Neural-Fuzzy model Based Steel Pipeline Multiple Cracks classification

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Abstract. While pipes are cheaper than other means of transportation, this cost saving comes with a major price: pipes are subject to cracks, corrosion etc., which in turn can cause leakage and environmental damage. In this paper, Neural-Fuzzy model for multiple cracks classification based on Lamb Guide Wave. Simulation results for 42 sample were collected using ANSYS software. The current research object to carry on the numerical simulation and experimental study, aiming at finding an effective way to detection and the localization of cracks and holes defects in the main body of pipeline. Considering the damage form of multiple cracks and holes which may exist in pipeline, to determine the respective position in the steel pipe. In addition, the technique used in this research a guided lamb wave based structural health monitoring method whereas piezoelectric transducers will use as exciting and receiving sensors by Pitch-Catch method. Implementation of simple learning mechanism has been developed specially for the ANN for fuzzy the system represented.

1. Introduction
Pipelines are used in virtually every nation around the globe to transport oil and gas from the fields to the market. Oil spills, gas leaks and their associated environmental problems has become a serious and major concern in the oil and gas industry; and consequently, this has led to significant losses in revenue, severe disruption of operations, persistent threat to marine life and the ecosystem. This accidental discharge of petroleum products on/offshore has hitherto caused untold and unimaginable environmental hazards and economic loss that requires urgent remedial action and attention [1,2].

Many researchers have studied inspection of this pipe line is critical, not only to maintain normal functions of various life support facilities, but also to prevent fires, explosions, water damage, and contamination from broken gas, water, or sewage lines. All pipes whether made of coated steel or plastic composites will
corrode and form some kind of a defect in the form of a crack or small pit on the surface of the pipe. In power industries any leakage due to these cracks might be hazardous to both man and nature. Also, such leaks will eventually cause economic losses since the resources are wasted. Periodic inspection of pipes is needed to satisfy regulatory requirements. The inspection characterizes the condition of the pipes and directs strategic planning on whether and when to replace, repair or continue operation of the pipe [2-4].

Starting from the fuzzy inference system and the combination of artificial neural networks has led to increased interest in research and the application of a variety of different applications [5-9]. There are an understanding between the development of this system due to the attitude of hole complement each other rather than for competition. In one part the FIS offering method of calculation that emphasizes the interpretability of results arises, imprecision and uncertainty data for system capability of ANN calculation. Additionally, ANN has the ability to understand, adapt to change is an advantage to the FIS. In-depth study has shown merger between FIS and ANN has been created [10-13]. Mamdani FIS is one of the neuro-fuzzy that have multiple branches, which includes fuzzy network adjustment control study [14], the controller of fuzzy neurons [15] and neuro-fuzzy function estimate [16]. In addition to the integrated neuro-fuzzy made by Takagi-Sugeno FIS is adaptive neuro-fuzzy inference system (ANFIS), and dynamically evolving fuzzy neural network [17].

This study will focus on the multiple cracks and holes detection of steel pipelines using PZT-based guided waves /monitoring of critical pipeline system utilizing embedded piezoelectric guided waves. The statistical modelling procedure aids in the proper classification of extracted features for various damage levels. The first class is supervised learning where a training set of known damage states is used to help classify extracted features. The second class is unsupervised learning where feature classification is based upon statistics of a given process.

2. Research Background

2.1 Typical defects of pipeline structures

The investigations result on the incidents of pipeline leakage introduce the main cause of this incident is the degradation mechanisms on pipeline structure. The degradation mechanism of the pipeline is due to various factors such as mechanical damage, corrosion, cracking caused by the environmental and the original manufacturer defect. Therefore, continues assessment is require ensure the integrity of pipeline structure and to prevent the incident of gas and oil leakage. Many defects may result in lowering the security of the pipeline working, and eventually lead to leakage, even explosion accidents as mention. Therefore, it is of importance to develop the defect detection method for pipeline structures by using an effective way such as the PZT-based guided waves. The typical defects of pipeline structures are shown in Figure 1[18,19].
2.2 Wave Propagation in Hollow Cylinders

Guided waves in cylindrical structures may travel in the circumferential or axial direction. Based on boundary conditions, material properties, and geometric properties of the hollow cylinder, the wave behaviour can be described by solving the governing wave equations with appropriate boundary conditions.

