]. 280,000 miles of gas transmission lines, 90,000 miles of gathering lines and 835,000 miles of distribution lines form a vast network across the country. It is imperative to assure the integrity of this vast network, for safe and economical transport of gas.

In recent years, there has been a growing interest in “in-line” inspection procedures, and non-destructive evaluation (NDE) systems based on magnetic flux leakage are used extensively in the inspection of gas pipelines [2]. The pipeline inspection vehicle, also called the “pig”, contains strong permanent magnets that magnetize the pipe wall axially as shown in Figure 1. The pig is conveyed through the pipes under the pressure of natural gas and a circumferential array of sensors pickup the magnetic flux which leaks out at the location of the defect. The leakage flux data is digitized and stored on an “on-board” data acquisition system.

Mechanical damage has been identified as one of the single largest causes of failures of gas pipelines [3]. Third party excavations and natural forces such as the movement of the earth, deform the shape of the pipe, scrape away metal and cold work the steel. Mechanical damage defects have been classified into three types, namely, gouges with metal loss, gouges with cold work and dents. The gouge with metal loss is a result of removal of metal from the pipe surface by an applied force. The remaining area of damage shows cold work. A forceful movement of metal in a local area on the pipe

![Figure 1. Pipeline inspection vehicle.](image-url)
surface, resulting in wall thinning and cold working gives rise to what has been described as a gouge with cold work. A dent is a localized depression or deformation in the pipe’s cylindrical geometry, resulting from an applied force but without an associated gouge. MFL tools can help detect mechanical damage but traditional MFL techniques offer poor sensitivity to gouges and scrapes. This paper presents a new approach that relies on both active and residual field measurements to characterize mechanical damage and determine stress distributions around the defects.

MAGNETIC FLUX LEAKAGE TECHNIQUES FOR INSPECTION OF FERROMAGNETIC MATERIALS

Among the various techniques that can be used for inspection of steels, magnetic methods are unique because they utilize the inherent ferromagnetic properties of steel. In general, changes in magnetic properties are easily measurable and do not require high-resolution electronics [4]. When a magnetic field is applied to a ferrous material, such as pipeline steel, the material tends to uniformly retain flux unless there is a local change in the material’s geometry or magnetic properties. Mechanical damage causes a local geometric and magnetic change and also changes the pipe’s ability to retain flux. The leakage signal which is produced due to redistribution of magnetic flux in the material can be used to determine the location and characteristics of the defect.

All ferromagnetic materials exhibit hysteresis in the variation of flux density B with the applied magnetic field H. Hysteretic properties such as permeability, coercivity, remanence, and hysteresis loss are known to be sensitive to such factors as stress, strain, grain size, and heat treatment. Hysteresis determination which can indicate the residual or remanant magnetic field is thus ideally suited for determination of intrinsic properties, such as stress in and around defects in steel pipelines.

![Active MFL Method](image1.png) ![Residual MFL Method](image2.png)

Figure 2. MFL techniques for inspection of ferromagnetic materials.
CHARACTERIZATION OF MECHANICAL DAMAGE

Figure 3 shows the overall approach used in the present study, for characterization of mechanical damage. The MFL signals are first classified by NN1 into mechanical damage and corrosion. NN2 uses these signals for characterization and a 3D defect profile is obtained. The residual leakage signals from mechanical damage is used for stress characterization. Three types of neural networks, the Multi-Layer Perceptron (MLP), the Radial Basis Function (RBF) [5] and the Wavelet Basis Function (WBF) [6] networks have been used in this scheme.

Step 1 : Classification (NN1)

In order to characterize different defects in the pipelines, the MFL signals from mechanical damage and corrosion need to be distinguished. MFL signatures from defect sets of the two types were obtained from the simulation facility at Battelle Memorial Institute, Ohio. The data consisted of experimentally recorded MFL signals from a set of machined mechanical damage and corrosion defects. An input data set of 30 defect signatures was prepared after considerable amount of preprocessing on the experimental signals. A multi-layer perceptron neural network was trained to classify the defects into two categories. The network was tested using a different data set. A classification accuracy of 93.3% was obtained. Results showed that 2 of the 30 signals were misclassified. The misclassified signals were identified as signals from gouge defects taken at high magnetization level.

