MONITORING FLEXIBLE GAS PIPELINE WITH A MICROPHONE AND ARTIFICIAL NEURAL NETWORKS

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ABSTRACT
Pipeline networks are complex systems of ducts transporting gas and chemical products through long distances. With the purpose to track these leaks a technique, based on the analysis of sound noises captured by a microphone and on pressure transients generated by leak occurrence, was developed. Neural Artificial Networks were applied to determine leak magnitude and leak location. The experimental results showed that it is possible to detect leaks in pipelines. The dynamics of these noises in time were used as input to the neural model to determine the location and magnitude of the leaks.

KEY WORDS
Leak detection, acoustic method, pipeline networks, neural model.

1. Introduction
Pipeline networks are complex systems of ducts used to convey gas and chemical products through long distances. They frequently cross highly populated regions, water supplies or natural reserves. Even small leaks in pipelines can lead to great losses of products and serious damages to the environment before it could be detected. Thus monitoring and supervision of pipelines systems are important and it has been the subject increased attention nowadays [1,2].

Many of the proposed leak detection systems are based on process variables (pressure, flow rate and temperature) measured in the pipeline. Techniques based on elastic wave propagation have also been developed for damage detection in metallic and composite structures, as nonlinear vibration and acoustic phenomena have been proposed for damage detection.

Nonlinear effects have been observed in acoustic waves propagating in structures. The generation of higher harmonics in acoustic signals and modulation of acoustic signals by vibration are the best known examples [3].

An acoustic emission (AE) technique has been applied to detect internal valve leakage and it has been widely used in the oil, gas, chemical and petrochemical industries [4].

Morozov et al. [5] described a domestic multi-channel automated acoustic system for monitoring leaks, called SAKT. The system was based on the generation of high frequency stress waves on the surface of pipes during outflow of high pressure liquid through a pipe rupture.

Acoustic sensors are highly versatile devices which begin to demonstrate their commercial potential. In these sensors the detection mechanism is through a mechanical or acoustic wave. As the acoustic wave propagates through the material, any change in the signal propagation characteristics (as a leak in a pipeline) affects the speed and/or amplitude of the wave [6].

Belsito et al. [7] used neural networks (ANN—Artificial Neural Network) to detect the leak in liquefied gas pipeline. In this work, they show that the artificial neural networks possess certain attributes that make them an extremely adequate approach for the processing of data obtained in systems of pipeline transference and could be used innovatively in methods of pipeline detection leaks small 1% of the flow rate.

Caputo and Pelagegge [8] proposed an inverse approach to detect and locate leaks based on conditions of pressure and flow rate using Artificial Neural Network (ANN). Two-level ANN architecture was also presented where a first-level ANN determines the leakage and a second-level ANN estimates the leak magnitude and location. The proposed architecture has been satisfactorily tested in a simplified case, obtaining promising results.

Gao et al. [9] presented the correlation technique the effect of reflections on time delay estimation for leak detection in buried plastic water pipes. This technique was tested on experimental data measured at a specially constructed leak detection facility located at a National Research Council in Canada. A model was developed of the correlation function including the pipe dynamics and the reflections due to discontinuities in the pipe. The theoretical predictions have been compared to data of hydrophone measured from actual water pipes, and it has been clearly shown that in addition to the main peak in the basic cross correlation (BCC) corresponding to the true time, there are several other spurious peaks due to discontinuities of reflections in the pipe as bends and valves. Moreover, it has been shown that by removing the effects of the reflections and the filtering properties of the pipe from the modulus of the cross spectral density (CSD), the additional peaks due to the reflections can be
largely removed from the cross-correlation function, and the time delay due to the leak is much more discernible.

Hait et al. [10] used a numerical simulation to analyze transients in gas flow and pressure in a horizontal straight pipe. For a single gas pipeline, eight representative cases corresponding to different causes of transient behaviour are simulated to predict unsteady state flow and the evolution of pressure profiles. The simulations predict an initial surge in gas flow rate greater than the final steady-state value if the pressure drop across the pipe is increased. Whenever there is an increase in pressure drop across the pipe, a surge in the mass flux occurs instantaneously which eventually subsides and a new steady state condition is achieved.

