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Towards Prevention of Oil/Gas Pipelines Vandalism

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ABSTRACT

Simulation of the detection, identification and classification of the vibration signature of oil/gas pipelines in response to acts of vandalism is presented in this paper. In a real experimental field work, vibration signal data were acquired from a sample oil/gas steel pipe subjected to different excitation forces from human traffic, vehicular traffic, and impact on the pipe by separately using a hammer and a drilling machine. The data acquired from the use of a drilling machine were used as the reference input data to an intelligent system modelled to classify the vibration data during a simulation process by the use of the MATLAB fuzzy logic toolbox. During the simulation process, the frequency and power components of the vibration data were fuzzified into five linguistic variables each. Results from the simulation shows that the triangular membership function is most appropriate for use in the intelligent system. Results from the simulation also show that a relatively uniform vibration output value of 1.0 (on a scale of 0 to 1), being the desired output, was achieved. This value serves as an ideal value that can be used for the design of a system to detect and diagnose an act of vandalism on oil/gas pipelines. Any values outside of this would not be regarded as a force due to an act of vandalism.

1. Introduction

The desire by professionals and researchers to make life more comfortable, easy and meaningful has resulted in the development of networks of equipment and systems that are potential targets of attacks by vandals and intruders. Over the years, the network of oil/gas pipelines in Nigeria has grown into a large system that is often attacked by vandals. This research aims at finding a solution to this problem by employing intelligent systems paradigm. Advancements in technology have helped to develop intelligent control systems that could be adapted for the design of a system that can identify intrusion on oil/gas distribution pipelines and promptly notifies operators of the pipelines to take appropriate action. This study simulates the process of detecting and diagnosing the signature of the vibration of oil/gas distribution pipelines in response to intrusions on the pipes by vandals. To achieve this, vibration signal data were acquired from an experimental field work and used as input to an Adaptive Neuro-Fuzzy Inference System (ANFIS), which was used as the simulation engine in this study. Results from the simulation would be very useful in the design and building of a real system that would detect and diagnose acts of vandalism when installed on oil/gas distribution pipelines. Such a system will forestall the incessant attacks on the pipelines since intrusion on them will in real time be reported promptly to the operators of the network. This will consequently improve on the safety of the pipelines and the lives and properties of those who live in communities across which the pipelines run.

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2. Related Works

Research works have been carried out in the field of Structural Health Monitoring (SHM) to detect and locate damages in civil and mechanical engineering facilities by constantly monitoring and assessing their health conditionsvia digital instruments, such as acceleration sensors [1]. SHM entails continuous monitoring of a structure, collection of its vibration data and analysing them in real-time to determine damage-sensitive characteristics of the structure, and the location of the perceived damage(s).It involves the use of an array of sensors [2,3] distributed over a structure to measure its dynamic response with the aim to undertake a more cost-effective condition-based surveillance on it [4]. Kaya and Safak [1] developed a real-time technique (software) which monitors and identifies the modal properties of a structure, along features for tracing and plotting time variations in the modal properties, which bear strong relationship with damage(s) in the structure. Capabilities of SHM technology allows remote monitoring of the behaviour and integrity of structures to detect any damages on pipelines and reports this to a remote control station by the use of Information and Communication Technology (ICT) tools [5], to enable the right actions to be taken to avoid or reduce any risks associated with the damage. A model which describes a system comprising of wireless sensor nodes that could be deployed to remotely carry out continuous monitoring of gas pipelines is discussed in [6]. According to the authors, the model can be implemented for monitoring and identifying fluid leakage in, or other kinds of damages on, oil/gas pipelines. A fault tolerant framework which uses a wired/wireless sensor network to remotely monitor pipeline network with a view to tracking acts of bunkering and vandalism on crude oil pipelines was proposed in [7]. A microcontroller-based system that uses distributed sensing technology to continuously monitor the integrity of oil and gas pipelines with a view to detecting leakages on them was designed by [8]. Shoewu et al [9] designed a microcontroller-based system that senses light, measures pressure drops and mechanical breaks (i.e., damages) in pipeline. A system for detecting cracks on oil pipelines was developed by Ezeh et al [10]. The microcontroller-based system is equipped with an electrical circuitry that provides a continuous electrical path. A break in the electrical signal path causes a detectable state change in the system. This causes an alarm module in the system to trigger, and a “text message” sent to the operators of the system through short message service (SMS) of their mobile telephones. In reviewing technologies for detection of leakages in pipelines in the Niger Delta Region of Nigeria, [11] suggested an integration of impressed alternating cycle current (IACC) and an acoustic system for use in the management of malicious and inadvertent pipeline potential damages. The paper suggested an integration of impressed alternating cycle current (IACC) and an acoustic system for use in the management of malicious and inadvertent pipeline potential damages. While the former traces encroachment on pipeline coating, the latter is used for monitoring changes in the sound generated by a pipeline in operation. Ononiwu et al. [12] developed and implemented a real-time oil pipeline monitoring system, equipped with acoustic sensors, that detects audio signals (from intruders) which are transmitted through wires laid along the pipeline.