Step 2 : Characterization (NN2)

The WBF neural network has been employed to perform 3D defect characterization from the MFL signal. The WBF network architecture is similar to that of the MLP network and it uses wavelets for functional approximation and can be expressed using Equation (1) [7].

\[ \text{where } c_0 \text{ and } c_\Psi \text{ are known as the centers of the WBF network. Training such a network involves determining basis function centers, the type of basis functions, their width, and the network output weights. The wavelet basis functions whose contribution is} \]
insignificant to the defect profile or who compete for the same niche, are removed. The Gaussian radial basis function is used for scaling and the Mexican hat wavelet which is related to the second derivative of a Gaussian, was used as a wavelet function. The basis function width at the finest resolution was obtained in order to cover the whole input space. The unknown weights can be calculated using matrix inversion. Results are shown in Figure 4.

\[ \sum_{i=1}^{n} a_i \phi(||x - c_{\phi_i}||) + \sum_{i=1}^{n} \sum_{j=1}^{m} d_{ij} \psi(||x - c_{\psi_{ij}}||) \]  

(1)

Figure 5. Approach for “stress” predictions.
Step 3 : Prediction Of Stress Profiles (NN3)

Figure 5 shows the method used to predict stress distributions due to mechanical damage in pipelines. An “in-house” experiment was designed to make residual leakage field measurements. A neural network was trained using finite element stress predictions around known defects, and experimental residual leakage field measurements.

Step 3.1 : Mechanical Damage Experiment

Defect Preparation

Figure 6 shows the technique used to prepare the defects. All the defects were made on 4”x1/4”x16”, 1018 cold finished flat steel plates. Only two defects were placed on each plate, so as to avoid the blooming effect of defects very near each other. Two basic methods were used to prepare the gouge and metal loss defects. Gouges were machined by pressing a steel ball bearing on the steel plate, with a hydraulic pressured machine. Two different sized ball bearings and ten pressure levels of the hydraulic pressured machine were used to get a total of twenty gouge defects. A set of twenty corresponding metal loss defects were made by drilling out material from the plate using a special machine.

Experimental Setup

The steel plates were magnetized with a custom designed magnetizer. The three components of the MFL signal from the defect were recorded with a gauss meter for the varying magnetization levels from about 1,300 A/m to 34,400 A/m. The specimen were magnetized to saturation and magnetizer was taken away, in order to measure the residual field signals. Data was recorded for the entire defect set. Two sets of signals were obtained, active leakage field at saturation and the corresponding residual leakage field signals. Results showed nearly identical MFL signatures from the gouges and the metal loss, at saturation. However, a large difference in the residual field signals was observed and hence can be used to distinguish between the two kinds of defects. Almost no or a very small residual leakage field signal was recorded for the metal loss defects.

Figure 6. Defect preparation.
Step 3.2: Finite Element Modeling

Finite element modeling of the stress effects on MFL involves two steps. Structural analysis is carried out first, in order to obtain the distribution of stresses resulting from known loading conditions. The stress distribution thus obtained is then incorporated into a magnetic FE model and the MFL signals are predicted for various magnetization levels. The stress condition of the material is described with a "stress profile", which is a "scan" of the stress values on the surface of the specimen. The "stress profiles" and the corresponding MFL signatures can be used as a training data for an intelligent stress characterization algorithm.

Gouging was modeled by applying pressure on a small spherical pit on the top surface of a steel plate. The elastic behavior of steel was represented by the Young’s modulus: E=30*10^6 psi, Poisson’s ratio: v=0.3 and specific density: 0.283 lb/in^3. The model was meshed with tetrahedral elements and care was taken that element side length ratio does not exceed 1:2. The nodes on the back of the plate were restrained (all degrees of freedom equal to zero), to avoid the change of geometry.

The results of elastic, static structural analysis, for a load of 10 ksi are presented in Figure 8. The left hand side represents the distribution of the component of stress, perpendicular to the top surface of the specimen while the right hand side shows the one dimensional “stress profile” corresponding to that stress distribution. It can be seen that the elements directly under the pit are under compression, while the nodes on the edge of the pit experience tension. This is reflected in the “stress profile” as positive peaks above the edges and a negative peak, under the pit.
It has been suggested [5-6] that: ‘ferromagnetic materials with positive magnetostriiction coefficient tend do increase the magnetization under a tensile stress and decrease it under compressive stress’. Also, ‘at low field strengths tension increases magnetization, and decreases at high strengths. Compressive stress results in a decreased magnetization.’ It was further observed, that tensile stresses perpendicular to the applied magnetic field and compressive stresses, parallel to the external field result in increased permeability whereas, tensile stresses parallel to the field and compressive stresses perpendicular to the field decrease the permeability.

In the case of gouges and dents, the load is perpendicular to the outer surface, therefore the largest strains and stresses appear along the normal to the pipe surface. The external magnetization is along the pipe axis and is therefore perpendicular to the largest component of the stress vector. The effect of compression can be modeled by increasing the permeability, and similarly areas under tension can be modeled by lowering their permeability values.

Step 4 : “Stress Profile” Mapping

A radial basis function neural network was trained using the residual leakage field signals from the mechanical damage experiment and the finite element predictions of the “stress profiles” for the corresponding defects. Mapping results are shown in Figure 9.
CONCLUSIONS

The paper presents a neural networks based system for characterization of mechanical damage. Three kinds of neural networks have been employed. Results demonstrating the feasibility of the approach for differentiating between mechanical damage and corrosion, characterizing defect profile from active leakage field and characterizing stress using residual leakage field signals, have been presented.

REFERENCES