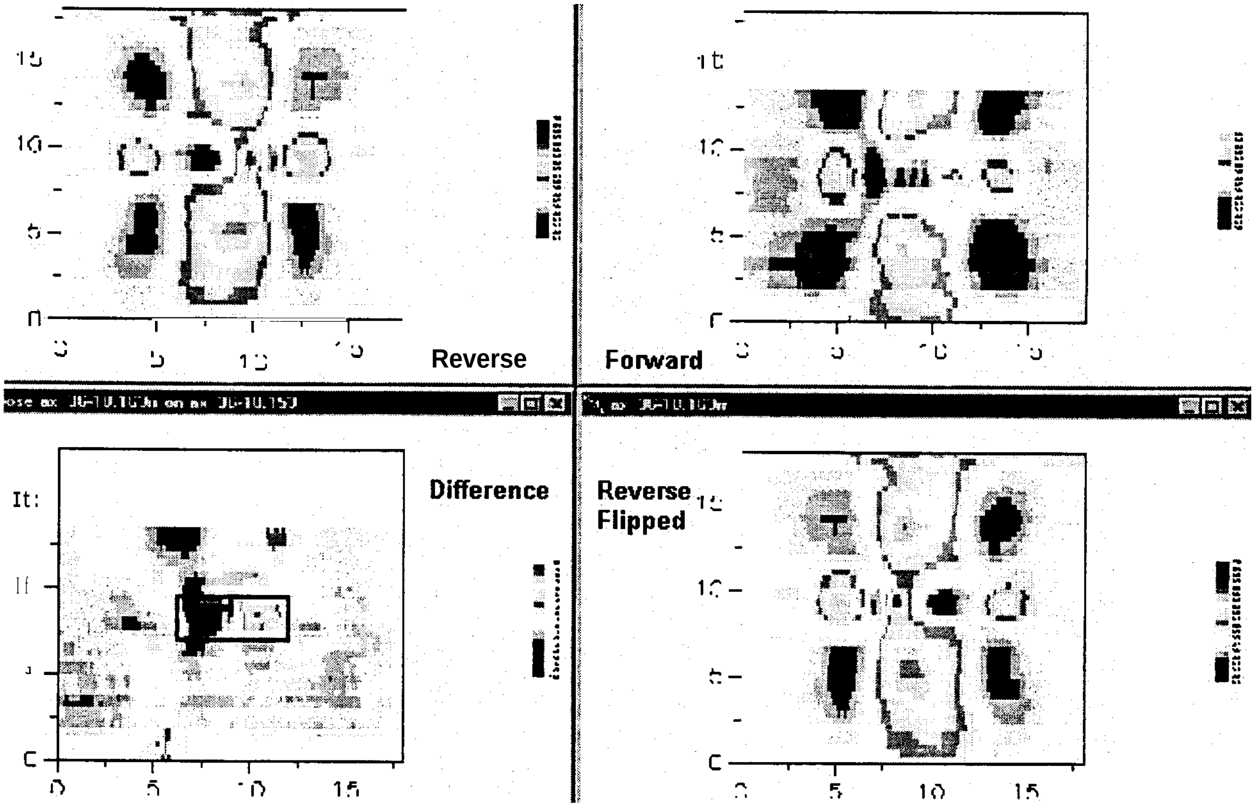
## Magnetic Dipoles

For mechanical-damage defects, the **MFL** signal appears to have a natural asymmetry. The asymmetry is not well understood but is related to the direction in which the defect is magnetized. That is, the asymmetry is a function of the orientation of the magnetizer's north and south poles relative to the defect. The magnetic dipole is always oriented in one direction relative to a magnetizer and is superimposed on the MFL signal caused by the damage itself.



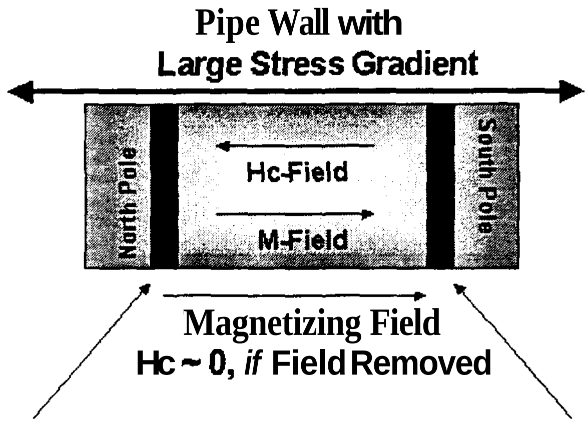

The figures shown above illustrate the dipole. The top two figures represent inspection signals from two different directions for a symmetric defect (some of the data in the top right figure is clipped). The figure at the lower right is the reverse of the figure on the upper left. If the two top-most signals were mirror images of each other, the two right-hand signals should be nearly identical. They are not.

Away from the center of the two signals, the far field is similar. The general pattern is the same in both signals, with nearly identical signal strength (color) and shape of dominant signal features. Here, the signals appear to be mirror images of each other

In the center of the defect, the two signals do not match. The lower right signal has a definite peak (red spot) near the left center of the defect. There is no corresponding peak on the upper right signal.

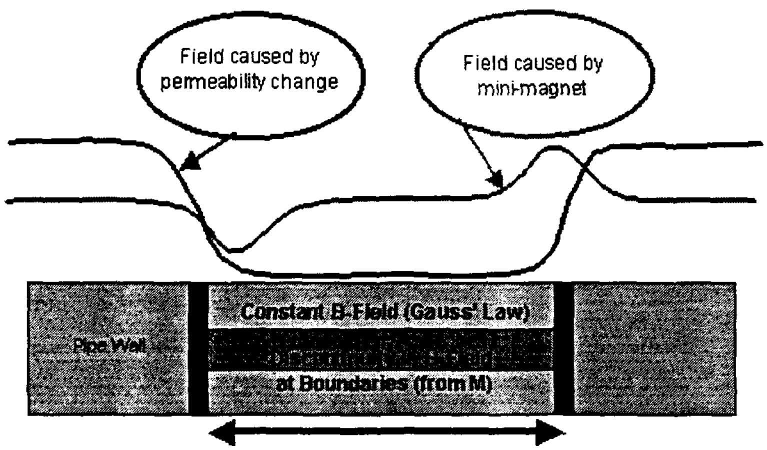
Subtracting the two figures on the right highlights the difference, which is shown in the lower left plot. The far field in this plot corresponds to a low level signal, which is probably the result of material property variations. In the center, there is a negative peak (dark blue in color) and a positive peak (yellow red) - the signal of a dipole.

