



Comparison Between Multilayer Feedforward Neural Networks and a Radial Basis Function Network to Detect and Locate Leaks in Pipelines Transporting Gas

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An artificial neural network is a technique of artificial intelligence that has the ability to learn from experiences, improving its performance by adapting to the changes in the environment. The main advantages of neural networks are: the possibility of efficient manipulation of large amounts of data and its ability to generalize results. Considering the great potential of this technique, this paper aims to establish a comparison between Multilayer Feedforward - a Multilayer Perceptron network (MLP) with feedforward learning - and a Radial Basis Function Network (RBF). The RBF and MLP networks are usually employed in the same kind of applications (nonlinear mapping approximation and pattern recognition), however their internal calculation structures are different. A comparison was made by using experimental data from a microphone installed inside a galvanized iron pipeline of 60 m length, under various operating conditions. The signal from the microphone coupled to a data acquisition board in a microcomputer was decomposed in different frequency noises. The dynamics of these noises in time were used as inputs to the neural models to locate and determine the magnitude of the leaks (model outputs). The results obtained from the test sets, with leaks caused intentionally, showed that the two neural structures were able to detect and locate leaks in pipes. Nevertheless, the Multilayer Perceptron network showed a slightly better performance.

1. Introduction

An artificial neural network (ANN) has the ability to learn from experiences, improving its performance and adapting to the changes in the environment. The main advantages of neural networks are: the possibility of efficient manipulation of large amounts of data and its ability to generalize results.

Artificial neural networks are parallel distributed systems composed of simple processing units (artificial neurons) that calculate with certain mathematical functions (usually nonlinear). Such units are arranged in one or more layers and interconnected by a large number of connections. In most models these connections are associated with weights, which store the knowledge acquired by the model and serve to consider the input received by each neuron network (Braga et al., 2007).

According Barradas et al. (2009), there is a special interest in application of artificial neural networks (ANN) for solving fault diagnosis problems because of their classification and function approximation capabilities. ANN approach is convenient when an analytical model is difficult to obtain.

Considering the great potential of this technique, the

paper aims to establish a comparison between a Multilayer Perceptron network (MLP) and a Radial Basis Function Network (RBF). The RBF and MLP networks are usually used in the same kind of applications (nonlinear mapping approximation and pattern recognition), however their internal calculation structures are different.

To perform the comparison between the two model structures, experimental data was used from an experimental pipeline system in order to detect and locate leaks. Some authors in literature, such as Caputo e Pelagagge (2003) have employed neural networks as a tool for data analysis aiming at the detection of leaks. The authors proposed a simplified approach to detect and locate leaks using ANNs as overall rating between the patterns of pressure and flow. They adopted ANNs architectures of two levels. The first level identifies the leakage, while the second level estimates precisely the magnitude and location of leaks. Shibata et al. (2009) developed a leak detection system when analyzing the sound noise generated by leak occurrence in a pipeline transporting gas. In order to diagnose pipeline crash, sound noise data were sampled by applying Fast Fourier Transform. The sound noise data were obtained through a microphone inserted at a certain distance from the crash position. Classification and discrimination of cracks are carried out using Neural Networks. The results showed that acoustic diagnosis can be used to classify a leakage sound noise in a pipeline. These studies have shown promising and flexible results, constituting an incentive for the development of this work.

1.1 Fundamentals of MLP networks

Multilayer Perceptron networks (MLP) have been applied to distinct areas, performing tasks such as function fitting and pattern recognition problems, by using the supervised training with an algorithm known as "error back propagation".

A basic neuron with R inputs is shown below (Figure 1). Each input (i) is weighted with an appropriate w . The sum of the weighted inputs and the bias are forming the input to the activation function f . Eq (1) is the appropriate mathematical expression.

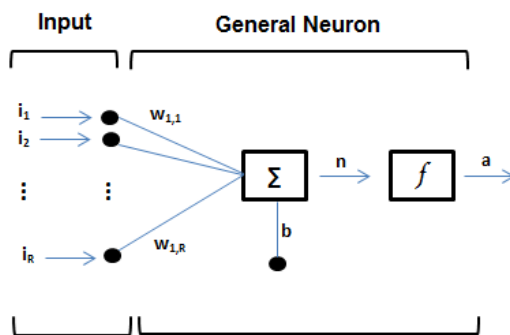


Figure 1: An elementary neuron with R inputs.

$$a = f(w \cdot i + b) \quad (1)$$

Where i – is the vector of input data; a – is the output signal of the neuron; w – are the weights between the neurons and b – is the bias added to the neurons.