Wave propagation in cylindrical waveguides has been studied on the theoretical and experimental levels by researchers at academic institutions and the industry. Such studies can be found in the literature [20-23]. There are basically two categories of guided waves that propagate in a hollow cylinder, the circumferential and the axial guided waves. Under the axial category, there are three types of modes generated when waves are propagating along a cylindrical structure. These are the longitudinal, torsional and flexural wave modes as seen in Figure 2.

The longitudinal and torsional waves inflict symmetrical displacement of particles in the axial direction across the structure while the flexural waves impose a non-symmetric particle displacement along the structure.
Fig. 2. Flow chart showing the types of guided waves in pipes.

2.3 Neuro-Fuzzy Systems

Various methods have been discovered in combining FIS and ANN which is called neuro-fuzzy system. Based on studies has conducted by Lin et al [24] and Hsiao [25] showing a combination of FIS and ANN system can be categorized into three forms, namely integrated (hybrid) neuro-fuzzy systems, cooperative and simultaneous.

Based on neuro-fuzzy cooperative system shows that FIS and ANN have a method for free initial phase. The determining the role of FIS membership or fuzzy rules which follow the learning method based on training data. After the completion of the first phase of the ANN is no longer used in the system and the FIS activated. This was shown by Abraham [26], based on the example of neuro-fuzzy system of cooperatives that have been created. It also been made by Kosko [27] in addition to fuzzy memories unite fuzzy rule extraction is applied to the map. This is also shown by Nomura [28] by means learning fuzzy set parameters.

The uses of ANN to FIS continuously in neuro-fuzzy systems simultaneously not only occur at the beginning just like in the cooperative system. The cooperative system is equivalent to that normally exists with a combination of ANN and FIS inherent in neuro-fuzzy system simultaneously and independently. The simplest example can be provided on the situations in which the input process is difficult to measure directly. The ANN serves as a pre-processor for the input parameter in the determination of requirements that need to be used (for example, fuzzy sets and fuzzy rules). Additionally, ANN also serves as a post-processor for fuzzy and its related output [26]. ANN application as a pre-processor or post-processor for neuro-fuzzy system simultaneously serves as a performance enhancer for FIS as shown in Figure 3.
3. **Proposed Model**

The combination of reduced power method has been implemented by Takagi-Sugeno as hybrid neuro-fuzzy systems (for the determination the parameters of linear coupled partly as a result of the rules) and the learning algorithm of back-propagation (to determine the parameters of the membership function in the antecedent rules) as shown in Figure 4. The Anfis model include six inputs present Harmonics in collected data and three outputs present crack Size, Number, and Types. (CS, CN, CT). The results were obtained using the software ANSYS 17.1 is used to simulate the Lamb wave propagation in the steel pipe. For the FEA, the 42 sample had been selected form 128 possible sample based on Design of Experiment (DOE). The pipe model section radius is 60mm and the wall thickness is 3mm. To simulate the defect, the degree of central angle is used to measure the size of defect, and two cracks and holes are simulated in the same way. The feature extraction process involves the extraction of damage sensitive features from sensor data collected during the data acquisition procedure to determine the presence of damage.

The extraction of features is done through signal processing of sensor data, which includes the processes of data normalization, compression and fusion. Data normalization reduces sensitivity to environmental variability such as temperature fluctuations. The data compression process decreases the dimensionality of the
acquired data. Data fusion involves combining data from multiple transducers to aide in feature identification.

4. The Numerical Model

It is possible to model pipes structures by ANSYS/ Multi physics product. The integration of control actions to the ANSYS solution is realized. Each of pipeline design should considered frequency response transient, and the model of the system into account. The material and dimensions of the pipe and types of the signal source and the placement measurement points. To analyse the transient dynamics problem full method will choose to simulate guided the pipe. The simulation test parameter is chosen as the excitation signal a 6-cycle 70 KHz sine wave, the step length is 1.52 µ/s, the load action is 100 µ/s, and propagating time is 1.52 m/s.