**Possible Basis for Dipole**




Domain Boundaries Locked, Act Like a Mini-Magnet

A possible explanation of the dipole is that it results from magnetic domains being held in place by very high stress and strain gradients around the defect. When the pipe is magnetized, as shown in the right, the domain boundaries on either side of the defect along the pipe axis can be locked by strain gradients, creating a mini-magnet with north and south poles. The strength of this mini-magnet depends on the stress and strain gradient and the strength of the magnetizing field.




Large Residual Stress
Large Stress Gradients

Residual stresses and plastic strains around a mechanical damage defect create changes in permeability. The measured field is inversely proportional to the change i e ili As t chan in permeability increases near areas of m anical r the measured signal decreases and produces a characteristic dip in the flux leakage signal.

The dipole created by the mini-magnet adds to the signal at one end and subtracts at the other end of a mechanical damage defect. Because the magnetic domain boundaries are locked, the mini-magnet can align itself with the magnetizing field. Hence, it always aligns itself with the magnetizing field.

## Implications

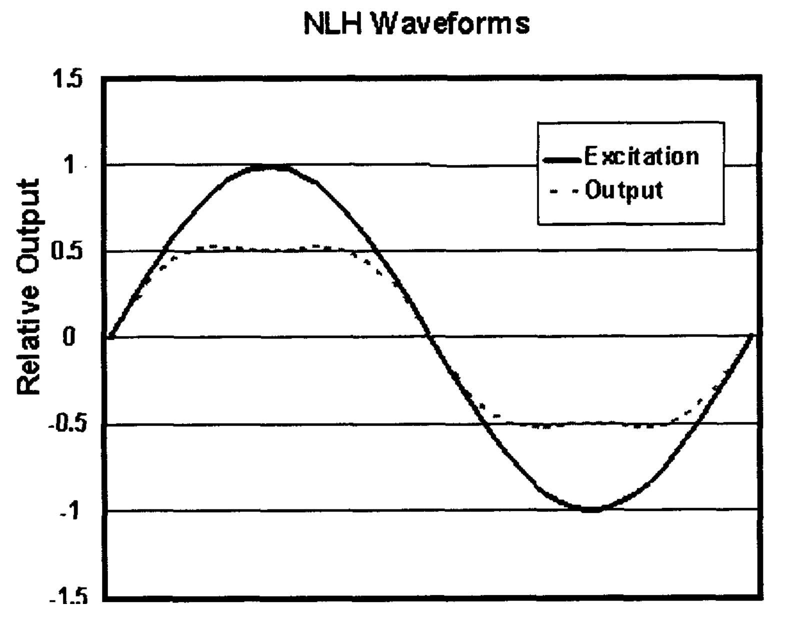
The direction of magnetization with respect to the defect must be considered when a dipole is created. Since MFL signals are a function of defect characteristics, characterization will be difficult when a dipole is present.

If the above explanation of the formation of the dipole is correct, the strength of the dipole should relate to the gradients of stress and strain in and around a gouge. The strength should also relate to the positions of maximum gradients - that is, it should be a function of the length, depth, and width between areas of maximum gradient. Using this knowledge, it may be possible to develop analysis procedures (and tool geometries) that take advantage of the dipole to provide improved defect characterization.

# Overview of Nonlinear Harmonic Method

Non-linear harmonics (NLH) refers to the use of an eddy current technique that is sensitive to the state of stress and plastic deformation in steel. Magnetic properties are affected by stress and deformation. As a result, harmonics of an input signal can be generated by the hysteretic characteristics of the magnetic properties of the pipe steel. In practice, the method begins with the application of a sinusoidal magnetic field at a fixed frequency to a material. A detector is used to sense odd-numbered harmonics of that frequency (typically the 3rd harmonic).

The following figure shows an excitation waveform as a solid line. The secondary voltage whose distortion represents a high third harmonic content is shown as a dashed line. This third harmonic can be detected using bandpass filtering or a lock-in amplifier. Because measurements can be accomplished using a relatively high excitation frequency, the method should lend itself to rapid scanning, and thus could be readily implemented on an inspection pig.



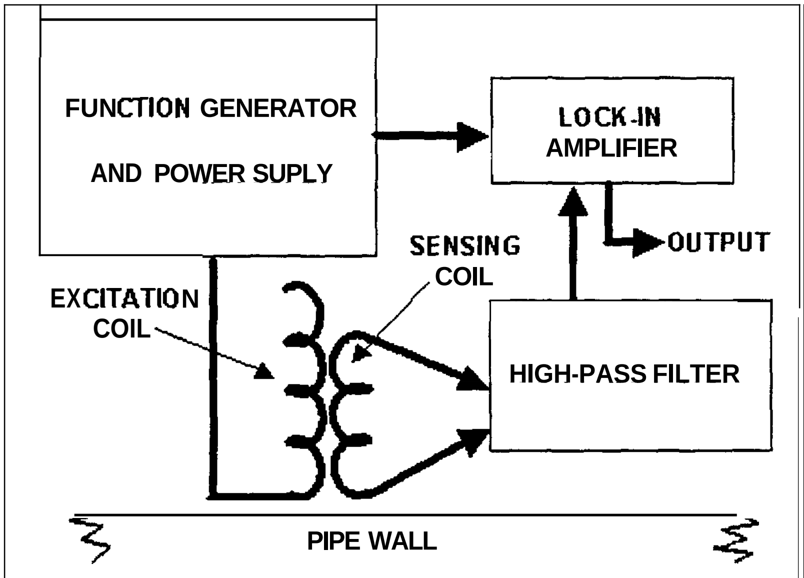

Nonlinear Harmonic Waveform

For more information on the effects of stress on nonlinear harmonic response, refer to Effects of Stress on the Harmonic Content of Magnetic Induction in Ferromagnetic Material .

## Details on Nonlinear Harmonics Measurements

### NLH Measurement Program

The use of nonlinear harmonic technology for detecting and measuring stresses around a mechanical damage defect was evaluated in this program. The block diagram given below shows the system connections and instrumentation used for the nonlinear harmonic system. In Task 1, fundamental data were collected to demonstrate and quantify the sensitivity of nonlinear harmonics to applied stress and plastic deformation.