None of the works reported above is suitable for monitoring pipelines against acts of vandalism since they were all designed/developed to detect damages on or leakages in pipes, and not forces that could cause damages on them. This brings to fore the limitations of SHM which include “anomaly detection, sensor deployment studies, model validation, threshold check, and damage detection” [13]. However, it was reported in [14] that a research organization awarded a contract to an Israeli company, Magal Security Systems Ltd, to improve the facilities of her product called Pipe Guard system. Capabilities of the new product were expected to include reporting of occurrences of excavation, and discriminating between types of excavation equipment within the vicinities of gas pipes. Oil/gas pipeline vandals do not use heavy excavation equipment. Consequently, the new product will not be suitable for detecting acts of vandalism on pipelines. A surveillance system based on phase-sensitive optical time domain reflectometry (*f*-OTDR) technology, and aimed at detecting and classifying threat signals within the vicinities of long range gas pipelines was presented in [15]. The proposed sensing system, which has capabilities for signal acquisition, uses discriminatively-trained multi-layer perceptions of Artificial Neural Networks (ANN) for classifying patterns of the acquired vibration signal features. Similar to that in [14], the system aims at detecting the presence of both dangerous (threatening) excavation equipment and other non-dangerous (non-threatening) machine operations near the pipelines.

An ideal system for prevention of acts of vandalism on pipelines should be able to detect and identify vibration signals that deviate from the normal operational vibration of the pipelines and could cause damages on them. This concept was employed in [16] that proposed an "optimized composite dictionary single-atom matching algorithm (CD-SaMP)" for extraction of vibration signal features from a gearbox with the aim of diagnosing any fault in the gearbox. This also informed the focus of this research, which simulates the process of detection of forces that could cause damages on pipes. The path of simulation was followed to avoid the risk, difficulty and high cost associated with direct experimentation with real insitu oil/gas pipeline.

3.0 Methodology

The following sections describe the procedures adopted to achieve the goal of this study.

3.1 Data Acquisition

An actual field experiment was carried out to acquire real vibration signal data that were used for the simulation of the process of detecting and identifying the signature of the vibration signal (forces) on the experimental steel pipe. The pipe was separately excited externally by human and vehicular traffic moving close to the pipe. It was excited also by hitting it with a hammer, and by the use of a drilling machine, which is assumed to be the tool used by vandals to bore hole on oil pipes to have access to their fluid contents.

3.1.1 Experimental Setup

Figure 1 depicts the experimental setup of the equipment used to acquire vibration signal data from the sample oil/gas pipe. The setup consisted of a pipe representing the oil pipeline, data acquisition (DAQ) device, a laptop and excitation tools (sources).

