

A neural network approach for leak detection and localization in liquid pipelines

Thiago Lessa Aramaki^{1,3}, **Marley M. B. R. Vellasco**², **Carlos R. Hall Barbosa**³

¹ Petrobras Transportes, Rio de Janeiro, Brazil; ² Pontifical Catholic University of Rio de Janeiro, Electrical Engineering Department, Rio de Janeiro, Brazil; ³ Pontifical Catholic University of Rio de Janeiro, Posgraduate Programme in Metrology, Rio de Janeiro, Brazil

E-mail: aramaki@petrobras.com.br

Abstract: This paper shows a new leak detection and localization technique based on artificial neural networks. The system developed aims at leak localization, although it could also be used to leak detection with some modifications. The system, based on neural networks, was developed and connected via OPC protocol to a pipeline simulator in real time in order to test the proposed system. The simulated model used was taken from a real pipeline operated by Petrobras Transportes. Leaks were simulated, as well as usual operational maneuvers which usually make leak detection systems generate false alarms and submitted to the proposed system in order to verify its performance.

Keywords: leak localization, artificial neural network, leak detection, simulation

1. INTRODUCTION

Leak detection is a major concern in oil industry. Many techniques can be found in literature, the more conservative ones being applied in the industry, while other techniques are still not well exploited by the software's vendors.

According to [1], the selection of a leak detection system depends on a variety of factors such as pipe characteristics, products characteristics, instrumentation, communication capabilities that includes the data acquisition system, thermal insulation if present, depth, operating temperature, background noise, operating conditions, among others. For economic reasons and in some cases vandalism, the instrumentation is only available at the pipeline extremities. Uncertainties from the instrumentation, pipeline characteristics, and

fluid characteristics also affect pipeline sensitivity to leak detection as it can be seen in the evaluation of pipeline uncertainties described in [2].

Some performance metrics and classification of methods can be found in [3], which provides some guidance to the industry on the selection criteria, but newer methodologies cannot be seen there. Other types of classification can also be found in [4]. Regarding the internal leak detection techniques, a better coverage can be seen in [5].

The leak detection scenarios can be one of three: shut-in condition, flowing condition and flowing or shut-in condition with slack line¹.

¹ Slack line is a condition where the pipeline absolute internal pressure is below the vapor

Most of the leak detection systems do not work under slack line condition, and so is the developed system.

The system proposed in this manuscript can be considered a leak detection system of the internal type, as it uses only flow process variables from either end of the pipe and, according to [5], it is also considered an adjunct method.

This means that it enhances other leak detection techniques. Reference [5] does not exploit well this kind of technique, stating that it has to be studied on a case by case basis. A technique solely based on neural networks for leak detection and localization can be found in [6] and this manuscript was based on it.

However, the system described in [6] does not consider common operational tasks related to pipe operation, such as pump starting and stopping, and flow variations due to changes in control valves.

Thus, the methodology herein described tries to investigate the system under the events mentioned above and also to verify some of the results already shown in [6].

2. METHODOLOGY

2.1. Leak detection principles

The main idea of the present work regarding the use of neural network for leak detection problems can be found directly in [6], but it is briefly reproduced here for the sake of completeness.

The pipeline is divided in many segments like the ones shown in **Figure 1**. The number of control volumes is directly proportional to the accuracy of the system regarding leak localization.

In order to conduct this present study, instead of developing a mathematical model for generating the leaks as in [6], a hydraulic

pressure of the product in any point of the pipe. At this point the product begins to vaporize.

commercial simulator was used. The neural network needs to be trained for every leak the hydraulic model simulates.

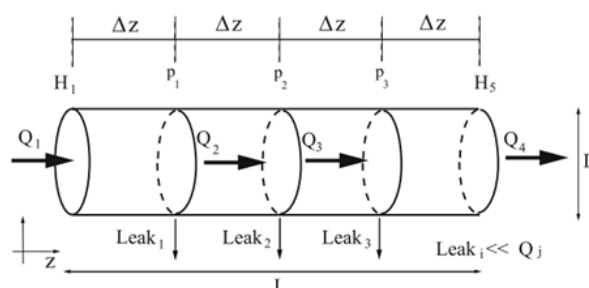


Figure 1. Pipeline segmentation [8]

As can be seen in [6], the neural network architecture considered to be the best was the multilayer perceptron with delayed inputs.

Another study based on neural networks [7] showed that, among Generalized Linear Model (GLM), Multi-Layer Perceptron (MLP) and radial basis function (RBF), the MLP presented the lowest validation error. So the architecture chosen was the MLP with delayed inputs.

Three topologies were presented in [6]. For the sake of comparison, the topology created for this present study was 2-4-4-4-2, which was similar to one of the three presented in [6] which was a 2-4-4-4-3 topology with one order delay. The one presented in this manuscript also has one delay order.

The activation function of all the layers was log-sigmoid, and the inputs considered were only the inlet and outlet flows of the pipeline. The leak detection behavior can be seen in table 1.

Table 1. Expected neural network behavior

Active leaks	F1	F2
No leaks	0	0
1 only	1	0
2 only	0	1
1 and 2	1	1
3	0	1

F1 and F2 are the output neurons. If there are no leaks present, the outputs of both neurons from the output layer have to be zero. If there is a leak in position 1, the output of one neuron is activated and the other output is zero. For the position 2 the opposite has to occur. If both leaks are present then both neurons have to be activated. If there is a leak in a position not trained before, then it is expected that one of the neurons activate, usually the nearest one.