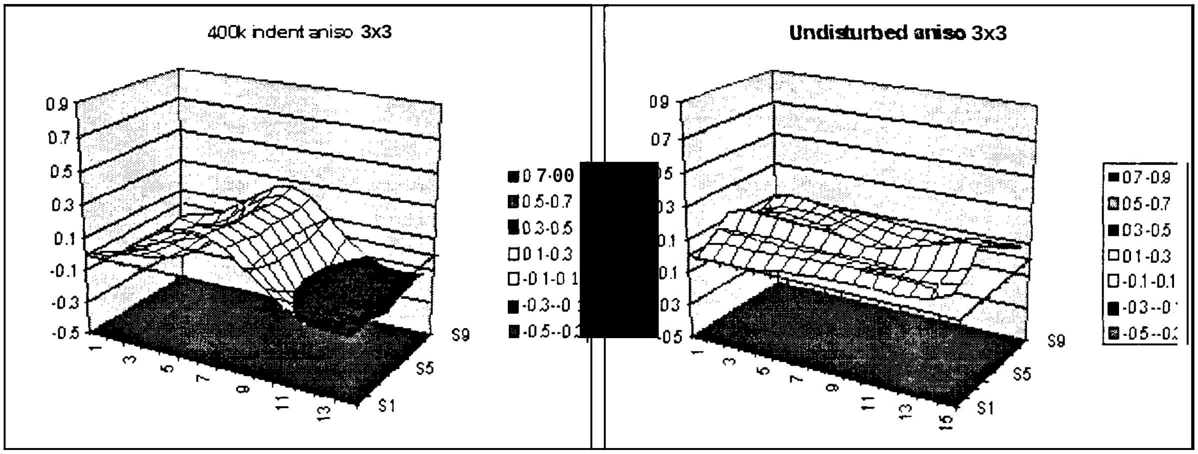

Nonlinear harmonic schematic

Using dog-bone and cruciform samples, small nonlinear harmonic probes were used to collect third-harmonic data as the samples were loaded both within and beyond the elastic range. The magnetic permeability of steel changes with applied stress and plastic deformation, and previous work also indicated that the nonlinear harmonic output changes with changes in magnetic permeability. It follows then, that nonlinear harmonic output should be an indicator of applied stress and plastic deformation. The laboratory experiments demonstrated that capability.

Following the initial laboratory experiments, several test specimens were fabricated with different types and severities of mechanical damage. The specimens were scanned with nonlinear harmonic probes oriented with the magnetic field in orthogonal directions. Amplitude and phase of the fundamental and third harmonic were collected and were used to generate line plots and color surface maps. These plots showed that nonlinear harmonic could be used to detect the stressed area around a mechanical damage defect.

Parameters that were varied included probe size, excitation frequency and probe orientation. There was also an initial evaluation of probe lift-off effects. The following figure shows a typical two-dimensional response to an undisturbed plate and a plate that has experienced plastic deformation. The figure on the left shows the initial nonlinear harmonic response, and the figure on the right shows the response after plastic strain has been applied. The change in signal is an indicator of the amount of strain that has accumulated.

Results to date show that it may be possible to use nonlinear harmonics to detect the stressed area around a mechanical damage defect. Additional parameters that are being studied include probe size, excitation frequency and probe orientation. There is also an evaluation of probe lift-off effects. This work is continuing, and conclusions will be drawn later in the program.

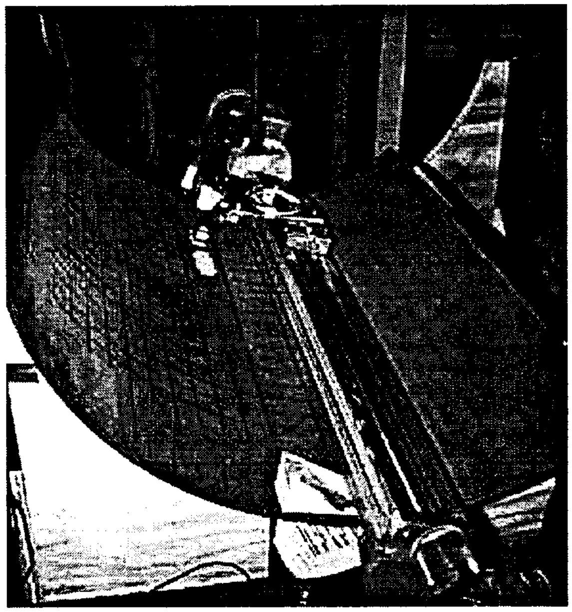



Nonlinear harmonic plots

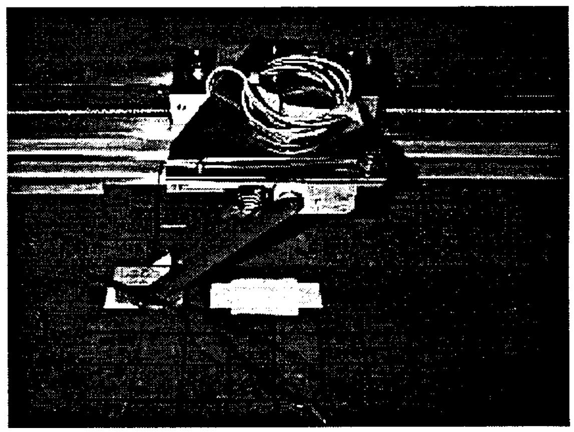
For more information on nonlinear harmonic measurements, refer to Nondestructive Measurement of Stress in Ferromagnetic Steels Using Harmonic Analysis of Induced Voltage and Application of the Nonlinear Harmonic Method to Stress Measurement in Steel.

## Evaluation of Liftoff Effects

### Apparatus



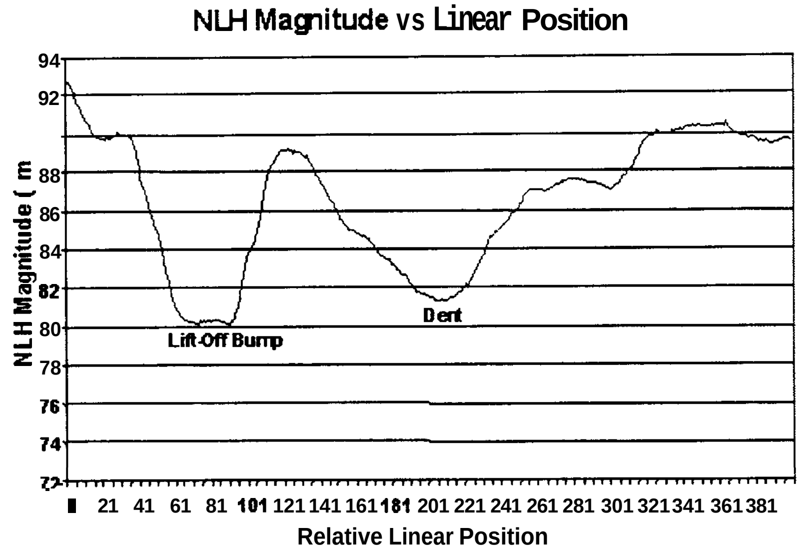
A NLH sensor is essentially a transformer whose core is composed of the ferrite core within the sensor plus the pipe material itself. There is a necessary air gap between the ferrite core and the pipe. The length of this gap, called "standoff', controls the amount of magnetic coupling between the primary and secondary windings of the sensor. As the gap increases, the amount of energy put into the workpiece drops with a resulting drop in NLH sensitivity.