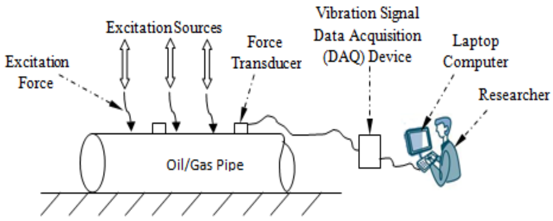

Fig. 1. Experimental Setup

3.1.2 Signal Measurement

Vibration signals were measured as the response of the experimental steel pipe to excitation forces from the various sources described in section 3.1.

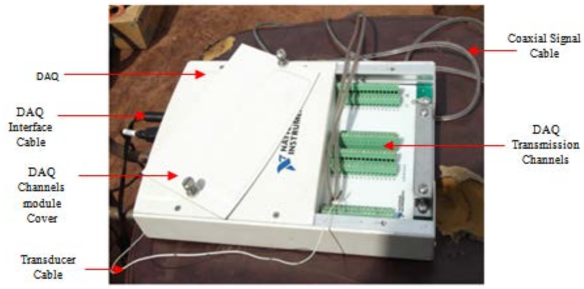

Fig. 2. Data Acquisition Instrument

The signal data were collected real-time from the field experiment by use of a National Instrument high channel industrial vibration signal data acquisition (DAQ) device shown in Figure 2.

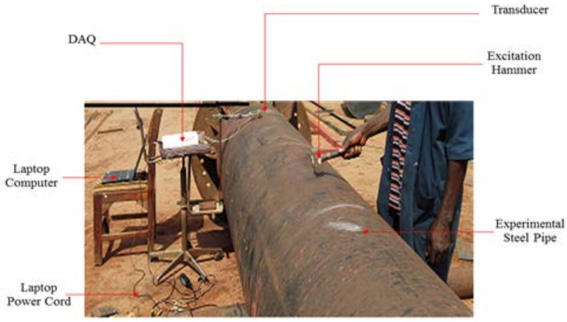

Fig. 3. Hitting Experimental Steel Pipe with a Hammer

Figure 3 shows the experimental pipe being hit with a hammer by a research assistant, while Figure 4 depicts an attempt at boring a hole into the pipe with a drilling machine.

Fig. 4. Drilling Operation

Vibration signal data acquired from the response of the pipe to the various excitation forces were stored into the experimental laptop computer. The stored data were later analysed using the Fast Fourier Transform from the signal processing toolbox of version 7.10.0.499 of the MATLAB software.

3.2 Simulation Procedure

For simulation of the detection and identification of forces that could cause breakage or damage of oil/gas pipes is shown by the Unified Modelling Language (UML) Activity Diagram of Figure 5.

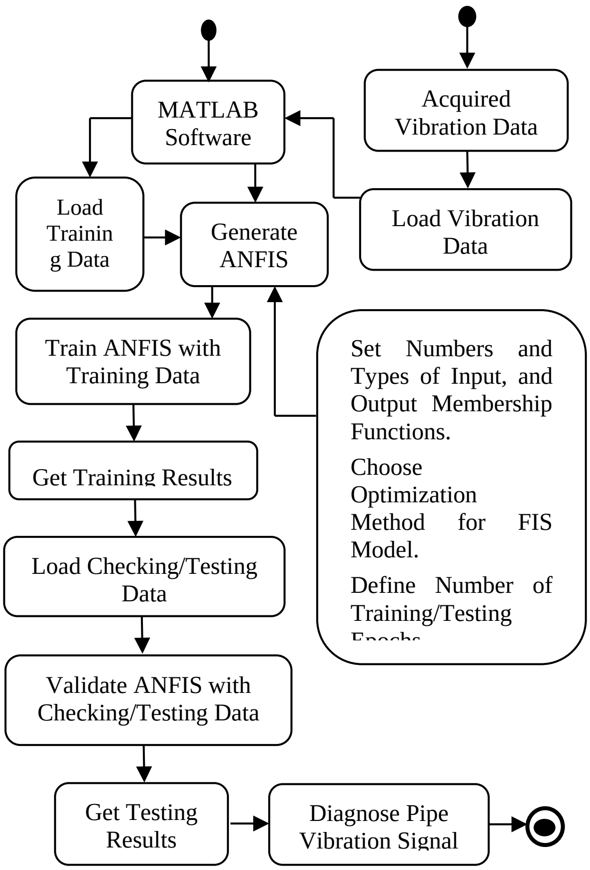

Fig. 5. UML Activity Diagram for ANFIS Simulation

Selected vibration signal data (as explained in section 3.1.2) were loaded into the running MATLAB software, and the ANFIS of Figure 6 structure was generated.

