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DETECTION AND ON-LINE PREDICTION OF LEAK MAGNITUDE IN A GAS PIPELINE USING AN ACOUSTIC METHOD AND NEURAL NETWORK DATA PROCESSING

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Abstract - Considering the importance of monitoring pipeline systems, this work presents the development of a technique to detect gas leakage in pipelines, based on an acoustic method, and on-line prediction of leak magnitude using artificial neural networks. On-line audible noises generated by leakage were obtained with a microphone installed in a 60 m long pipeline. The sound noises were decomposed into sounds of different frequencies: 1 kHz, 5 kHz and 9 kHz. The dynamics of these noises in time were used as input to the neural model in order to determine the occurrence and the leak magnitude. The results indicated the great potential of the technique and of the developed neural network models. For all on-line tests, the models showed 100% accuracy in leak detection, except for a small orifice (1 mm) under 4 kgf/cm² of nominal pressure. Similarly, the neural network models could adequately predict the magnitude of the leakages.
Keywords: Pipeline network; Leak detection; Neural networks.

INTRODUCTION

The automatic supervision of pipeline networks is a challenge for the engineering community, since the economic loss and environmental issues caused by a deteriorated network are significant in the world (Verde *et al*., 2007). Pipeline networks are con-structed with the aim of transporting different chemi-cal and petrochemical products, in liquid and/or gas phase conditions, over long distances. Pipelines are very safe when compared to the other ways of transportation, but they may have to operate under different conditions, requiring suitable inspection of operation (Taghvaei *et al*., 2007). Every year, the number of pipelines transporting gases and liquids underground or under the sea increases. Crossing densely populated areas and natural reserves, the

operational reliability of pipelines should be im-proved, minimizing the risk of leakages. Serious environmental pollution problems and disastrous consequences may occur if the leak takes place near residential areas. In addition, the leaks can cause serious financial damage to companies. Therefore, it is desirable that the appearance of a leak in a pipe be identified and located as soon as possible. Thus, detection and location of leaks become the most important components of the supervision system and control of pipelines. Leaks in general are associated with deterioration of the material, such as corrosion and mechanical fatigue, or with bad operation that can leave the pipelines vulnerable.

Aiming at improving levels of safety, reliability, efficiency and effectiveness of operation, new technologies for pipeline monitoring have been

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supported and developed worldwide (Sousa *et al*., 2009).

In recent years, many techniques for leak detection have been implemented for several operating pipelines. These techniques can be classified into two categories: internal and external methods. The visual inspection is an example of an external method. In the internal methods, the inspection is carried out inside the tube (Taghvaei *et al*., 2007). This category involves mathematics, such as computing and signal processing, and methods of assessment of volume or empirical models. These methods are usually based on some kind of measuring instrument to acquire data, such as pressure transducers or flow meters.

Hossam and Hossam (2010) provided a review and analysis of all aspects related to pipeline integrity. Inspection techniques were studied and used as a basis for describing the corresponding integrity assessment techniques. According to the authors, pipeline integrity practices and technologies must continue to evolve.

Souza *et al*. (2000) developed a technique for leak detection in pipelines. The technique is based on the spectral analysis of pressure signals measured in the pipeline, allowing leakage detection during the start/stop of pumps. Experimental tests were performed in a 1250 m long pipeline for various operational conditions of the pipeline. Pressure transients were obtained by four transducers connected to a PC computer. The obtained results show that the spectral analysis of pressure transients, together with the knowledge of reflection points provide a simple and efficient way of identifying leaks during the start/stop of pumps in pipelines.

According to Zhong *et al*. (1997) when a tube starts to leak, the sensitive variables start to change in response to that leak. Such a differential in the sensitive variables is the main source of information about the presence of a leak for the human operators that monitor the process.

There are several studies in the literature about the detection of leaks in pipes, largely based on process variable measurements, for example: Belsito *et al*. (1998), Tolstoy *et al*. (2008), Selli and Seleghim Jr (2007).

Considering the importance of computational systems for detecting leaks in pipelines, the general aim of this work is to develop and test a technique to detect gas leaks in pipes based on an acoustic sensor and analysis by artificial neural networks (ANNs). The experimental data were used as input to the neural model to determine the magnitude and occurrence of the leakages.