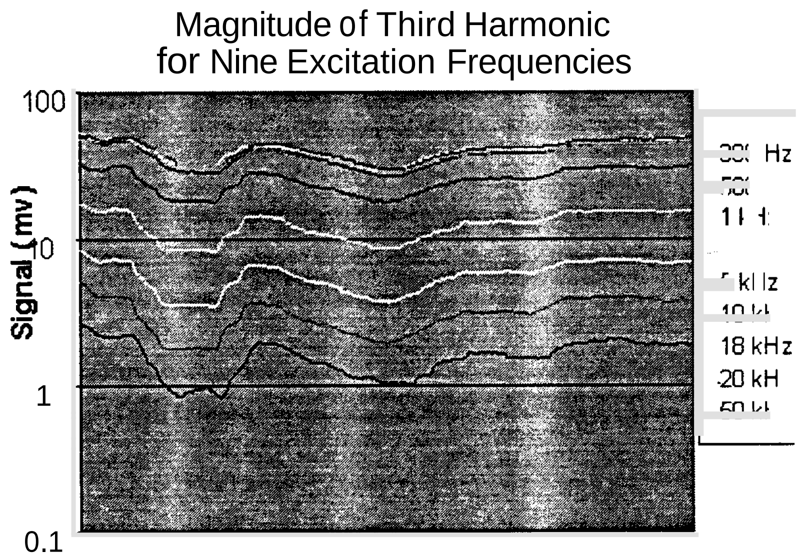
If a probe is held is a position with one air gap and then is moved to a position with a different air gap, there will be an NLH signal from the sensor, even though the properties of the pipe wall may not have changed. Such a change in standoff can occur if the sensor passes over a deposit adhering to the pipe surface, or if it bounces off the pipe due to mechanical impact.

To evaluate the lift-off effect, a test apparatus was assembled, as shown at right. The apparatus consisted of a segment of 24-inch pipe onto which a computer controlled scanner was attached. An NLH sensor was spring loaded against the pipe surface and scanned in an axial track down the specimen.

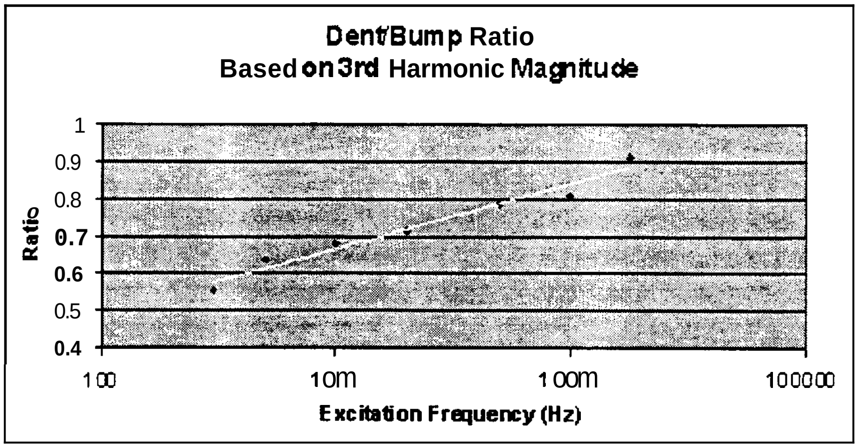
Before passing near the dent, the sensor was caused to ride over a non-metallic bump that momentarily changed the standoff. The resulting NLH waveform then shows both the bump (lift-off) and the dent, as shown at right.



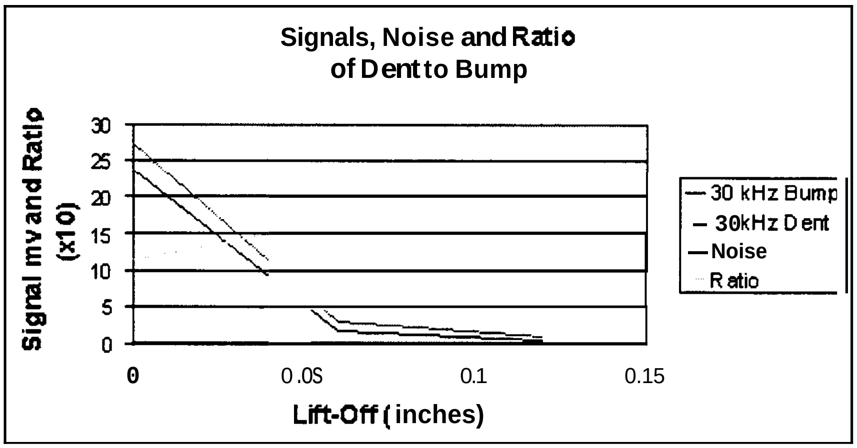

With this set-up it is possible to evaluate probe operating parameters in the way they affect the relative strength of dent and lift-off. For example, successive scans at different excitation frequencies reveal the effect of frequency on the NLH response. If the ratio of dent to bump signals is plotted as a function of frequency, it is noted that the best operating point is at the highest frequency (see below)



In addition to the bump, fixed amounts of lift-off may be added to the system by adding various thickness shims to the bottom of the sensor, i.e. between the sensor and the pipe surface. It is important to protect the NLH sensor core and windings from damage by contact with pipe wall irregularities and debris in the pipeline. A non-conductive material can be added to the sensor face to provide protection, but it also adds lift-off. By running successive scans with increasing thickness of non-metallic shims, a curve of dent and bump amplitudes and ratio can be developed.




For more information on the effects of stress on nonlinear harmonic response, refer to Effects of Stress on the Harmonic Content of Magnetic Induction in Ferromagnetic Material.