3.2.1 Loading the Training and Checking data

8192 data pairs, comprising of 4096 training data and 4096 checking data, selected from the transformed experimental vibration signal data were loaded from a file into the MATALAB Workspace. At this point the number of linguistic terms for each input variable is stated. For this study the data sets are divided into two input variables namely, Frequency and Power.

Table 1: ANFIS Input Parameters

Linguistic Terms	Linguistic Variable	
	Frequency (KHz)	Power (dB)
VERY LOW	-0.1747 to 0.1747	-107.34734 to -84.95
LOW	0.08485 to 0.4242	-95.14 to -59.47
AVERAGE	0.3244 to 0.6737	-69.66 to -33.99
HIGH	0.5739 to 0.9232	-44.18 to -8.514
VERY HIGH	0.8234 to 1.173	-18.71 to 16.97

Table 1 shows a summary of the input data pairs ranging from -0.1747 KHz to 1.173 KHz for the frequency variable, and -107.34734 dB to 16.97 dB for the power variable. The linguistic variables (Frequency and Power)in Table 1 are further subdivided into qualitative partitions expressed in linguistic terms, namely: VERY LOW, LOW, AVERAGE, HIGH, and VERY HIGH.

3.2.2 Training of ANFIS Structure with Training Data

The ANFIS was trained with 4096 data pairs loaded from a file into the MATLAB Workspace. Following are the steps taken to train the ANFIS to learn the profile of the signals.

(i) Loading of the training data into the ANFIS Editor Graphical User Interface (GUI) from the MATLAB Fuzzy Logic Toolbox.

(ii) Generating the Fuzzy Inference System (FIS). MATLAB fuzzy logic toolbox has the capability of determining the architecture (i.e., model or structure) of Adaptive Neuro-Fuzzy Inference System (ANFIS) automatically. With the Genfis1 command of the fuzzy logic toolbox, the ANFIS model of Figure 6 having two inputs and one output was generated using the grid partition algorithm technique

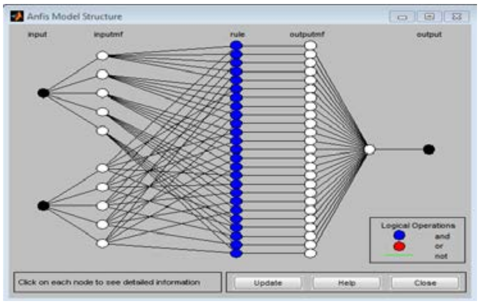

Fig. 6. Adaptive Neuro-Fuzzy Inference System Structure

The ANFIS model (shown in Figure 6) consists of a five-layer neural network that simulates its working principles. The nodes in the first layer represent the input variables. Nodes in the second (i.e., condition elements) layer are linguistic term nodes that act as the membership functions for the input variables. The third layer is a layer of neurons where each neuron represents a fuzzy rule. The action elements are represented by the nodes in the fourth layer. Outputs from the fourth layer are aggregated in the fifth (output) layer to give one single output.

(iii) Choosing the hybrid optimization method in the ANFIS Editor GUI to train the membership function factors to imitate the training data.

(iv) Specifying the number of training cycles (epochs) and the training Error Tolerance to set the criteria for stopping the training. The training procedure stops when the maximum number of epochs is reached or the training error goal is realised.

(v) Training of the ANFIS to adjust the parameters of the membership function and display the error plots.