Acoustic sensors are highly versatile devices that start to demonstrate their commercial potential. These sensors are so named because their detection mechanism is through a mechanical or acoustic wave. As the acoustic wave propagates through the material, any change in the path characteristics (i.e., a leak in a pipeline) of signal propagation affects the speed and/or amplitude of the wave. Investigations in oil pipelines were performed (Avelino *et al*., 2009).

Yang *et al*. (2008) proposed a leak detection system using approximate entropy to discriminate leak signals from non-leak acoustic sources. According to the generation mechanism of leak acoustic signals, the characteristics of the leak signals were investigated to water distribution pipelines. An autocorrelation function was adopted to describe the characteristics of the leak signal. A neural-network model was developed as a classifier which used the identified characteristics as the network inputs.

Caputo e Pelagagge (2003) proposed a simplified approach to detect and locate leaks using ANNs as an overall rating between the patterns of pressure and flow. They adopted ANN architectures of two levels. The first level identifies the leakage, while the second level estimates precisely the magnitude and location of leaks.

Garcia *et al*. (2010) used artificial neural networks to detect leaks of compressed air in a section of duct. The training of the neural model was performed using vibroacoustic signals picked up by a piezoelectric accelerometer. The optimization algorithm for training was the Levenberg-Marquardt, allowing a fast convergence of training for the ANN. From the results, they could detect 98% of cases of leakage and 99% in other situations with the generation of vibrations, but no leak.

Indeed, applications of neural networks are disseminated in several research areas. Choubey *et al*. (2006) used a finite element model to obtain the dynamic characteristics of intact and damaged vessels for the first eight modes of these structures. These characteristics were used as the input pattern of an ANN (artificial neural network) obtaining as output the size of the crack in the vessel.

ANNs present several attractive properties such as universal function approximation capabilities, insensitivity to noisy or missing data, and accommodation of multiple non-linear variables for unknown interactions (Garcia *et al*., 2010). Because of these features, the present work is concerned with the application of ANNs for automatically detecting the occurrence of leakages in gas pipelines, replacing the human operator which monitors the online trends from the acoustic sensors.

MATERIAL AND METHODS

In this paper the characteristics of the noise generated by gas leakage in a pressure vessel – pipeline system have been analyzed.

The pipeline consisted of a ½" diameter 60m long galvanized iron pipeline, made of 6m long tubes connected with short elbows. A domestic type LGP vessel was used as the pressure vessel.

The pipeline was operated with a continuous feed of compressed air, which was fed through the pressure vessel, installed at the inlet end of the pipeline. In order to keep it pressurized, a nipple with a 0.8 mm hole was attached to the exit end of the pipeline.

Gas leakages were triggered manually through an on/off valve installed in a side outlet of the pipeline, located just after the pressure vessel. A nipple containing an orifice, which varied in size from 1mm to 3 mm in diameter, was installed in the side outlet, providing various magnitudes of leak flow.

In this work the pipeline operated under nominal pressures of 4 kgf/cm² and 6 kgf/cm², with the gas leaking through orifices of 1, 1.5, 2, 2.5 and 3 mm in diameter.

The monitoring of leaks was performed through a microphone, installed in the pressure vessel, and connected to a microcomputer. Figure 1 shows a scheme of the experimental setup.

The first phase of this work consisted of collecting the leak detection data by using the acoustic method, generating data for training the neural model.

In each experiment the pipeline was set to operate with a continuous feed of air, at a given pressure, between 1 and 6 kgf/cm². Soon after, the data acquisition software was initiated and the leak was provoked by opening the on/off valve installed in the side outlet at the inlet end of the pipeline.

When the experiment was completed, the data file was generated, providing the dynamics of three-frequency signals.

Data Acquisition System

The data acquisition system consisted basically of a sensor (microphone), a signal conditioning circuit, an Analog/ Digital/ Analog (ADA) converter, a microcomputer and a data acquisition software, developed in C language. This system performs the real-time monitoring of data from the pressure transducer and the microphone installed in the pressure vessel.