Qu et al. [11] presented technique leak detection in pipe and one pre warning system monitoring and locating when the abnormal events are taking place along the pipe. In this system an optical cable is laid in parallel with a pipe in the same ditch and three single mode optical fibers inside constitute the distributed vibration sensor. The sensor is based on Mach–Zehnder optical fiber interferometer and can detect the vibration signals along a pipeline in real time. The system has consisted on four pipelines with a total length of around 150 km. The system can recognize the abnormal events along a pipeline with good recognition correct rate (normally > 95%) in real time and locate the abnormal events along a pipeline with good precision (normally ± 200 m) so as to prevent potential loss as much as possible. The pipe leak detection and a pre warning system is safe and reliable and the corrosion proof with excellent electric insulate. The performance of the system will not be affected by the property of material transported in a pipeline.

ANNs present several attractive properties such as universal function to noisy or missing data, and accommodation of multiple nonlinear variables for unknown interactions [12]. Considering these features, the present work was concerned with the development and test of a technique for detecting and locating the occurrence of leakages, based on the sound noise captured by microphone and the application of ANNs.

2. Experimental Setup

This work was based on the analysis of the sound noise amplitude and pressure transient generated by gas leakage in a pressure vessel - flexible pipeline system. The pipeline consisted of ¼” in diameter, 100 m long transparent helical wired tube, while a domestic type gas vessel was used as pressure vessel. Figure 1 shows the experimental assembly used to simulate and detect leaks in a pipeline.

The pressure vessel - pipeline system operated with compressed air at pressures that could vary between 1 kgf/cm² and 6 kgf/cm². At the outlet end of the pipeline the gas discharged through an orifice 0.8 mm in diameter, so that the pipeline was kept pressurized.

Gas leakages in the pipeline were generated manually through on/off valves installed in side outlets, at the inlet end and at 50 m from the inlet end of the pipeline. In these side outlets the gas leaked through an orifice which size was varied between 1 mm and 3 mm in diameter. The experimental conditions used in this work are shown in Table 1.

Table 1. Experimental conditions

<table>
<thead>
<tr>
<th>Operating pressure</th>
<th>6 kgf/cm²</th>
</tr>
</thead>
<tbody>
<tr>
<td>Leak orifice diameter</td>
<td>1 mm; 2 mm; 3 mm</td>
</tr>
<tr>
<td>Leak position</td>
<td>inlet end (0 m); 50 m from the inlet end, of the pipeline</td>
</tr>
</tbody>
</table>

Pipeline supervision was performed through a pressure transducer and an acoustic sensor (microphone), both installed in the pressure vessel and connected to a computer.

3. Detection System

The data acquisition system consisted of a pressure transducer and a microphone installed in the pressure vessel, a signal conditioner circuit, ADA converter, computer and data acquisition software, developed in C language.

The pressure transducer was a piezoelectric transducer, with pressure range up to 300psig (accuracy ± 0.02) and output signal from 1 to 5 V. The acoustic sensor was an omnidirectional microphone (type CZN-15E), which responds equally to sounds coming from any direction. The sound noise signal was sent to a signal processing circuit where it was pre amplified and filtered through band pass filters, each with a full specific frequency. The frequencies used were 1 kHz, 5 kHz and 9 kHz, showing the best response to the generated signal.

The acquisition software was written to read and process all data, and to display the sound noise amplitude and pressure transient profiles plots. The sampling rate of data acquisition system was 0.1649 ms.

4. Determining Leak Magnitude and Leak Location through Artificial Neural Networks

Sound noise amplitude and pressure transient data that have been acquired during the leak experiments were used as input to the neural model in order to determine leak magnitude and leak location (model outputs). The sound noises were processed in the filter bank, resulting in three voltage signals with frequencies of 1 kHz, 5 kHz and 9 kHz. These noises signals were first smoothed by calculating the moving average from 40 steps back. Each current step measurement was the average of 500 readings.
Network training was carried out with data sets from the leak detection tests, with and without leakage occurrence at the inlet end (0 m) and at 50 m from the inlet end of the pipeline. These data were organized in files, separating the training data sets from the tests data.

The pressure and the 1 kHz, 5 kHz and 9 kHz amplitude signals were used as input to the neural model. The pressure signal was used only at current time (k) and the amplitude signals were used at current time (k) and three previous instants (k-1, k-2 and k-3), making a total of 13 entries and 2 exits, as shown in Figure 2.