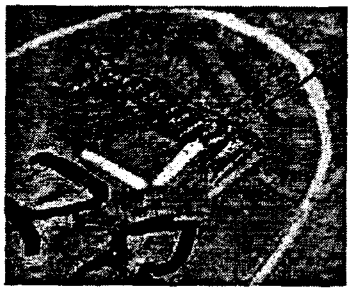
# Details on Quantitative Damage Measurements

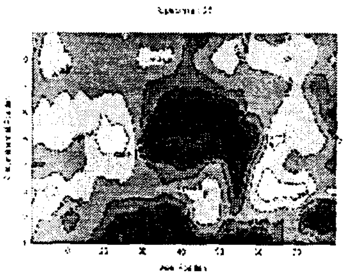
| DEFECTS FOR QUANTITATIVE EVALUATION OF NLH RANKED BY ESTIMATE OF RELATIVE SEVERITY | | | | |
|---|---|---|---|---|
| | Dent | | Gouge | |
| Defect No. | Depth (%) | Length (in.) | Depth (%) | Length (in.) |
| 31 | 6 | 2 | 10 | 2 |
| 28 | 0 | 2 | 25 | 2 |
| 86 | 2 | 4 | 5 | 4 |
| 84 | 2 | 2 | 5 | 2 |
| 85 | 2 | 2 | 5 | 2 |
| 29 | 6 | 0.25 | 5 | 0.25 |
| 87 | 5 | 0 | 0 | 0 |

An important aspect of any system for detecting mechanical damage is how well it is able to characterize the detected damage. Although methods for precise assessment of mechanical damage have not been clearly established, there are some generally accepted guidelines that make it possible to assign relative severity ratings to mechanical damage defects.

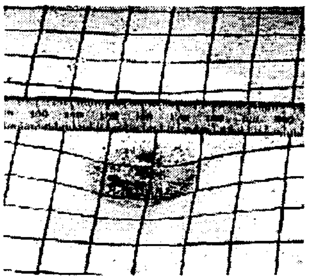
To evaluate the NLH ability to characterize mechanical damage defects, seven artificial defects were scanned with an NLH probe, using the same settings in each case. The defects were various combinations of dents and gouges of different depths and lengths. **All** defects were in 2-foot square coupons of 24-inch pipe. **All** defects were scanned in a 2D matrix of sample points and data were reduced to color maps of NLH output. Data were taken with the probe in axial alignment with the pipe and also perpendicular alignment,

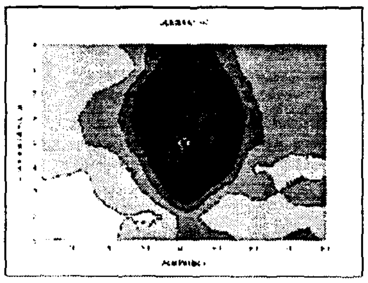
Correlation of the physical description of the defect and the NLH signal is apparent by examination *of* the data output (see below - each photograph and signal is a link). One particularly interesting defect is No. 28, a gouge without dent. **A** contour plot shows that there is an easily recognized signal pattern that corresponds to the defect geometry even though there is no residual deformation of the pipe inside surface.

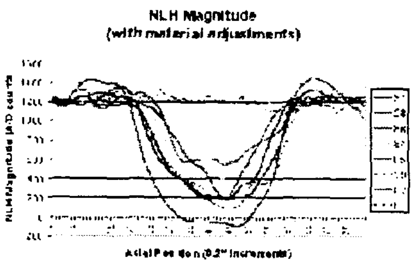




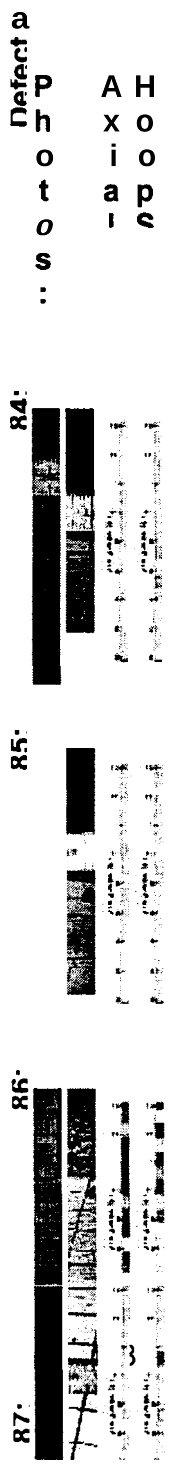
**A** simple round dent, defect 87, produces a similarly shaped contour pattern. The NLH ability to detect the whole range of defects with a good signal to noise ratio is illustrated in sinale-trace plots

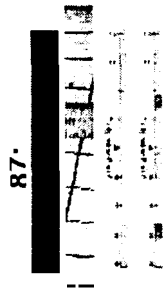






across the defect
centers, including
a plate with no
defect to
illustrate typical
noise level