The microphone used was an omnidirectional type microphone (CZN-15E). This type of microphone makes little distinction as to the direction from which the sound emanates, responding equally to sounds from all directions.

The signal conditioning circuits used in this study consisted of the microphone pre-amplifier and the band-pass filter circuits, which are electronic circuits capable of adjusting the analog to digital signal conversion.

Thus, the signal emitted by the microphone first passed through the signal pre-amplifier and then through a bank of band-pass filters, so as to transform the signal from the preamplifier into three independent amplitude signals, each with a specific frequency of 1 kHz, 5 kHz and 9 kHz.

Pavan (2005) built and tested several band-pass filters designed for frequencies of 1 kHz, 3 kHz, 5 kHz, 7 kHz, 9 kHz, 11 kHz, 13 kHz, 15 kHz and 17 kHz. Among them, the best response to the noise signal generated was found from the 1 kHz, 5 kHz and 9 kHz filters.

The data acquisition software was developed to read, filter, and process the sound noise signal data and also organize them graphically. The sampling rate of the data acquisition system was 0.1649 ms.
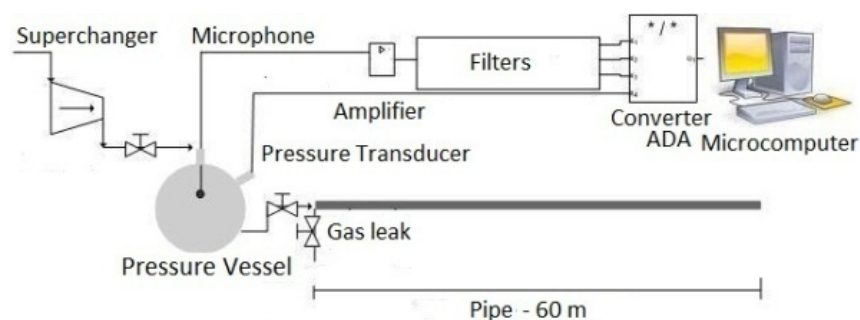

Figure 1: Experimental setup with the microphone installed in the pressure vessel.

Determining Leak Magnitude Through Artificial Neural Networks (ANN)

With the experimental data coming from the acoustic system (microphone and signal conditioning circuit), noises of different frequencies were obtained. These noises were processed in the filter bank, resulting in three voltage signals with frequency bands of 1 kHz, 5 kHz and 9 kHz.

The dynamic of these noises in time were used as input to the neural network model in order to determine the magnitude of the leak (model output). These signals were first smoothed by calculating the moving average from 40 steps back. Each current step measurement represents the average of 500 readings of voltage signals.

Network training was carried out with data obtained with and without leak occurrence. These data were organized in files, separating the training set from the test data. Neural models were developed with experimental data for each operating pressure in the pipeline, namely 4 kgf/cm² and 6 kgf/cm². The number of data patterns used for training was 23166 and 23504 for the pressures of 4 and 6 kgf/cm², respectively.

The measured voltage signals, corresponding to the three frequency bands of 1 kHz, 5 kHz and 9 kHz, were used as input to the neural model at current time (k) and at three previous instants (k-1, k-2 and k-3), totaling 12 entries, as shown in Figure 2.

Several tests were performed off-line to determine the best network configuration, such as: the number of steps back for each signal frequency, the number of hidden layers and the respective number of neurons. The activation functions of the hidden layer neurons were also assessed to obtain the best performance for the situation under study: the hyperbolic tangent and/or sigmoid function.

The artificial neural network training program used in this study was implemented in Matlab software. The method chosen for training the neural network was the Levenberg-Marquardt with Bayesian regularization ("trainbr" function in Matlab) to avoid over-fitting of the neural model.

The software in C language was developed not only for data acquisition, but also for on-line testing of the neural models. With the weights and biases generated by training in Matlab, the neural models were implemented in this software, allowing the real-time monitoring of the pipeline.