Each neuron in the network includes an activation function (f). Multilayer Perceptron networks (MLP) often have one or more hidden layers of sigmoid neurons, followed by an output layer of linear neurons. The logarithmic and hyperbolic tangent functions are the most important nonlinear activation functions for MLP (*logsig* and *tansig* Matlab functions, respectively). These sigmoid output neurons are often used for pattern recognition problems, while linear output neurons are used for mapping problems. In Matlab the command for linear activation function is *purelin*. Multiple layers of neurons with nonlinear activation function allow the network to learn nonlinear relationships between input and output vectors.

1.2 Fundamentals of RBF networks

Radial basis function (RBF) networks have the advantages of an easy design (just three layer architecture), good generalization, and high tolerance of input noises and ability of online learning. From the point of generalization, RBF networks can respond well to patterns that were not used for training (Yu et al., 2011).

A radial basis function neural network has an input, hidden and output layer. The input layer is composed of an input vector i (Figure 2). The hidden layer consists of RBF activation function as networks neuron. The net input to the RBF activation function is the vector distance between its weight (w) and the input vector (i), multiplied by the bias b . Equation (2) shows the mathematical expression of one artificial neuron of a radial basis function network.

Radial functions are a special class of functions whose value increases or decreases in relation to the distance from a central point. There are different types of radial basis functions, but the most used is the Gaussian function. In Matlab the command for using a radial basis function is *radbas*.

According to Yu et al. (2011), RBF networks are simpler than MLP networks. In spite of having more complex architectures, it is well known that the MLP networks have been applied successfully in several difficult problems. RBFs act as local approximation networks and their outputs are determined by specified hidden units in certain local receptive fields. On the other hand, MLP networks work globally and the network outputs are decided by all the neurons.

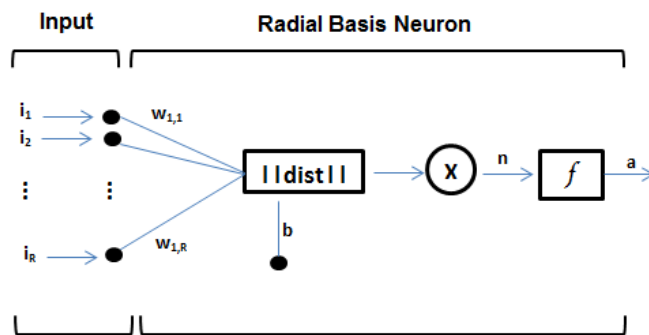


Figure 2: Radial basis network with R inputs.

$$a = \text{radbas}(\|w - i\|b) \quad (2)$$

2. Experimental System

To perform the comparison between the two models, experimental data were obtained in the piping system located in the laboratory of the School of Chemical Engineering/ UNICAMP. The pipeline consisted of galvanized iron with a length of 60 m and $\frac{1}{2}$ " in diameter. A domestic type LGP vessel has been used as pressure vessel. The pipeline was operated with a continuous feed of compressed air, which was fed through the pressure vessel, installed at the inlet of the pipeline.

Outputs were installed at two positions along the pipe. One directly at the inlet of the pipe (0 m) and the other one 3 m further. To get information about various magnitudes of leak flow, inside the installed outlets plates of iron with an orifice in it were installed as well. The size of these orifices varied from 1 mm to 3 mm in diameter. So with these settings it was possible to simulate leaks at two different positions with various magnitudes.

Leaks were monitored through a microphone, installed inside the pressure vessel and connected to a computer. Figure (3) shows a scheme of the experimental setup.