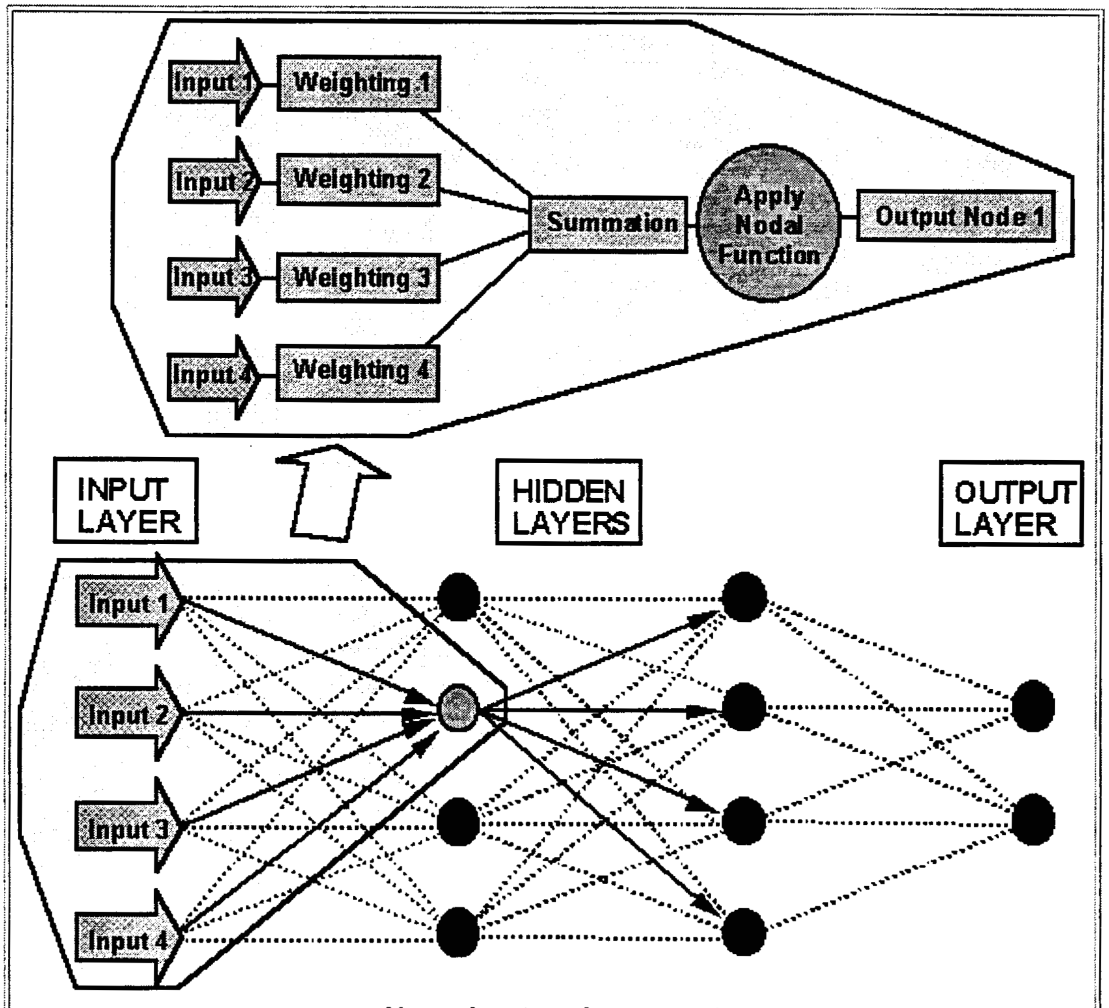


Careful examination of the single-trace plots and the severity table shown above shows that even though there is good detection of all the defects, there **is** not a clear indication of defect severity in the relative NLH signal amplitudes. This suggests that the NLH data should be considered in consort with other measurement technologies for determining severity of mechanical damage.

# Introduction to Neural Networks[Haykin99]

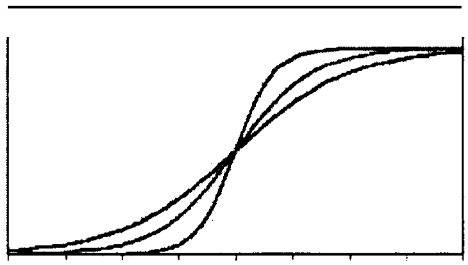
A neural network is an analysis method that uses a large number of relatively simple calculations to make a prediction. For example, a neural network can be designed to predict the shape of a corrosion defect or classify an indication based on information contained in the MFL signal. Although the calculations are simple, the large number of computations performed in concert allows neural networks to perform fairly sophisticated tasks.

The following figure is a graphical representation of the structure of a neural network. In the following figure, the input to a node (a connecting point) is shown by lines from the left and the output is shown by lines to the right. Each line represents a calculation, such as multiplying an input value by a constant. Each input parameter (e.g., signal amplitude, length, etc.) is multiplied by a (different) constant and used as input to the nodes. The action taken on the input is termed *weighting* or *synaptic weighting.*



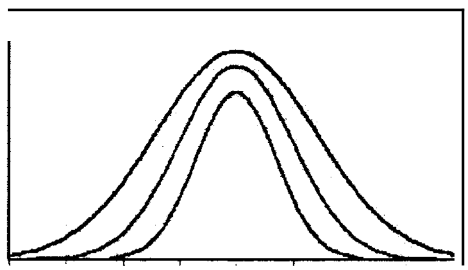

Neural network concept

A nonlinear function of the sum of the inputs to a node is calculated at the node. The function that is applied at the node to the sum is called the *nodal function.* Each nodal function has a set of parameters that further define it. The nodal functions are the building blocks used for fitting the neural network's output to the training data. Nonlinear basis functions allow nonlinear fits to the data, which are needed for more complicated problems.



**Sigmoid basis function**

In a sense, each nodal function has a shape associated with it (for example, the shape of a logarithmic curve), and the output is made by summing various combinations of these shapes. For simple neural networks, such as those that make binary or yes/no decisions, sigmoidal or arctangent functions work best. For more complicated problems, such as predicting the shape of corrosion, certain functions are better suited than others in representing the intended output.



**Gaussian basis function**

In work done to date, several types of basis functions have been considered. In the multilevel perceptrons, a sigmoid function was used. The sigmoid function is a gradual step, from zero to one, as its input varies from negative to positive. It works best for binary decisions, such as whether a defect signal is from mechanical damage (output equals one) or not (output equals zero). The network can be trained to identify mechanical damage if the output is larger or smaller than some value.

For the more complicated problem of predicting defect geometry, *radial basis functions* were employed. Several radial basis functions were considered including Gaussian (an inverted bell shape), logarithmic (values ranging from negative infinity to positive infinity), and a multiquadric (values ranges from a finite number to infinity).

Typically, radial basis functions are centered about some point (a fixed value of an input parameter) and they vary with the "distance" or difference from that point. Radial basis functions provide a better ability to simulate the shapes of corrosion defects. They are considered good approximators near the training data but are less accurate away from the training data.

In addition, a third set of basis functions, called *wavelet functions,* is being investigated. Wavelet functions are similar to radial basis functions. However they offer better approximation properties both locally and globally.

For more information on neural networks, refer to An Introduction to Computing with Neural Nets, Neural Networks: A Comprehensive Foundation, and Multivariate Functional Interpolation and Adaptive Networks.

# Overview of Training for Perceptron Neural Networks[Haykin99]

Determining the unknown parameters in a neural network is called training. Training is analogous to fitting a nonlinear curve through several points - there are many curves that pass through the same set of points. The key is to determine a set of parameters that reasonably matches the data and that can be extrapolated or interpolated to other sets of data. Forcing the fit to exactly match the data is possible, but usually produces poor results. When this happens, a neural network is said to be over-fitted. This is possible when the amount of training data is limited and is to be avoided.

The process of learning the values of the unknown parameters is at the heart of neural networks. The choice of the training method is important. Different methods have been developed (or are being developed in this program) with the goal of efficiently learning the parameters and producing a network that works well over a wide range of input conditions.

## Training Example

Understanding the learning process of a neural network may not be intuitive. While different techniques are used, the method outlined below is fairly typical for multilayer perceptrons. The procedures for training radial basis function and wavelet networks are different.