RESULTS AND ANALYSIS

Detection of Leaks by the Acoustic Method

Figures 3 and 4 show the change in the amplitude of the sound noise generated by gas leakage in the pipeline through holes of 1 mm, 2 mm and 3 mm in diameter, the operating pressures being 4 kgf/cm² and 6 kgf/cm², respectively. These are the trend plots which allow the operator to notice the occurrence of leakage. In order to make the ANN training easier, the original data from the data acquisition system was smoothed by calculating the moving average from 40 steps back. By doing so, the moving window inputted to the neural model (instants k, k-1, k-2 and k-3) represent the actual tendency of the experimental curves.

At the time that the leak was provoked, the variation in the amplitude of the noise allowed leakage to be readily detected. The amplitude of the noise increased abruptly and remained relatively constant, reaching a new steady state.
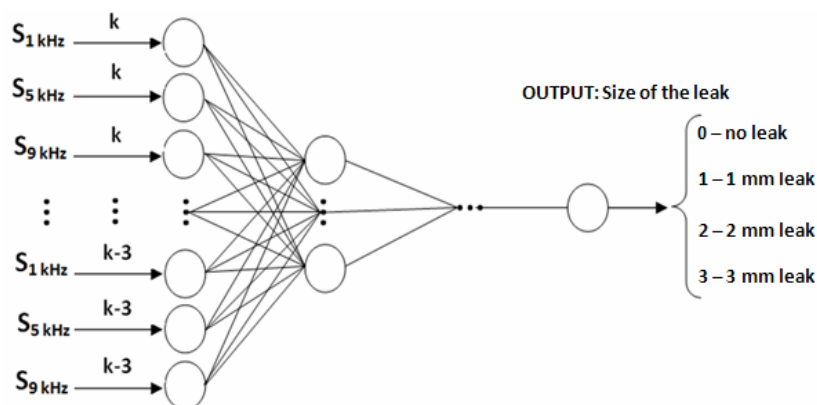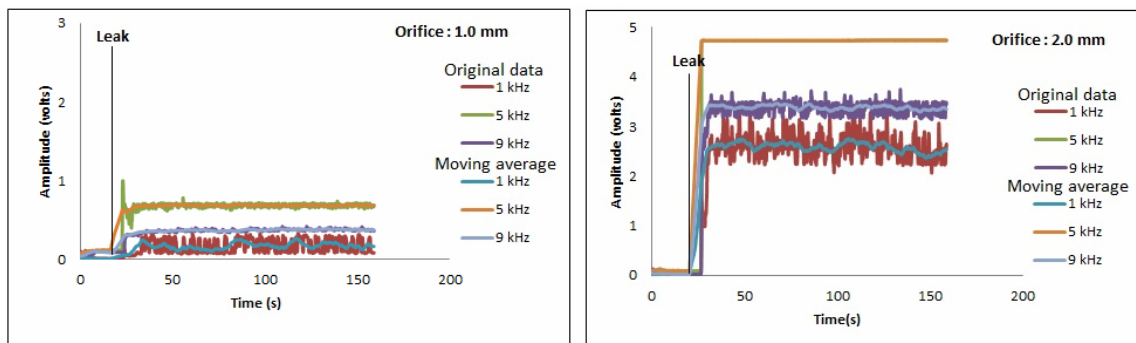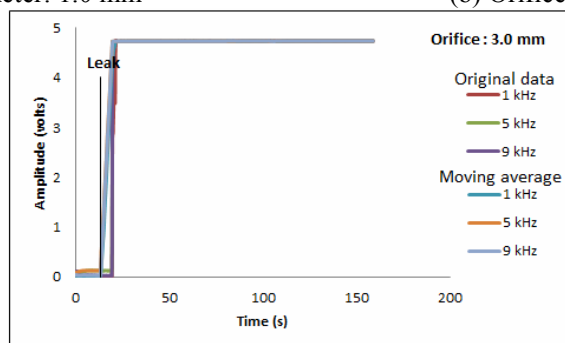