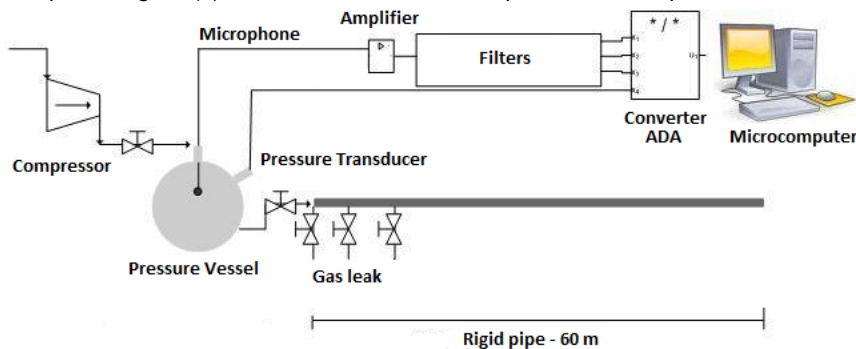


Figure 3: Experimental setup with the microphone installed in the pressure vessel.

The signal conditioning circuits used in this study consisted of the microphone pre-amplifier and the band-pass filters circuits, which are electronic circuits capable of converting the analog signals into digital signals.

Thus, the signal emitted by the microphone first passed through the pre-signal amplifier and then through a bank of band-pass filters. Signals were transformed from the preamplifier into three independent amplitude signals, each with a specific frequency of 1 kHz, 5 kHz and 9 kHz. These three frequencies were chosen because they showed the best response to the noise signals which were generated by the microphone.

In the first stage of this work leak detection experiments were carried out, with the amplitude signal data acquisition, when leakage occurred, thus providing the required data for training the neural models (MLP network and RBF network). The data files were the same for both types of networks, in other words, the data used for training and testing the Multilayer Perceptron network were the same used for the Radial Basis Function network.

In each experiment the pipeline was set to operate with a continuous feed of air, at a pressure of 6 kgf/cm². After the data acquisition software was ready to record noises, leaks in the pipeline were simulated by opening the valves installed in the outlets located at the inlet of the pipeline or 3 m further.

With a complete set of experiments, a data file was generated, showing the dynamic profiles of three-frequency signals.

Initially, the system pressure was not used as input of the neural models, therefore when working with gas there is a small pressure variation in the occurrence of leaks, becoming less significant compared to the microphone signal.

3. Development of the neural models

With the experimental data coming from the acoustic system, 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 for the neural models in order to determine the magnitude and location of the leaks (models outputs). These signals first were smoothed by calculating the moving average from 40 steps back.

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.

The measured noise signals, corresponding to the three frequency bands of 1 kHz, 5 kHz and 9 kHz, were used as input to the neural models at current time (k) and at three previous instants ($k-1$, $k-2$ and $k-3$), so in total 12 entries.

The artificial neural network training program used in this study was implemented in Matlab software.

For each type of neural network (MLP and RBF), two independent models (neural model 1 and 2) were developed. In the training, data from two different locations of leakage were used to determine the magnitude and location of the leak. So that, the first neural model, was responsible for leak occurrence and leak magnitude. And the second model to locate the leak, detected by the first model.

The data set used for training neural model 1 were those obtained without leak occurrence and with leak occurrence through orifices of 1, 2 and 3 mm in diameter, the leak locations were at the inlet (0 m) and 3 m further from the inlet of the pipeline. Neural model 2, which has the function of locating the leak detected by neural model 1, is activated when the output of neural model 1 is different from zero. For its training, data were used from leakage situations at 0 and 3 m from the inlet of the pipe.

4. Results

Figure (4) shows the change in the amplitude of the sound noise generated by gas leakage in the pipeline through orifices of 1 mm and 3 mm of diameter. At (0m) the beginning of the pipeline, the operating pressure was 6kgf/cm². These are the transient profile plots which allow the operator to notice the occurrence of a leakage. Figure (4) also shows that, when the leak occurs, the amplitude of the sound noise changes directly and very heavily so that it's very easy to detect a leak.

Two neural models for each type of neural network (Multilayer Perceptron network and Radial Basis Function Network) have been developed to predict the leak magnitude and leak location. Neural model 1 for each type of neural network was developed to detect the leak and to determine its magnitude. Neural model 2 was developed to locate the leak detected by model 1 and only gets activated when the output of neural model 1 is different from zero.

To find out the best configuration of the neural models, several off-line tests were conducted, observing the dispersion plots obtained (predicted output versus actual data - target). To obtain an accurate model, the test data should appear in the form of a straight line coincident to the diagonal.