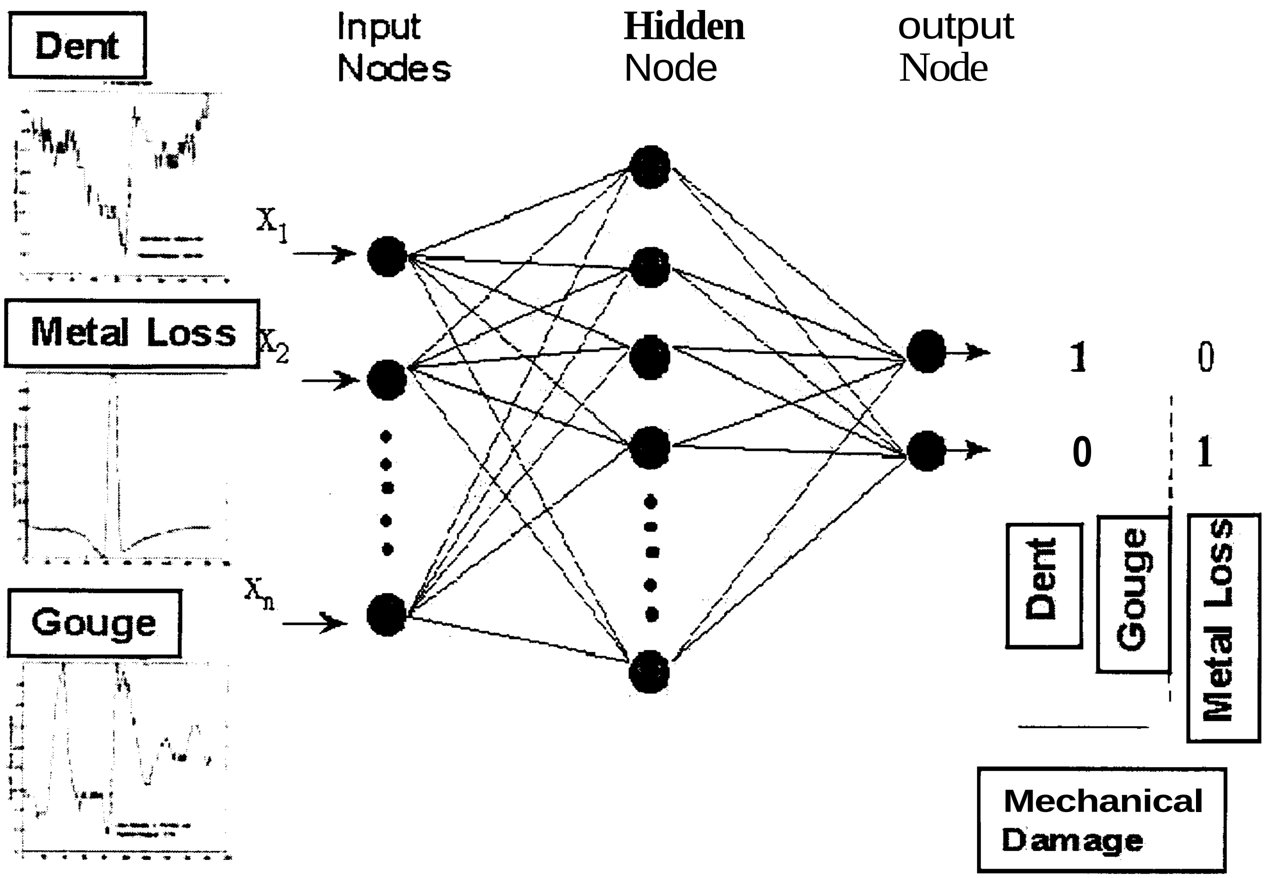
Typically, at the start of training, random values are assigned to the unknown parameters. Hence, at this stage, the neural network will produce some arbitrary output. One set of input data is used, and the calculated output is compared to the desired output. As expected, they will differ. Next, the derivative of the output is taken with respect to each unknown parameter - that is, calculations are made to determine the gradient of the error function (how the output will change as each parameter changes independently).

Based on the gradients, a change is calculated for each parameter. Then, the changes are applied and the process is repeated with the next set of input data. If the problem were linear, one set of changes might produce a network that matches the data exactly. Usually, though, a change in one parameter affects all other calculations, and so, the network's output does not match the data. The process is repeated, and it is continued iteratively, until the remaining error falls below some arbitrary threshold. This process is known as learning.

The process of determining the derivatives and using them in the manner described above is called backward propagation. The term backward propagation is used to suggest that the errors are corrected back through the network using the derivatives or gradient of the error function.

Training the radial basis function networks and the wavelet networks is far more straightforward and does not involve the use of iterative procedures. The training procedure typically involves the inversion of a data matrix and is consequently easy to implement.

## Graphical Representation of Perceptron Neural Networks




Multilevel perceptron structure

## Additional Details on the Prediction of Two-Dimensional Stress Fields [Ivanov98]

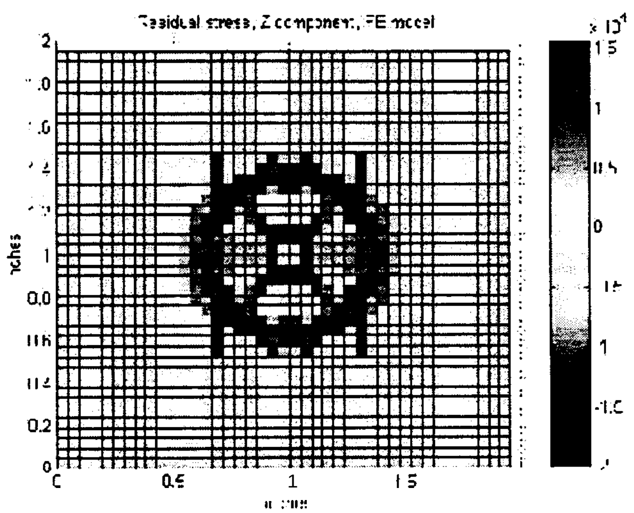
### Test Measurements

Two-dimensional stress fields were studied using defects installed on 4-inch by 1/4-inch by 16-inch 1018 cold-finished flat steel plates. Two defects were placed on each plate to avoid the blooming effect of MFL signals for defects that are very near each other.

Two basic methods were used to prepare the defects. Simulated gouges were made by pressing a steel ball-bearing on the steel plate with a hydraulic pressure machine. Two different sized ball-bearings and ten pressure levels of the hydraulic pressure machine were used for a total of twenty gouge defects. **A** set of twenty corresponding metal loss defects was made by drilling out material from the plate.

The steel plates were magnetized with a custom magnetizer. The three components of the MFL signal from the defect were recorded with a Gauss meter for varying magnetization levels from about 1,300 A/m to 34,000 A/m. The specimens were magnetized to saturation, and the magnetizer was removed in order to measure the residual field signals.

Data were recorded for all defects for the 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. **A** very small residual leakage field signal was recorded for the metal loss defects, while the leakage field was larger for the gouge defects.