Figure 7.a&b, show sample of simulated pipeline and the concept of active guided wave focusing where time delay-amplitude phasing is applied to the segmented guided wave transducer array to cause constructive interference of the guided wave energy to occur at a given focal point along the pipe.

![Fig.5](image)

(a) (b)

**Fig.5** The meshing model of perfect pipe using FEM simulation demonstrating the concept of axisymmetric guided wave excitation

Figure 6, show the averaged signal and shows the induced signal from the transmitter to the receiver which directly refers by guided wave propagation.
5. Results and Discussion

The signal harmonic extracted from converting time domain response to Frequency domain using Fast Fourier Transform (FFT) method for responses of the circumference, slop and holes defect in the pipe as shown in Table 1. Forty two samples from ANSYS simulation data was used to construct to verify the performances of ANFIS models. In order to improve the ANFIS model, about 85% of data are used for training and the remainder for testing performance. In Table 1, the training and testing Experimental available data are specified at different run number. Figure 7 show the training optimized structure has been selected as ANFIS, based on the percentage error minimum at 25 epochs.

Table 1. Training and testing data

| Sample No. | ANFIS input | ANFIS output |
|------------|-------------|--------------|
|            | H1          | H2           | H3          | H4          | H5          | H6          | CS          | CN          | CT          |
| Training Sample |             |              |             |             |             |             |             |             |             |
| 1          | 11.48139    | 0.4511       | 0.26651     | 0.20033     | 0.16621     | 0.15146     | 1.5         | 3           | 0.25        |
| 2          | 12.89888    | 0.11014      | 0.07199     | 0.05419     | 0.04677     | 0.04111     | 2           | 3           | 0.25        |
| 3          | 15.89129    | 0.06144      | 0.04194     | 0.03127     | 0.02688     | 0.02441     | 2.5         | 3           | 0.25        |
| 4          | 9.45601     | 0.13304      | 0.06977     | 0.05143     | 0.04307     | 0.03375     | 1.5         | 1           | 0.25        |
| 5          | 10.08956    | 0.14195      | 0.07444     | 0.05487     | 0.04595     | 0.03601     | 2.5         | 1           | 0.25        |
| 6          | 10.03205    | 0.14114      | 0.07402     | 0.05456     | 0.04569     | 0.0358      | 2.5         | 1           | 0.25        |
| 7          | 9.46022     | 0.13309      | 0.06985     | 0.05145     | 0.04308     | 0.03376     | 2           | 1           | 0.25        |
| 8          | 9.31359     | 0.13103      | 0.06871     | 0.05065     | 0.04242     | 0.03324     | 2           | 1           | 0.25        |
| 9          | 10.5165     | 0.24362      | 0.11708     | 0.07767     | 0.05862     | 0.05739     | 2           | 2           | 0.25        |
| 10         | 10.58317    | 0.24516      | 0.11782     | 0.07816     | 0.059       | 0.05775     | 2.5         | 2           | 0.25        |
| 11         | 10.04755    | 0.23276      | 0.11186     | 0.07421     | 0.05601     | 0.05483     | 1.5         | 2           | 0.25        |
| 12         | 10.13676    | 0.23482      | 0.11285     | 0.07486     | 0.05651     | 0.05532     | 1.5         | 2           | 0.25        |