2.2. System description

The main idea of the present work can be seen in **Figure 2**. The hydraulic simulator SPS® is arranged in a manner where some leaks are present in different positions in the model, as can be seen in **Figure 3**.



Figure 2. Training scheme for the neural net

Besides the position, the magnitude of the leaks can also be varied in order to enhance the accuracy. After running the model, flow data were exported to EXCEL® spreadsheets which were the input for the Matlab® system. The last one is responsible for the neural network training.

The data generated by the simulator was used for training of the neural network, in a total of 677 patterns. Within these patterns, 70% were randomly chosen for training, 15% for validation and the remaining 15% for test. However, not all of the leaks were activated, so the ones not trained were used for further testing while the system was running in real time.

After the neural network was trained all the weights, bias and initial input states were transferred to a system developed in VB.NET, called Neura.

The execution part is done according to **Figure 4**. The system developed communicates with the hydraulic simulator using the well-established industrial protocol OPC [9]. It reads in real time the flow values from both pipeline

ends and, based on its inputs, calculates outputs ranging from 0 to 1, where 0 represents no leak and one represents leak occurrence, according to table 1.

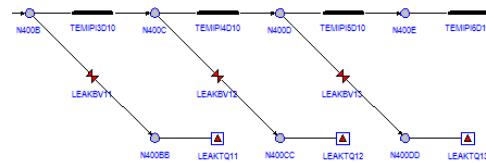


Figure 3. Leak simulation in different positions

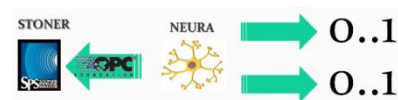


Figure 4. Real Time Leak detection system developed

2.3. System developed

As stated before, a leak detection system was developed to test the neural network in real time. The system has inputs for all the common process variables: flow, pressure, density and temperature. These are common variables used by leak detection systems in general, but for the one described here only the flow variables were used.

3. RESULTS

The model used represents a real pipeline with 225 km long and 10 inches of external diameter. The initial condition was steady state flowing and the pipe was filled with diesel. Some scenarios were prepared and described below. The initial condition was a steady state flowing pipeline, henceforth scenario 0. Scenario 1 is a leak test next to the first position trained. Scenario 2 was done with the second leak initiated, while the first one was still running. The third test, scenario 3, was the leak in a position which was not submitted to the neural network during training phase.

The main issue with the present system is related to false alarms. It was found that, during increase or decrease of inlet or outlet pressure the system indicates a leak in the position next to the

process variable being changed. For instance, when simulating a pipeline depressurization by closing outlet control valve, scenario 4, or due to pump shutdown, scenario 5, the system recognized those events as leaks. The scenarios tested can be summarized in table below.

Table 2. Summarized test response

Scenarios	Response
0	TRUE POSITIVE
1	TRUE POSITIVE
2	TRUE POSITIVE
3	TRUE POSITIVE
4	FALSE POSITIVE
5	FALSE POSITIVE

4. CONCLUSIONS

The system proposed was considered to be very good regarding localization of leaks, but not so good in their detection. The first issue is the training. The target has to represent the leak transient only, otherwise if the target is the whole leak which means transient plus steady state, the system produces a lot of false alarms. The second issue is the time step of the simulator, as the system is trained to learn the dynamic of real time systems, if one tries to use a large time step the system will not respond as expected.

As it can be seen in table 2, the present system is still not reliable to detect common transients that occur in a real pipeline operation, such as starting and stopping of pumps and changes in control valves opening fraction intentionally by the operator. So, it is recommended using it as a leak localization system that will analyze the data only after the leak is detected by another system. An alternative would be providing to the system information about pressures, in order to inhibit those situations mentioned before.

5. REFERENCES

- [1] Bai, Y and Bai Q. Subsea pipeline integrity and risk management, Elsevier Inc., 2014.
- [2] API 1149. Pipeline variable uncertainties and their effects on leak detectability. Washington, DC: American Petroleum Institute; 1993.
- [3] API 1130. Computational pipeline monitoring for liquid pipelines. Washington, DC: American Petroleum Institute; 2012.
- [4] Zhang J. Designing a cost effective and reliable pipeline leak detection system. Manchester, UK: REL Instrumentation Limited, 1996.
- [5] Learn S, Cheng Y, Dolan R and Shahidi S. Evaluation of internal leak detection techniques. *Pipeline simulation interest group annual meeting*, 2015.
- [6] Barradas I, Garza L, Menendez R and Martínez A. Leaks detection in a pipeline using artificial neural networks. *Progress in Pattern Recognition, Image Analysis, Computer Vision and Applications*, V. 5856 pp.637-644, 2009.
- [7] Verde C, Morales-Menendez R, Garza L, De La Fuente O, Vargas-Martínez A. Velasquez P, Aparicio C, Rea C.: Multi-Leak Diagnosis in Pipelines - A Comparison of Approaches. In: Special Session of the Mexican *Int. Conf. on Artificial Intelligence*, pp. 352–357, 2008
- [8] Abdulla M, Herzallah R and Hammad M. Pipeline leak detection using artificial neural network: Experimental study. *Proceedings of International Conference on Modelling, Identification & Control (ICMIC)*, 2013.
- [9] OPC Foundation. Available in: <<https://opcfoundation.org/>>. Accessed in: 20 mai 2015