Volume 8, No. 5, May – June 2017
International Journal of Advanced Research in Computer Science
RESEARCH PAPER
Available Online at www.ijarcs.info
ISSN No. 0976-5697

Characterization of LF and LMA signal of Wire Rope Tester

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Abstract: Safe use of ropes implies different methods of inspection: destructive inspection and nondestructive testing with visual and instrumental inspection. Destructive inspection can only bring the information about tested part of rope. Magnetic non destructive evaluation is regularly done for assessment of rope condition. Magnetic flux leakage techniques are widely used for wire rope inspection to assure its integrity and safe operation. MFL signals are captured from wire rope tester with the help of hall sensors. Two types of defects are present in wire rope i.e. LF and LMA. These defects are captured with the help of hall sensors. Hall sensors were used in such a way so that it can capture signals both axially and circumferentially. Hall sensors are organized to produce a MFL image. To preprocess the MFL image digital image processing technique is used. Gray level co-occurrence matrix is used to extract the features of MFL image. BP network based feature extraction technique is used to detect defects in a wire rope.

Keywords: Wire rope defects; MFL image; Feature extraction; Gray level Co-occurrence matrix; BP network

I. INTRODUCTION

Wire ropes would generally utilize within streamlined production, bridges, under water networks, metallurgy, elevators and mining. Therefore, it is essential to guarantee the protection of the wires constantly utilized. The study of the residual strength of wire rope is significant for developing advanced instruments that can quantitatively detect wire rope defects [1]. MFL strategies would generally utilize for wire rope investigation to confirm its protected operation and integrity. This strategy requires that the wire rope under test may be magnetized to saturation. The magnetization generates magnetic flux streaming in the wire rope in specific direction; magnetic flux is perpendicular to axis of the defects to be distinguished. The existence of any defect will be visible as a sudden transform of the magnetic flux exuding from wire rope. This leakage flux is perceivable by a magnetic sensor spotted in the region of wire rope surface. This leakage testing can be divided into two categories forward and inverse problem. The forward problem includes the computation of the distribution of the MFL signals. Inverse problem includes the computation of defects parameters from the distribution of the MFL signals. The defect parameters that disturb the distribution of the leakage flux are sharpness, depth, width, length at the edge. Permanent magnets are usually used as a magnetization device. Hall sensors can be used to measure the leakage field [2]. With the help of sensor array, the MFL signals can be shown in the form of a digital image, which is transformed to program defect identification. The texture analysis methodology is used to describe the defect detect ability. Wire rope defects might make described with features extracted from the gray level co-occurrence matrix of MFL image [3]. Organization of paper is as: In section II Magnetic flux leakage inspection is explained, in section III feature extraction technique is discussed, in Section IV recognition of defects is discussed and section V concludes the paper.

II. MAGNETIC FLUX LEAKAGE INSPECTION

MFL System for Wire Rope Inspection

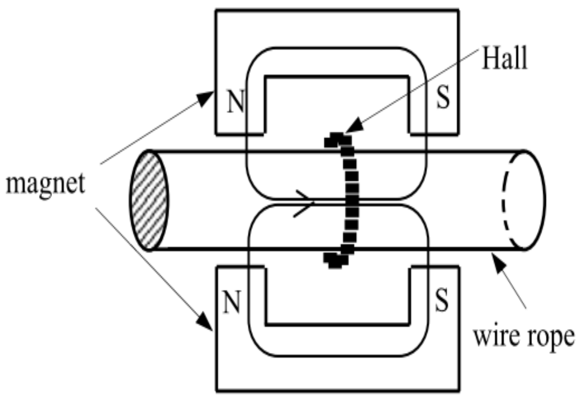


Figure1 Schematic view of system structure [2]

The wire rope non-destructive test system is mainly composed of a Hall sensor array, magnetizer mechanism and data acquisition system. The magnetizer mechanism with eight circumferentially uniform pole pairs is used to longitudinally magnetize the wire rope to saturation. The Hall sensor array is composed of 12 Hall sensors that are distributed around the magnetized wire rope. The signals of magnetic flux leakage are captured by the Hall sensors as the defects passes by [4].