Software in C language was developed for data acquisition. As soon as the ANN training procedure has ended, the data acquisition software was supplied with weights and biases found from MATLAB.

5. Results and Analysis

Figures 3 to 5 show the pressure transient and the sound noise amplitude profiles generated by leak occurrence in the flexible pipeline operating under pressure of 6 kgf/cm².

With gas leakage the pressure drops while the sound noise amplitude increases, remaining approximately constant during leakage. The change in the pressure and amplitude profiles depended on the magnitude of the leak (orifice size) and on the distance between leak and sensors.

Independently of leak magnitude and leak location, the dominant frequency of the noises generated by leakage was 5 kHz, i.e., leak occurrences have always generated medium level sound noises.
When the orifice of 1 mm was used the change in pressure was not enough to detect the leak (Figure 3). With the orifices of 2 mm and 3 mm the pressure variations were similar and so the leak could be detected through the pressure transient.

With the orifice of 2 mm (Figure 4) the noise amplitude increased when compared with that obtained with the 1 mm orifice. In Figure 5(b) the sound noise amplitude was lower than that obtained with the 1 mm orifice because the gain in the pre amplifier was smaller.

The neural model was developed to determine leak magnitude and leak location at the same time, thus providing two model outputs. To make the ANN training easier, the original pressure data were used at current time (k) and the amplitude signal data were smoothed by calculating the moving average from 40 steps back. Therefore, the moving window inputted to neural model represents the actual tendency of the experimental curves using instants k, k-1, k-2 and k-3.

![Flexible Pipeline - Orifice: 1.0 mm](image)

Figure 3. Sound noise amplitude and pressure transient profiles in the pipeline (leak orifice=1mm).

![Flexible Pipeline - Orifice: 2.0 mm](image)

Figure 4. Sound noise amplitude and pressure transient profiles in the pipeline (leak orifice=2mm).

Figure 6 show the training performance of the neural model for the conditions shown in Table 1. The Square Error Summation (SSE) of training was approximately 0.01, a considerable small error, and the Effective Number of Parameters was about 566.

Off-line tests were carried out to obtain the best configuration of the neural model, observing the obtained dispersion plots (predicted output versus actual data – target). The test data should be appearing in the form of a straight line coincident to a diagonal to obtain an accurate model. The best network configuration to determine leak magnitude and leak location was 15x16x16x13x2.

Figure 7 show the dispersion plots for leak magnitude and leak location obtained with test data, about 600 data point.
In Figure 7.(a) the first set of points (set 1) indicates “no leak” occurrence in the pipeline. The second set (set 2) indicates a leak with the magnitude of 1 mm, so the third set (set 3) indicates a leak of 2 mm and the fourth set (set 4) a leak of 3 mm. The adjustment of the network was considered accurate, because R = 1, the linear coefficient = 0.001 and the slope = 1.0.

In Figure 7.(b) the first set (set 1) indicates “no leak” occurrence in the pipeline. The second (set 2) and the third sets indicate leakage at the inlet end (0 m) and at 50 m from the inlet end of the pipeline, respectively. The adjustment of the network was considered accurate, because R = 1 (one), the linear coefficient = 0.0 and the slope = 1.0.

Figure 8 show the difference between the predicted and actual leak magnitude and leak location. The maximum difference between the predicted and actual leak magnitude was 0.0308 mm at the time of the leakage magnitude was 2.0 mm, representing less than 10% of the real leak orifice diameter. A precise result was also obtained as the maximum difference between the predicted and actual leak location was smaller than 1 m.
6. Conclusion

A technique based on the analysis of pressure transients and sound noise amplitude generated by leak occurrence has been developed and tested in a 100 m flexible pipeline operating with gas.

The change in the pressure and sound noise amplitude depended on leak magnitude (orifice size) and on the distance between leak and sensors. Leak occurrences were readily detected by the acoustic sensor generating medium level sound noises, dominant frequency of 5 kHz. The change in pressure transient profiles did not allow leak detection through the smallest leak orifice (1 mm).

Leak magnitude and leak location were successfully predicted through artificial neural networks. The absolute errors when predicting leak magnitude were less than 10% of the real leak size. A precise result was also obtained as the maximum difference between the predicted and actual leak location was smaller than 1 m in the 100 m long pipeline.

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