Figure 2: Neural model architecture, to detect leakages and to determine their magnitude. k= current time; S= moving average of the voltage amplitude from the three frequency bands (1 kHz, 5 kHz and 9 kHz).
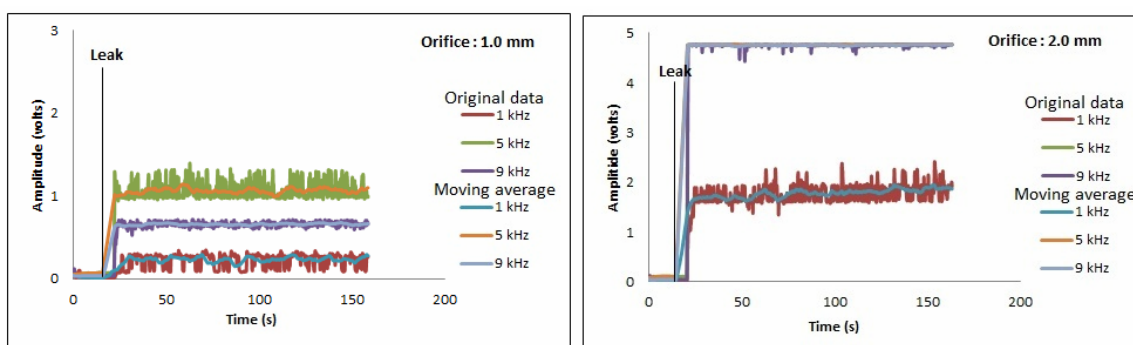
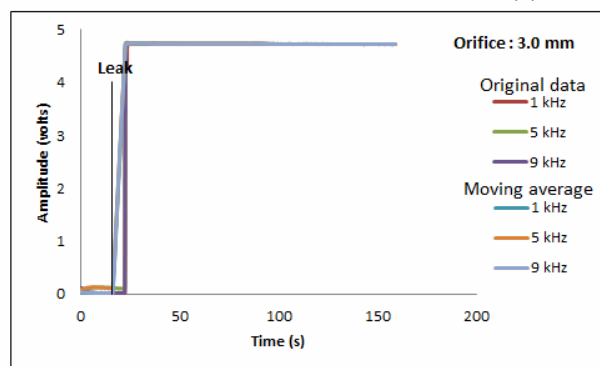(a) Orifice diameter: 1.0 mm

(b) Orifice diameter: 2.0 mm

(c) Orifice diameter: 3.0 mm

Figure 3: Variation of the noise signal amplitude versus time at a pressure of 4 kgf/cm².

(a) Orifice: 1.0 mm

(b) Orifice: 2.0 mm]

(c) Orifice: 3.0 mm

Figure 4: Variation of the noise signal amplitude versus time at a pressure of 6 kgf/cm².

On-line Prediction of Leak Magnitude

Two neural models have been developed in order to determine the occurrence and the magnitude of the leaks occurring at the inlet end of the pipeline, under nominal pressures of 4 and 6 kgf/cm².

Aiming at the performance analysis of neural models, when applied to real-time monitoring, several off-line tests were performed to determine the best configuration of the neural models. Table 1 illustrates the configurations of the chosen neural models that have showed better responses.

Table 1: Settings of selected ANNs.

Po (kgf/cm²)	Topology ANN	Activation function (intermediate layers)	SSE (training)	$\sqrt{MSE}$ (mm)
4	12x15x15x1	Tansig	0.0099	$6.5 \cdot 10^{-4}$
6	12x12x1	Tansig	0.0099	$4.2 \cdot 10^{-4}$

Figure 5 illustrates a leak test using an orifice of 1 mm in diameter and pressure of 4 kgf/cm², under constant monitoring of neural networks. As can be seen, the result was not efficient in this situation. The output of the ANN model showed that something happened in the pipeline (nonzero magnitude). However, this initial prediction of leakage was not retained, coming back to the "no-leak" status.
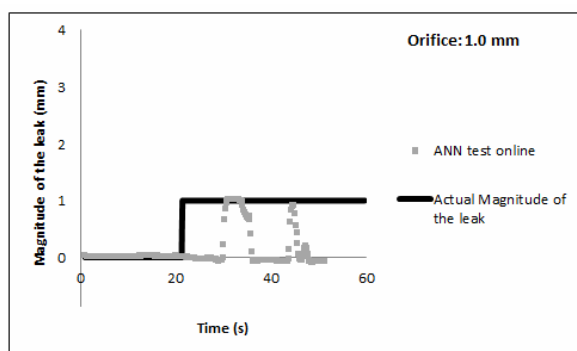