LF/LMA defects and corresponding Signal

Electromagnetic inspection, detection and evaluation of external and internal rope deterioration. This allows inspection through the entire cross-section of a rope to its core. There are two types of defects, LF (Local Fault) and LMA (Loss of Metallic Area) that are present in wire ropes [3].

1. Local Faults (LF): Discontinuities of the wire rope, such as broken or damaged wires, corrosion pits on the wire rope, grooves worn into the wire rope or any other physical conditions that degrade the integrity of the wire rope in a localized manner [3].

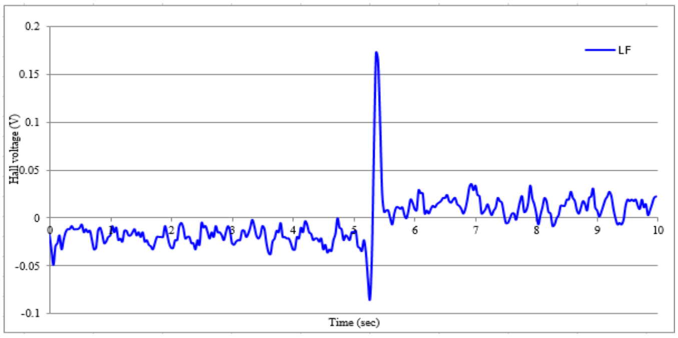


Figure 2 Plot of LF Signal

2. Loss of Metallic Area (LMA): A relative measure of the amount of material (mass) missing from a location along the wire rope and is measured by comparing a point with a reference point on the wire rope [3].

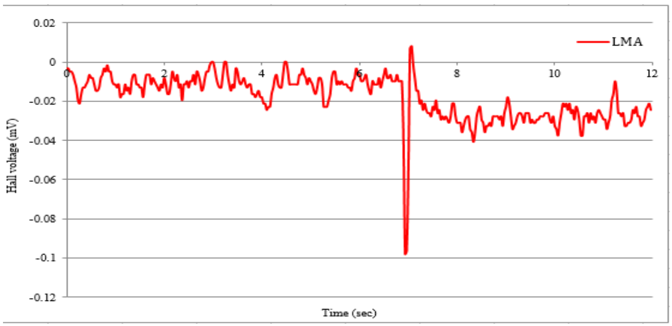


Figure 3 Plot of LMA Signal

III. FEATURE EXTRACTION

MFL image of wire rope tester signal is presented; the statistical features of this image are used to detect defects. Here, Gray level co-occurrence matrix (GLCM) is used to extract the features. Different features are derived from a MFL image. Firstly, the MFL image is converted into GLCM matrix. More specifically, 16 features are derived from that GLCM matrix. These features are: [5]

Autocorrelation, Contrast, Correlation, Cluster Prominence, Cluster Shade, Dissimilarity, Energy, Entropy, Homogeneity, Maximum Probability, Variance Sum average, Sum variance, Sum Entropy, Difference Variance, Difference Entropy.

Contrast, Correlation, Energy and Homogeneity are among the four most important features that are given below:

S.No.	Type of Signal	Contrast [min, max value]	Correlation [min, max value]	Energy [min, max value]	Homogeneity [min, max value]
1	LF at 33 cm	[5.615, 5.588]	[6.218, 6.219]	[8.710, 8.896]	[9.624, 9.704]
2	LF at 34.5 cm	[5.474, 4.954]	[6.241, 6.244]	[8.968, 9.078]	[9.715, 9.769]
3	LF at 36 cm	[5.590, 4.727]	[6.240,6.244]	[8.859,9.041]	[9.683, 9.778]
4	LF at 41 cm	[5.910, 4.917]	[6.233, 6.239]	[8.852, 9.028]	[9.677. 9.774]
5	LF at 47 cm	[6.068, 4.615]	[6.232, 6.239]	[8.744, 8.992]	[9.645, 9.784]
6	LF at 49.5 cm	[5.915, 5.037]	[6.231, 6.236]	[8.844, 9.013]	[9.675, 9.765]
7	LF at 75 cm	[5.928, 4.610]	[6.234, 6.241]	[8.780, 9.008]	[9.656, 9.783]
8	LMA at 33cm	[3.902, 7.674]	[6.191, 6.173]	[8.725, 8.707]	[9.727, 9.634]
9	LMA at 34.5cm	[5.058, 8.192]	[6.162, 6.147]	[8.510, 8.566]	[9.654, 9.610]
10	LMA at 36cm	[5.023, 6.770]	[6.202, 6.193]	[8.761, 8.813]	[9.693, 9.680]
11	LMA at 41cm	[5.028, 6.775]	[6.200, 6.192]	[8.747, 8.802]	[9.691, 9.680]
12	LMA at 47 cm	[5.419, 8.948]	[6.148, 6.131]	[8.397, 8.469]	[9.621, 9.582]
13	LMA at 49.5 cm	[3.783, 6.927]	[6.213, 6.198]	[8.926, 8.862]	[9.768, 9.669]
14	LMA at 75 cm	[5.394, 5.880]	[6.210, 6.208]	[8.639, 8.827]	[9.642, 9.722]

Table 1 Feature extraction of LF and LMA signal images with GLCM method

IV. RECOGNITION OF DEFECTS

Defect recognition is done using neural network. For such kind of recognition, the network is trained to associate outputs with input patterns. When the network is used, it identifies the input pattern and tries to output the associated output pattern. In this work back propagation algorithm has been used to train the network.

Back Propagation Algorithm

Back propagation neural network is a multilayered network which is most widely used for a classification process and for pattern recognition. Back propagation network works on non-linear mapping between the input and output layer [4]. In this paper a three layered BP network is implemented (input layer, hidden layer, output layer). BP network consist of one or more hidden layers. Classification performance is affected by the hidden layers node [6].

This algorithm repeats a two phase cycle, propagation and weight update. When an input vector is presented to the network, it is propagated forward through the network, layer by layer, until it reaches the output layer. The output of the network is then compared to the desired output, using a loss function, and an error value is calculated for each of the neurons in the output layer [7]. BP uses these error values to calculate the gradient of the loss function with respect to the weights in the network. In the second phase, the gradient is fed to the optimization method, which in turn uses it to update the weights, in an attempt to minimize the loss function [8].

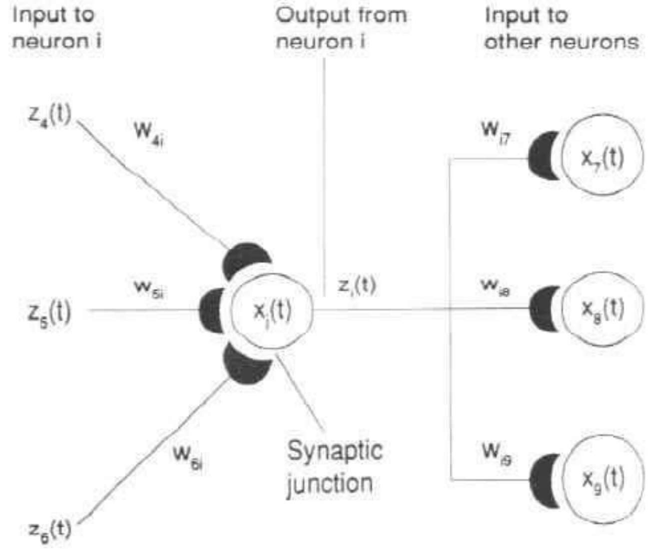


Figure 4 Diagrammatic representation of BP network [7]