3.2.3 Validation of Trained FIS Model with Checking Data

After training, the Fuzzy Inference System (FIS) model was checked for validation by use of the 4,096 checking data pairs loaded from a file into the MATLAB Workspace. This process allows the generalization capability of the fuzzy inference system to be checked. The convergence checking error is displayed after the validation exercise.

Table 2: Training and Checking/Testing Errors from various Membership Function Types

S/N	Membership Function Type	Membership Function Matrix	Number of Epochs	Average Training Error	Average Checking Error
1.	Triangular	[5 5]	100	1.7184e-07	2.9842e-08
2.	Trapezoidal	[5 5]	100	6.9032e-08	8.7495e-08
3.	Generalized Bell	[5 5]	100	1.3612e-05	1.1138e-02
4.	Gauss	[5 5]	100	9.3592e-06	2.3475e-02
5.	Gauss2	[5 5]	100	1.1385e-06	8.3919e-02
6.	Pi	[5 5]	100	1.6592e-07	3.0364e-07
7.	DSigmoid	[5 5]	100	4.7981e-06	3.405e-04
8.	Psigmoid	[5 5]	100	4.7981e-06	8.2781e-02

Table 2 shows the training/checking converging errors recorded from training the FIS with the 4096 training and 4096 checking data sets using various membership functions.

It is observed from the table that the Trapezoidal membership function produced the least average training error value of 6.9032e-08 after 100 epochs, in comparison with the error produced by the use of the other membership functions.

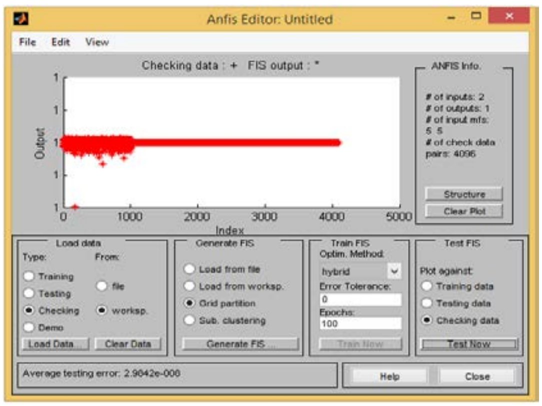

Fig. 7. FIS Model Showing Average Testing Error

However, this is not the best membership function for the system. The best is the Triangular membership function, which produced the least average checking (i.e., validating) error of 2.9842e-08 as shown in

Table 2 and in the average error plot of Figure 7. The Triangular membership function curves for the linguistic variables (Power and Frequency) are shown in Figures 8 and 9 respectively.

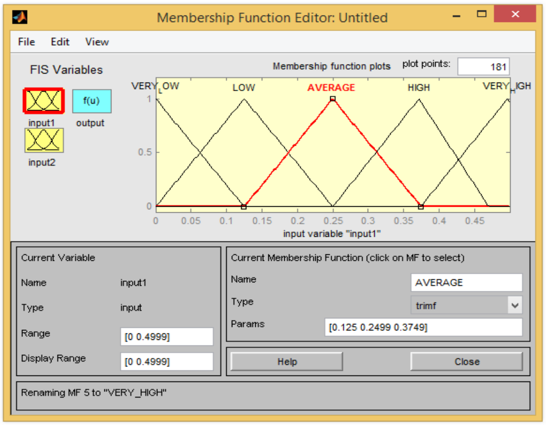

Fig. 8. Vibration Signal Power Input Membership Function

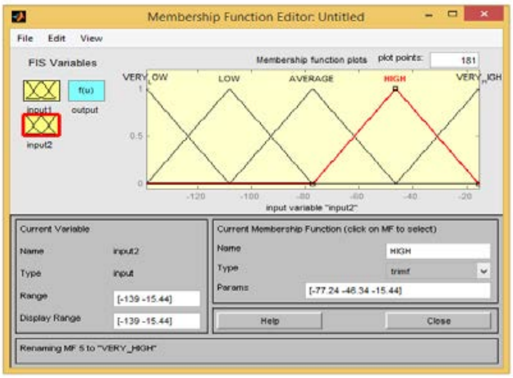

Fig. 9. Vibration Signal Frequency Input Membership Function

Every point in the input space is mapped to a membership value between 0 (zero) and 1 (unity) by a membership function to show the degree of belonging of the point to the input space. The Fuzzy Logic Toolbox works out the membership function parameters and automatically selects the membership function curve appropriate for a particular input space.