Fig. 6 Steel pipeline displacement-time curves and propagation along 1m of perfect pipe.
| No. | Value 1 | Value 2 | Value 3 | Value 4 | Value 5 | Value 6 | Value 7 | Value 8 | Value 9 |
|-----|---------|---------|---------|---------|---------|---------|---------|---------|---------|
| 14  | 10.21542| 0.23665 | 0.11373 | 0.07545 | 0.05695 | 0.05575 | 2       | 2       | 0.25    |
| 16  | 1.27668 | 0.01518 | 0.01169 | 0.00886 | 0.00718 | 0.00297 | 2       | 3       | 0.5     |
| 17  | 2.27802 | 0.01869 | 0.00764 | 0.00452 | 0.00484 | 0.00441 | 2.5     | 3       | 0.5     |
| 18  | 1.11069 | 0.02408 | 0.01399 | 0.00979 | 0.00837 | 0.00586 | 1.5     | 1       | 0.5     |
| 19  | 1.1851  | 0.02569 | 0.01492 | 0.01034 | 0.00893 | 0.00625 | 2.5     | 1       | 0.5     |
| 20  | 1.17835 | 0.02554 | 0.01484 | 0.01029 | 0.00887 | 0.00621 | 2.5     | 1       | 0.5     |
| 22  | 1.09396 | 0.02371 | 0.01377 | 0.00953 | 0.00824 | 0.00571 | 2       | 1       | 0.5     |
| 23  | 1.10435 | 0.02394 | 0.01391 | 0.00964 | 0.00832 | 0.00582 | 1.5     | 1       | 0.5     |
| 24  | 1.14845 | 0.01898 | 0.01299 | 0.01046 | 0.01263 | 0.01057 | 2       | 2       | 0.5     |
| 25  | 1.09662 | 0.01994 | 0.01365 | 0.01099 | 0.01152 | 0.0125  | 2.5     | 2       | 0.5     |
| 27  | 1.15573 | 0.0191  | 0.01307 | 0.01052 | 0.01274 | 0.01063 | 1.5     | 2       | 0.5     |
| 28  | 1.1647  | 0.01925 | 0.01318 | 0.01061 | 0.01284 | 0.01072 | 2       | 2       | 0.5     |
| 30  | 53.59083| 0.27824 | 0.15317 | 0.10365 | 0.09158 | 0.08365 | 2       | 3       | 0.75    |
| 31  | 70.96711| 0.36506 | 0.21695 | 0.17027 | 0.13646 | 0.13254 | 2.5     | 3       | 0.75    |
| 32  | 41.62189| 0.06814 | 0.02106 | 0.00971 | 0.01118 | 0.00888 | 2       | 1       | 0.75    |
| 33  | 43.03703| 0.07045 | 0.02177 | 0.01004 | 0.01156 | 0.00918 | 2.5     | 1       | 0.75    |
| 35  | 40.27142| 0.06592 | 0.02037 | 0.00934 | 0.01081 | 0.00859 | 2       | 1       | 0.75    |
| 36  | 39.5862 | 0.06476 | 0.02016 | 0.00922 | 0.01062 | 0.00843 | 2       | 1       | 0.75    |
| 37  | 41.33886| 0.06767 | 0.02091 | 0.00964 | 0.01139 | 0.00881 | 1.5     | 1       | 0.75    |
| 38  | 43.94270| 0.32027 | 0.12356 | 0.07493 | 0.0623  | 0.0525  | 2       | 2       | 0.75    |
| 39  | 46.13162| 0.33638 | 0.12971 | 0.07866 | 0.06541 | 0.05511 | 2.5     | 2       | 0.75    |
| 40  | 43.79685| 0.31921 | 0.12315 | 0.07468 | 0.06212 | 0.05232 | 1.5     | 2       | 0.75    |
| 42  | 44.52860| 0.32455 | 0.12521 | 0.07593 | 0.06314 | 0.0532  | 2.5     | 2       | 0.75    |