V. RESULTS & DISCUSSION

The Hall sensors convert the variations of magnetic field into voltage. This voltage vs. time data is obtained in an excel sheet (.xlsx). Then this .xlsx file is converted to .mat file. That .mat file is loaded and is converted into array format. An image file is then obtained from the matrix. The image file is superimposed on the actual image of wire rope defect (i.e. captured manually using camera). This superimposed image is converted into Gray scale format. Linear spatial filter is applied on the MFL image using different spatial masks. The defects are thus clearly differentiated from the rest of the image. Gray level Co-Occurrence matrix analysis is then applied on the filtered image. Four texture measures are computed from GLCM matrix: Energy, Homogeneity, Correlation and Contrast.

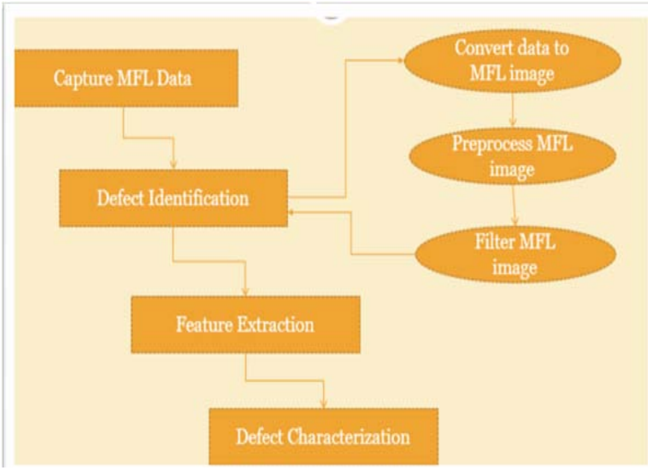


Figure 5 Steps of System Flow

Data for classification problem is set up for a neural network by organizing the data into two matrices, the input matrix X and the target matrix T. Each ith column of the input matrix will have four elements representing a type of defect; contrast, correlation, homogeneity and entropy. Each corresponding column of the target matrix will have two elements. LF defects are represented with a one in the first element, LMA defects with a one in the second element. (All other elements are zero). Two-layer feed forward neural network with a single hidden layer of 10 neurons is used. and network is trained. The samples are automatically divided into training, validation and test sets. The training set is used to teach the network. Training continues as long as the network continues improving on the validation set. The test set provides a completely independent measure of network accuracy. The trained neural network is then tested with the testing samples. This gives a sense of how well the network will do when applied to data from the real world. To measure how well the neural network has fit the data confusion matrix is plotted across all samples.
Regression defines the amount of correctly classified data. For **Training data set** R=1 Network is trained with 100% efficiency. For **Validation data set** R=0.96722 validation check are performed with the efficiency of 96.7%; which is a satisfactory result.For **Testing data set** R=0.97085: Testing checks are performed with the efficiency of 97.08%. The **overall value** for R=0.9901 i.e. the network performance is 99%.

As shown in figure 7 the least value of mean square error for validation data is 0.020002 at epoch 16 which is considered as the best validation performance.