Figure 5: Results of on-line neural model tests (orifice diameter = 1mm)

In order to explain this ANN failure behavior, a comparison was established between training and test signals (Figure 6). High similarity was observed for the amplitude trends of 5 kHz and 9 kHz frequencies. On the other hand, the low frequency signal (1 kHz) was not captured in the same way

since it returned to 0 V even under occurrence of the leakage. Indeed, for this operating point, the 1 kHz signal was not able to represent the leakage properly and, consequently, the neural model was confused.
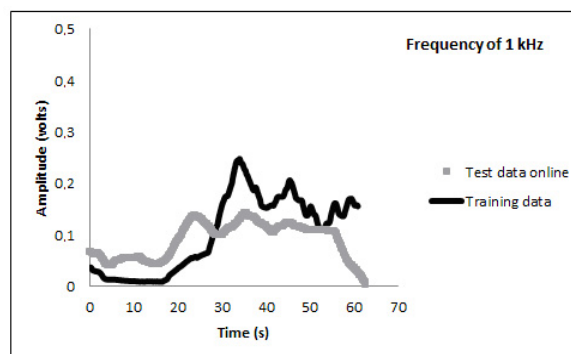

Figure 6: Comparison between training and test signals.

In Figure 7 the actual size of different orifices through which the gas leaked under anominal pressure of 4 kgf/cm² is compared to that predicted by the neural model. It is observed that, in both situations (orifices of 2 and 3 mm in diameter), the on-line prediction was practically coincident with the actual size of the orifice. That indicates proper operation of the microphone, with reproducibility of data, besides the perfect fit in training the neural model for these conditions.

It is also observed that the neural model does not provide an instantaneous value of leak magnitude. This was expected because there is a transition region before the buzzer is stabilized. The network predicts that there is a leak occurring because the output of the model goes from zero to the diameter orifice value, immediately after occurrence of the leakage.

To evaluate the ANN ability to interpolate, tests were applied to orifices of sizes different than those used in training. As shown in Figure 8, the on-line prediction for a leak occurring through an orifice of 1.5 mm in diameter presented an error of 0.5 mm, approximately 33% higher than the actual value. For the leak occurring through an orifice of 2.5 mm in diameter the on-line prediction presented an error of about 20%.
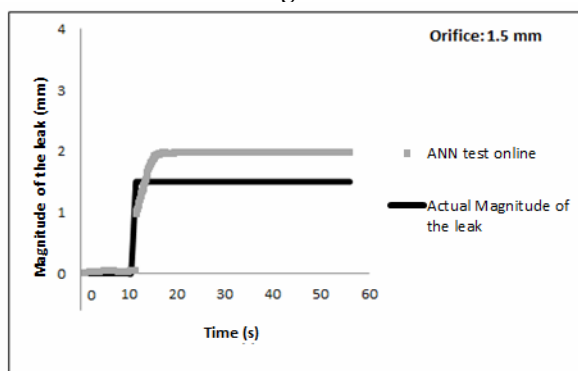
From Figures 7 and 8 it can be seen that, in all cases, the neural model could predict the occurrence of leakage. In all situations of leak occurrence the neural model was able to detect the leak, but in some cases there was a slight delay.
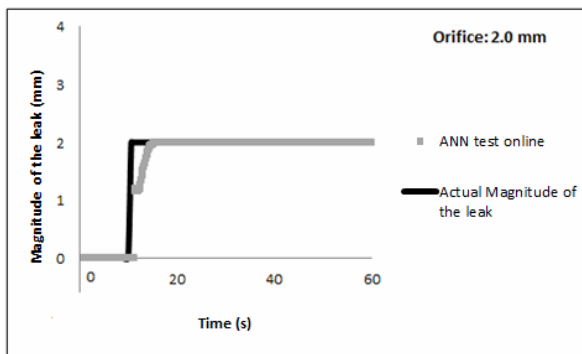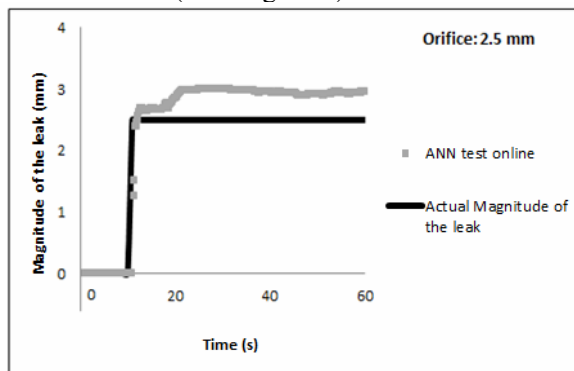
(a) Orifice diameter: 2.0 mm
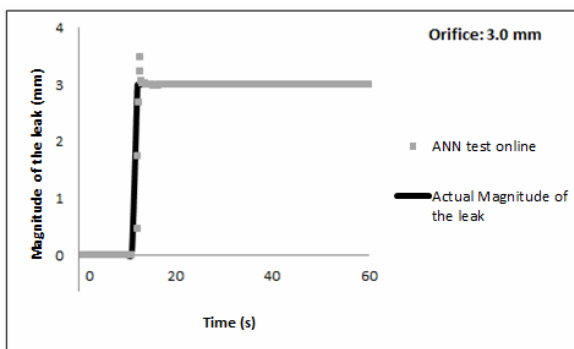
(b)Orifice diameter: 3.0 mm