**Testing data**

| No. | Value 1 | Value 2 | Value 3 | Value 4 | Value 5 | Value 6 | Value 7 | Value 8 | Value 9 |
|-----|---------|---------|---------|---------|---------|---------|---------|---------|---------|
| 9   | 9.40211 | 0.13228 | 0.06937 | 0.05113 | 0.04282 | 0.03355 | 1.5     | 1       | 0.25    |
| 15  | 1.26707 | 0.03858 | 0.02656 | 0.02215 | 0.02325 | 0.01652 | 1.5     | 3       | 0.5     |
| 21  | 1.11851 | 0.02409 | 0.01396 | 0.00974 | 0.00837 | 0.00586 | 2       | 1       | 0.5     |
| 26  | 1.14556 | 0.01893 | 0.01296 | 0.01043 | 0.01263 | 0.01054 | 1.5     | 2       | 0.5     |
| 29  | 45.44689| 0.39232 | 0.17486 | 0.11701 | 0.10421 | 0.0866  | 1.5     | 3       | 0.75    |
| 34  | 42.70564| 0.06914 | 0.0216  | 0.00962 | 0.011471| 0.00916 | 2.5     | 1       | 0.75    |
| 41  | 44.18572| 0.32205 | 0.12424 | 0.07534 | 0.06265 | 0.05279 | 1.5     | 2       | 0.75    |
Fig. 7. ANFIS training

The relative error results of ANFIS model are shown in Figure 8 for training data, where the percentage Error (ER) for input test variable and the average error (AER) are estimated as:

\[ ER\% = \frac{Y_{Ex} - Y_{pre}}{Y_{Ex}} \times 10 \]  \hspace{1cm} (1)

\[ AER\% = \frac{1}{N} \sum_{i=1}^{N} (ER\%) \]  \hspace{1cm} (2)

Where (ER\%), (Y_{Ex}) and (Y_{pre}) stand for error percentage values, experimental test data and ANFIS predicted values respectively.

The ANFIS models for training and testing data are shown in Figure 8. It is observed that the maximum error among the numerical and predicted for Slop, circumference, and Hole defect using ANFIS model are in good agreement with value of 99.83\%.
Fig. 8. Percentage error of ANFIS models for training data: a) CS b) CN c) CT.

From Table 2, it is also observed that the higher percentage error of crack size was approximately 0.0.3239 and the average error is 0.01898. The higher values of percentage error of crack Number was approximately 0.04383 and the average error is 0.0259. The higher values of percentage error of crack Types was approximately 0.00559 and the average error is 0.00288. From this result it can approve that Anfis predication model has same superior as ANSYS simulation result.

Table 2. Comparison between the numerical result and ANFIS models for testing data.

| Sample No. | 9   | 15  | 21  | 26  | 29  | 34  | 41  |
|------------|-----|-----|-----|-----|-----|-----|-----|
| CS         | 1.5 | 1.5 | 2   | 1.5 | 1.5 | 2.5 | 1.5 |
| ANFIS ER   | 0.0139 | 0.03239 | 0.002 | 0.00667 | 0.0383 | 0.0104 | 0.02923 |
| AER        | 0.01898 |
| CN         | 1   | 3   | 1   | 2   | 3   | 1   | 2   |
| ANFIS ER   | 1.043832 | 3.027557 | 1.060253 | 2.00163 | 3.043815 | 1.035197 | 2.034869 |
| AER        | 0.04383 | 0.00919 | 0.06025 | 0.00082 | 0.0146 | 0.0352 | 0.01743 |
| CT         | 0.25 | 0.5  | 0.5  | 0.5  | 0.75 | 0.75 | 0.75 |
| ANFIS ER   | 0.251398 | 0.500111 | 0.501819 | 0.501753 | 0.75337 | 0.751879 | 0.750163 |
| AER        | 0.00559 | 0.00022 | 0.00364 | 0.00351 | 0.00449 | 0.0025 | 0.00022 |

6. Conclusion

The GW-SHM technique, which can be regarded as the integration of actuators and sensors into structural components combined with automated advanced signal processing procedure for implementing a crack identification strategy, makes this challenging demand realizable. This work showed the effectiveness and the generality of Integrated nural Fuzzy (ANFIS) with guided lamb wave to detect and localize crack in pipes in the presence of significant operational. A data-driven
framework based on pattern recognition and machine learning is then developed to differentiate between different types of cracks. Several simulation trials were performed using ANYSIS software to validate the feasibility and applicability of the modified model. Under the simulation effort, various crack types with different sizes and number along a pipeline were analyzed. It was found out that the model can accurately estimate the extent and number and size of crack. These findings indicate that the model can accurately estimate the location and the size of the flaw as the location of the flaw changes.

7. References
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