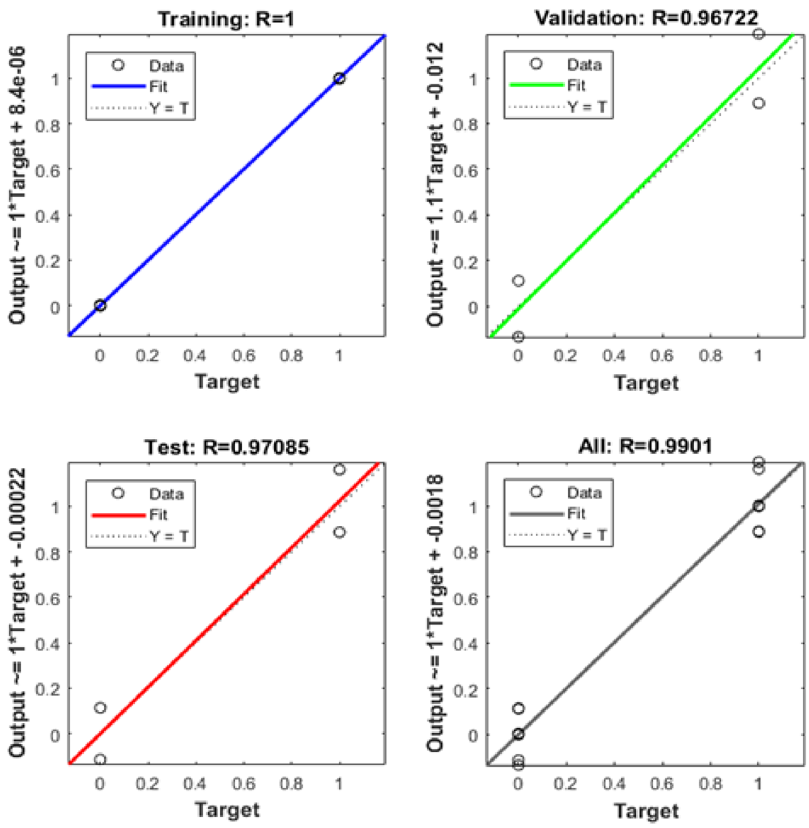


Figure 6 Regression Plot

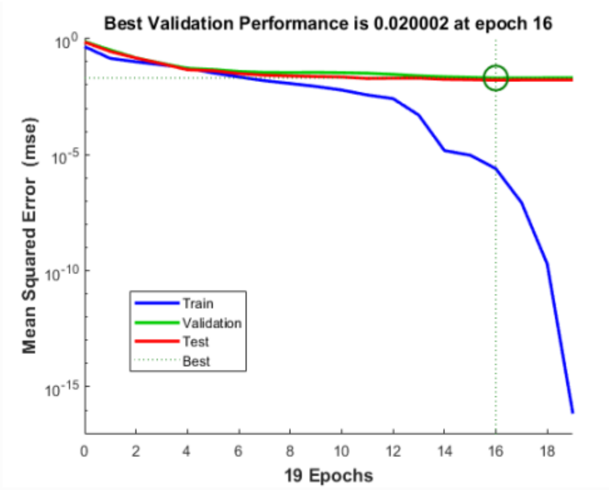


Figure 7 Performance Plot

As shown in figure 8 Minimum value of gradient is 1.1329e-08 at epoch 19. Minimum value of mu is 1e-11 at epoch 19. Maximum validation checks failed are 3 at epoch 19. The performance in the upcoming epochs would degrade hence the training is stopped at this point.

As shown in figure 9 for maximum of the data the error value is close to 0. The maximum error value obtained is |0.1842|.