Figure 7: Results of on-line neural model tests (P = 4 kgf/cm²).
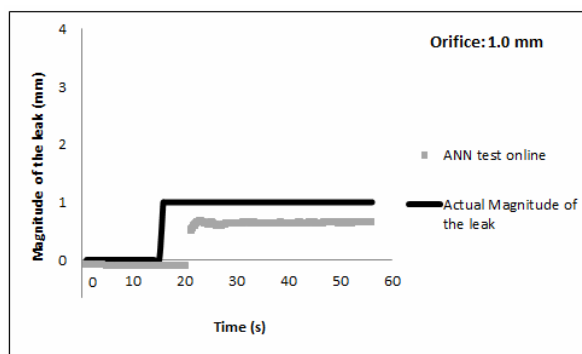

(a) Orifice diameter: 1.5 mm

(b) Orifice diameter: 2.5 mm

**Figure 8:** Interpolation results of on-line neural model tests (P = 4 kgf/cm²).

Figures 9 and 10 illustrate the results obtained with the neural model developed for monitoring the pipeline operating under pressure of 6 kgf/cm².

Figure 9 shows the comparison between the neural model prediction and the actual size of the leak (1, 2 and 3mm). It is observed that, for all cases, the neural model was able to detect the leak, but there was a delay of approximately 5.44 s for the case of a leak occurring through the 1mm diameter orifice. The neural model presented an error of about 40% for the 1 mm orifice, while for the 2 and 3 mm orifices on-line predictions were almost coincident with the actual size of the orifice. Those results indicated a perfect fit in training the neural model for those conditions.