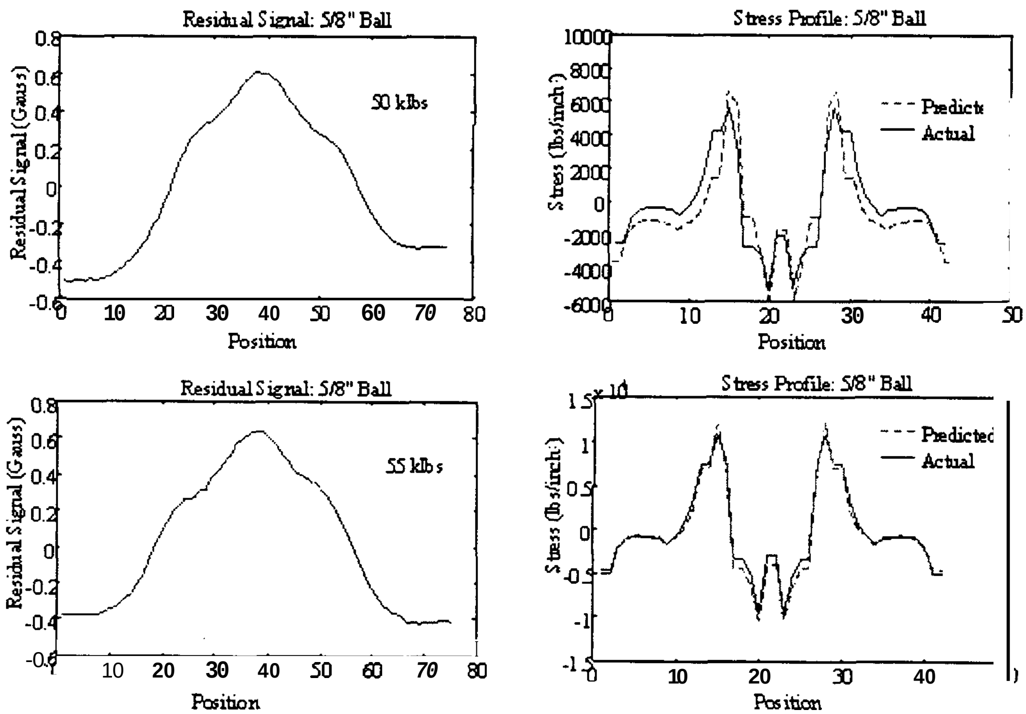
Residual stress distribution

## Finite-Element Modeling [Ivanov97]

Finite element modeling involved a structural analysis of the specimen in order to obtain the distribution of stresses from known loading conditions. An active "stress profile" was defined as the aggregate stress around the defect. The stress profiles and corresponding residual MFL signals were used as training data for the stress characterization algorithm. Finite Element Modeling of Defect Installation Process.

Mapping from the MFL signal to the stress profile was accomplished using a radial basis function network. The input to the network was taken from the residual MFL signal. In order to determine the optimal network configuration (i.e., to find the synaptic weights), both the training data and the support of the radial basis functions were varied (the support is one of the parameters that defines the functions).

The network was tested with MFL signals that were not part of the training set and the predicted stress profiles were compared with those generated by the mechanical damage finite element model. Typical results are shown below. The agreement between the predicted and desired profiles indicates that this method shows considerable promise.

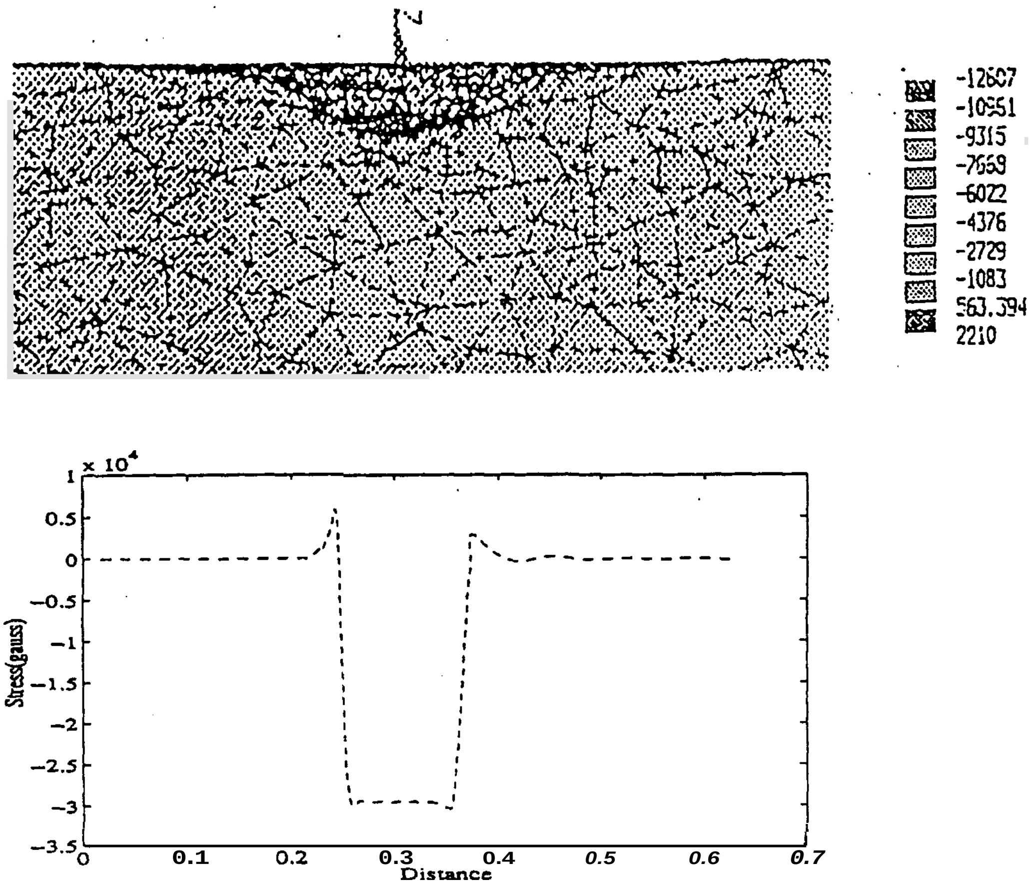



Two-dimensional stress distributions

## Finite-Element Modeling of Defect Installation Process

The defect installation process 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 with a Young's modulus of $30\times10^6$ psi, a Poisson's ratio of 0.3 and specific density of 0.283 $lb/in^3$. The model was meshed with tetrahedral elements and care was taken that the element side length ratio did 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 load was perpendicular to the outer surface: therefore, the largest strains and stresses appear normal to the pipe surface. The external magnetization is along the pipe axis and is perpendicular to the largest component of the stress vector. The effect of compression was modeled by increasing the permeability, and similarly areas under tension were modeled by lowering their permeability values.




Stress distribution and stress profile for a 10 ksi, gouge

The results of elastic, static structural analysis for a load of 10 ksi are shown above. The top figure represents the distribution of the stress perpendicular to the top surface of the specimen, while the bottom figure shows the one-dimensional "stress profile" corresponding to that stress distribution. 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.