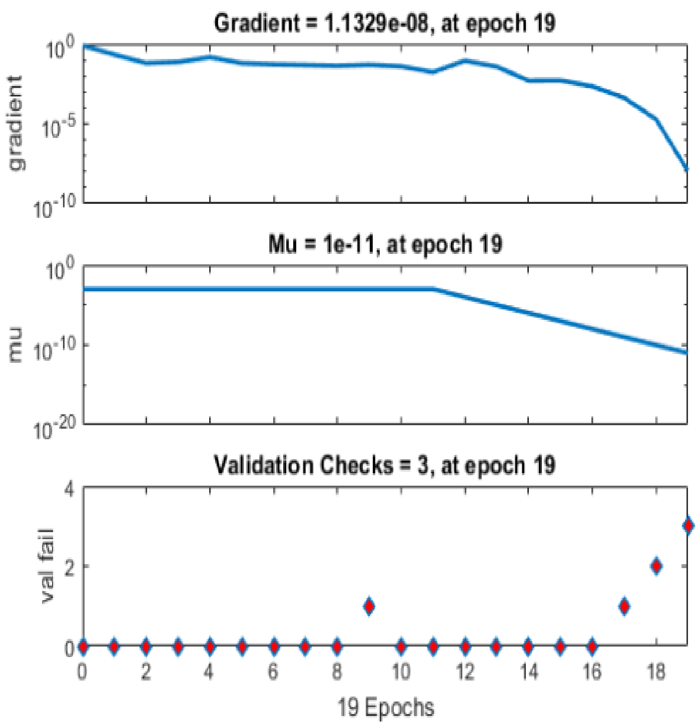


Figure 8 Training State Plot

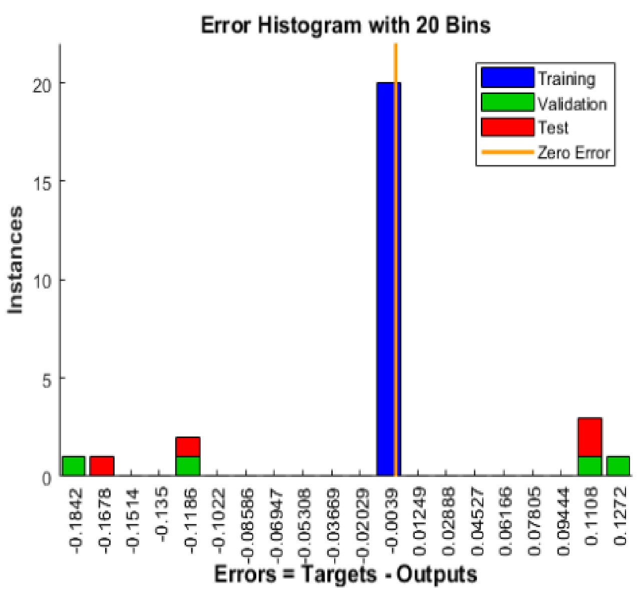


Figure 9 Error Histogram Plot

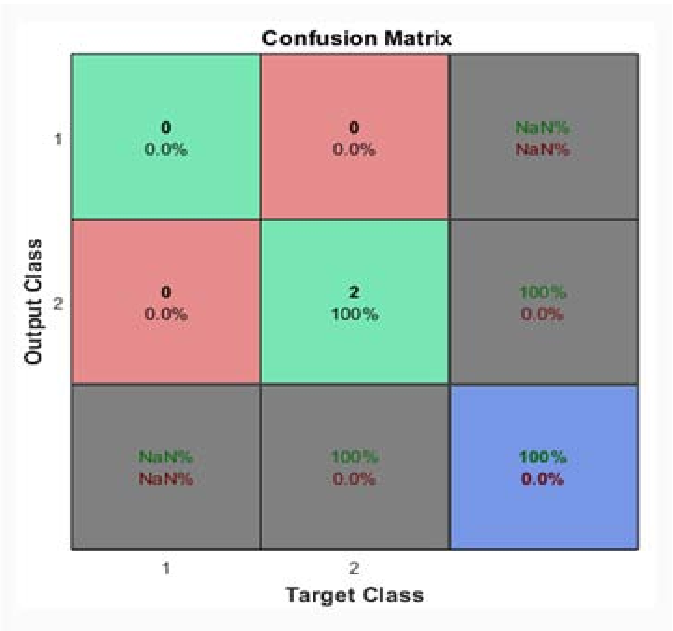
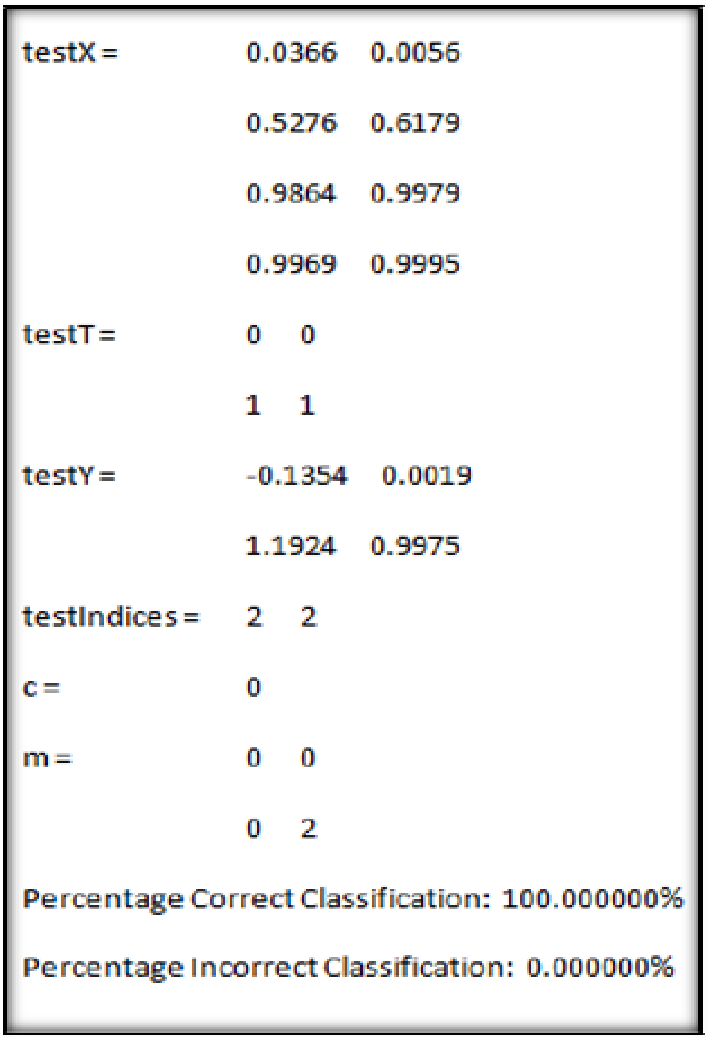