(a) Orifice diameter: 1.0 mm
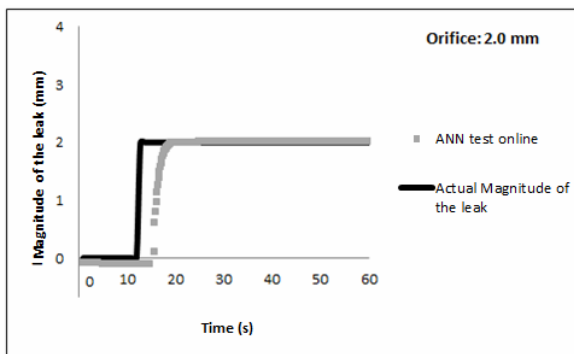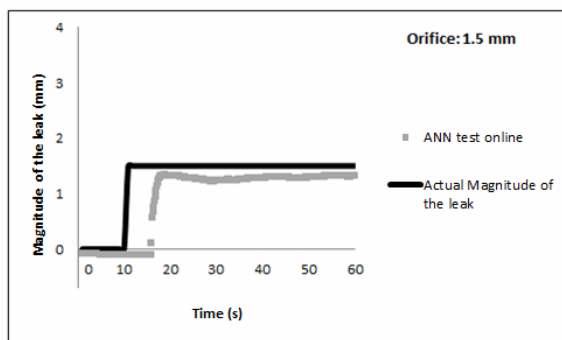
(b) Orifice diameter: 2.0 mm
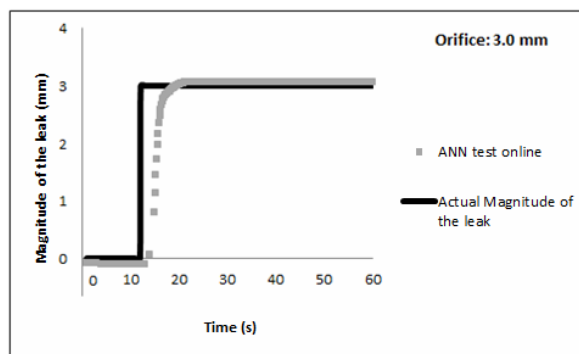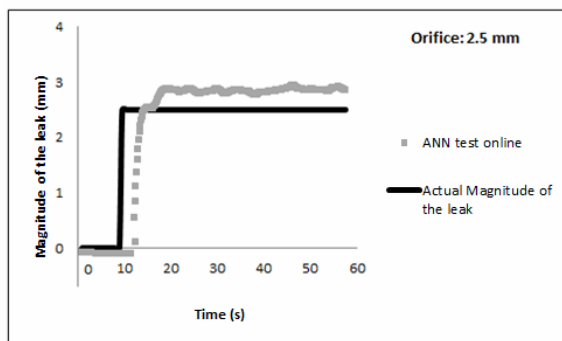
(c) Orifice diameter: 3.0 mm

Figure 9: Results of on-line neural model tests (P = 6 kgf/cm²).

Figure 10 shows the comparison between the model prediction and the actual size, using orifices of sizes different than those used in training. It is observed that, for all cases, the neural model was able to readily detect the leakage, although there were delays in the detection of about 5.27 s and 2.70 s for leaks when using the orifices of 1.5 and 2.5 mm, respectively.

As shown in Figure 10, the on-line leak size prediction for the 1.5 mm orifice presented an error of about 10%. When using the 2.5 mm orifice, the prediction presented an error of about 13%.

(a) Orifice diameter: 1.5 mm

(b) Orifice diameter: 2.5 mm

Figure 10: Interpolation results of on-line neural model tests (P = 6 kgf/cm²).

CONCLUSIONS

The experimental results showed that it is possible to detect leaks in low pressure gas pipelines based on the acoustic method, because a sharp increase in the amplitude of noise is observed in the presence of the leak. This is a successful complementary technique for leak detection systems, mainly in situations where pressure transducers do not work properly, such as: low pressure operating conditions and small orifices.

The developed system was able to determine the occurrence and magnitude of the gas leakage, using neural networks in real time to monitor a 60m long galvanized iron pipeline with ½" diameter. It was observed that the models could adequately predict online the leaks of 1 mm, 1.5 mm, 2.0 mm, 2, 5 mm and 3 mm in diameter. The neural model showed 100% accuracy in detection of leaks in the online tests with a nominal pressure of 6 kgf/cm².

While leak detection is easily performed by neural models, building the models for leak magnitude prediction requires an extensive data base for training. Different band frequencies must be carefully chosen for a suitable sound decomposition, depending on the diameter and material of the pipeline, nominal operating pressure, distance between microphones and the compressors, and expected orifice size.

In conclusion, the data analysis carried out by efficient neural network models could replace the human operator in the task of monitoring acoustic signal trends to warning the staff on the occurrence and inform the size of the leakage. This methodology could be applied to monitor distribution networks of natural gas as well as industrial, commercial and residential gas pipelines in order to provide a safe operation and to avoid severe human health injuries caused by toxic gas leakages.

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