Figure (5) shows the dispersion plots obtained from the test points, which data was not used to train the network. The first set of points (set 1), in the two graphs, mean “no leak” occurrence in the pipe. The second set (set 2) indicates a leak with a diameter of 1 mm. The third set (set 3) points out leakages of 2 mm and, finally, the fourth set (set 4) means a leak of 3 mm in magnitude.

It is observed that the Multilayer Perceptron (MLP) and Radial Basis Function (RBF) were able to determine the occurrence and size of the leak. The adjustments of both networks were considered accurate, because: The MLP network showed the following results: $R = 0.9998$ (approximately one), the linear coefficient = 0.0102 (close to zero) and the slope = 0.9969 (close to unity) (i. e., a straight line coincident to the diagonal) and the RBF network showed: $R = 0.999$ (approximately one), the linear coefficient = 0.016 (close to zero) and the slope = 1.0061 (close to unity) (i. e., a straight line coincident to the diagonal).

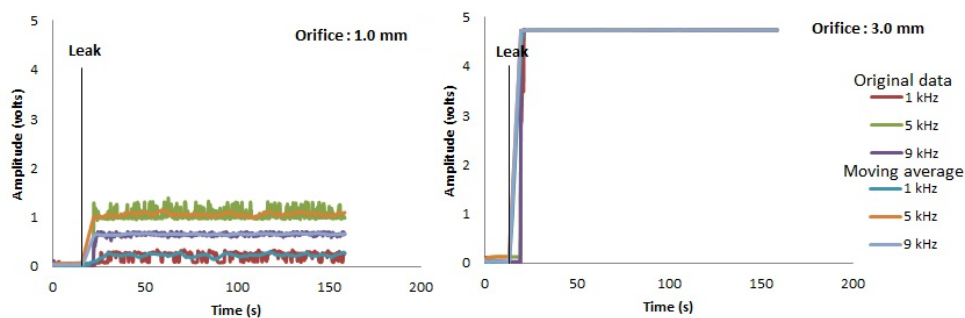


Figure 4: Amplitude of the sound noise generated by gas leakage in the pipeline through orifices of 1 mm and 3 mm (leak location at the inlet of the pipeline).

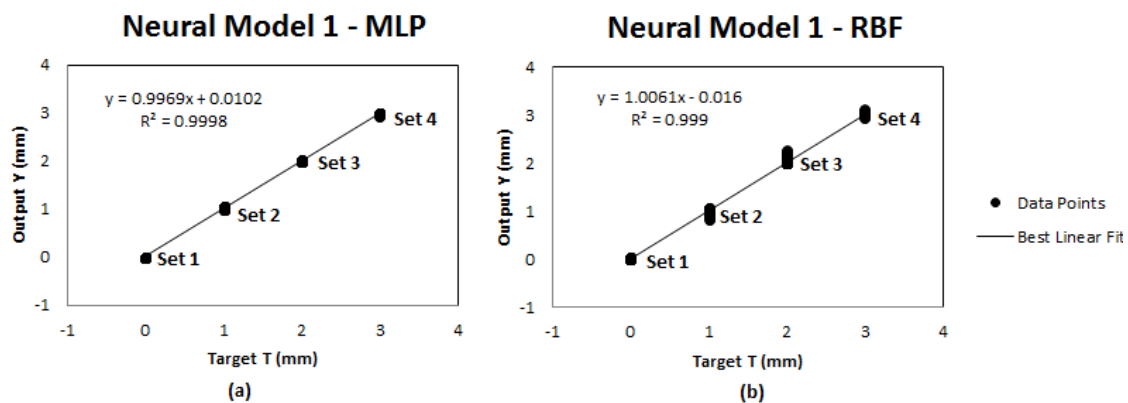


Figure 5: Test set dispersion plots (predicted output versus actual data) from the neural models 1: (a) Multilayer Perceptron network and (b) Radial Basis Function network.

After training and test from neural models, it was found that the RBF networks less time to training, about 3 times faster than the MLP network. On the other hand, the MLP networks showed smaller maximum absolute errors than models RBF as Figures 6 and 7.