Figure 10 Confusion Matrix Plot



testX = 0.0366 0.0056

0.5276 0.6179

0.9864 0.9979

0.9969 0.9995

testT = 0 0

1 1

testY = -0.1354 0.0019

1.1924 0.9975

testIndices = 2 2

c = 0

m = 0 0

0 2

Percentage Correct Classification: 100.000000%

Percentage Incorrect Classification: 0.000000%

Figure 11 Performance values of Confusion matrix

Figure 10&11 shows the %age of testing data correctly and incorrectly classified. Class 1 represents the LF defects in testing data and class 2 represents the LMA defects in testing data. The green blocks specify the correctly classified testing data in each class whereas the red blocks specify incorrectly classified data. The overall performance of the testing classifier obtained in this matrix was 100% and was represented by the blue block.

VI. CONCLUSION

In this work, Magnetic Flux Leakage (MFL) technique is used which is a non- destructive electromagnetic technique to find out the defects in the wire ropes. An intelligent MFL testing equipment, consisting of the sensing detectors has been used which led to detection of any kind of leakage of flux from the wire. The signal data from this setup is taken in form of signal and processed in MATLAB. As a part of processing, the captured MFL data is converted into images and the images are filtered to obtain a clear picture of the defects present in the wire rope. For each defect GLCM matrix is obtained and through this matrix features like homogeneity, correlation, energy and contrast for various defects are identified.

Defect recognition and classification has been done using neural networks. A two-layer (i.e. one-hidden-layer) feed forward neural network with a single hidden layer of 10 neurons is used to which input matrix fed was the values of GLCM features of all the defects obtained. To see how the network's performance improved during training, various plots such as regression, performance, error histogram and training state are displayed and then analyzed. Our network got trained in just 19 iterations because of the less amount of data used. For this data the average efficiency (for training and then testing the neural network used) came out to be 99.01% which is a good result. To measure how well the neural network has fit the data confusion matrix is plotted across all samples. The trained neural network is then explicitly tested with the testing samples apart from the data set used. This gave an insight of how well the network will do when applied to data from the real world. This system will be really useful in detecting various defects in wire ropes in real life and thus many major accidents due to wear and tear of wire ropes can be avoided easily.

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