The Rule Editor of Figure 10 shows part of the 25 fuzzy rules generated by the fuzzy system in the ANFIS during the fuzzification of the input data.

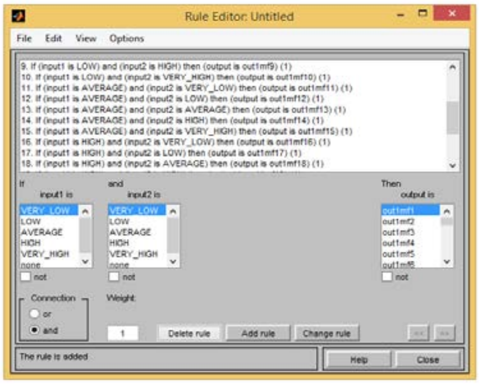

Fig.10. Fuzzy Rules

Fig. 11. Rule Viewer

The rule viewer of Figure 11 shows that the system has an average output value of 1.0 (on a scale of 0.0 to 1.0). A row in the rule viewer corresponds to one of the 25 generated rules.

A 3-dimensional output surface plot of the fuzzy inference system (FIS), based on the inputted vibration frequency and power data, is shown in the surface viewer of Figure 12.

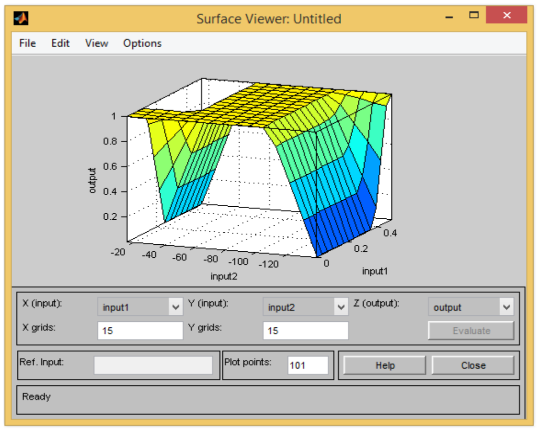

Fig. 12. Simulation Output (Surface Viewer) Plot

The figure shows that the output of the system is relatively stable at a value of 1.0. This represents the working force from the drilling machine. Other points on the surface represent the system output when the drilling operation just commenced or when it was being relaxed or withdrawn from the experimental pipe.

5. Conclusion

This paper presents a report of the simulation of a process by which the vibration signature of oil/gas pipes subjected to acts of vandalism can be detected, identified and classified. An Adaptive Neuro-Fuzzy Inference System (ANFIS) model was used as the simulation engine. Actual vibration data, acquired from the response of a sample experimental oil/gas steel pipe, excited by an attempt to bore a hole in it using a drilling machine, were inputted into the model. Results from the simulation show that the Triangular membership function is most appropriate for the Fuzzy Inference System (FIS) model generated because it gave the least "average checking error" value in comparison with the error values produced by the simulation when other membership functions were used. The results also show a relatively uniform output of 1.0 (on a scale of 0 to 1), being the desired output, was achieved. Using this value and the Triangular membership function to design and build a system that can detect forces that could cause damage on pipes would be of immense benefit to operators of oil/gas pipeline networks. Such a system should be equipped with facilities that can report intrusion on pipes, using Information and Communication Technology (ICT) tools for appropriate actions to be taken to forestall or prevent acts of vandalism. This will improve on the safety of lives and properties of those who live in communities across which the pipelines run.

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