Figure (6) shows the difference between the predicted, calculated output (of leak occurrence and magnitude) and the real, measured output (error - mm). And Neural model 1 showed a satisfactory error performance. The maximum absolute errors for the Multilayer Perceptron (MLP) and Radial Basis Function (RBF) of detecting leakages were considered acceptable: 0.06 mm and 0.17 mm.

The training of Model neural 1 for Multilayer Perceptron and Radial Basis Function networks was carried out using data with and without the occurrence of leak and training of the Model neural 2 (for MLP and RBF) was performed only with data leak occurrence, being activated with the leak detected by the Model neural 1.

Figure (7) as well shows the difference between the predicted, calculated output and the actual unseen data (error - m). But this time the error performance is watching output 2 (location of the leakage). Also

neural model 2 showed satisfactory results. The maximum absolute errors of the Multilayer Perceptron (MLP) and Radial Basis Function (RBF) networks for the location were: 0.1109 m and 2.17 m. But it clearly turned out, that the MLP network is way better suitable to locate a leakage than the RBF network.

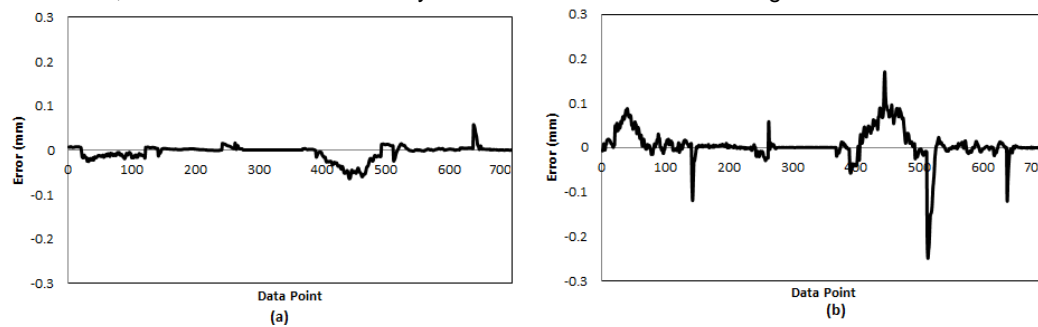


Figure 6: Difference between the predict output and actual data (leak magnitude). (a) Neural model 1 using Multilayer Perceptron network and (b) Neural model 1 using Radial Basis Function network.

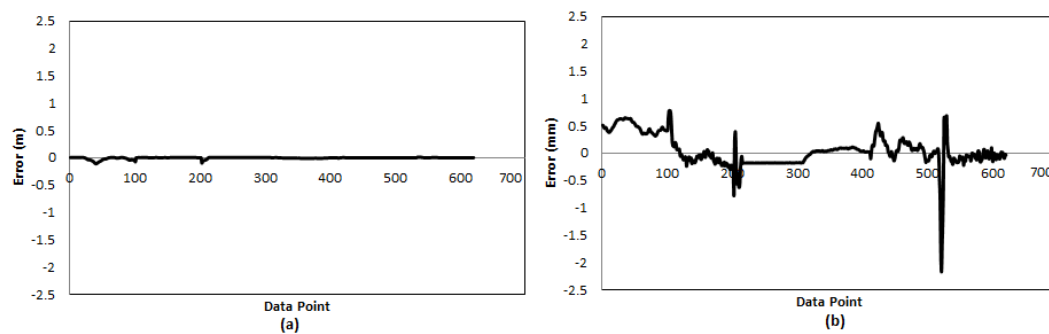


Figure 7: Difference between the predict output and actual data (leak location). (a) Neural model 2 using Multilayer Perceptron network and (b) Neural model 2 using Radial Basis Function network.

5. Conclusions

The experimental results showed that it is possible to detect leaks in gas pipelines based on the acoustic method, since there was a sharp increase in the amplitude of noise in the presence of the leak.

The neural models 1 were successfully developed in order to detect and determine the size of a leak and the neural models 2, locate the leak detected by the neural models 1. From the results, it was observed that the two types of networks (Multilayer Perceptron and Radial Basis Function) were able to detect and locate leaks. However, the Multilayer Perceptron network showed higher accuracy mainly to locate the intentionally triggered leakages. The Radial Basis Function network showed maximum absolute error of about 2 meters from the actual local of the leak, i. e., twenty times the error of the MLP model. This is probably due to the global approximation usually obtained from MLPs.

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