Intelligent Pipeline Leakage Detection and Diagnosis System

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Abstract-- **This work proposes and implements and validates a methodology to develop a leakage detection and diagnosis system applied to a pipeline distribution system of petroleum. This system helps to improve the operation reliability when transferring petroleum and its products through pipeline, minimizing the accident probability with personal and environmental consequences. In order to reach all goals mentioned the system uses a pipeline phenomenological model concept to achieve fault detection. By using a real time computational pipeline monitoring tool, based on a neural network implementation, this work increases considerably the chance to detect and diagnosis a leakage prematurely.**

Index Terms **- Neural Networks, Fault Detection, Fault Diagnosis.**

I. Nomenclature

Q – Volumetric flow,
T – Temperature,
l_1 – Distance from origin to point 1,
z – Gravitational Energy,
P – Pressure,
U – Mean Flow Velocity,
g – Gravitational Constant,
D or d – Pipeline Diameter,
γ - Dynamic Viscous.

II. Introduction

Computational Pipeline monitoring (CPM) is a new term that has been developed to refer an algorithmic monitoring tools that are used to enhance the abilities of a pipeline controller to recognize anomalies which may be an indicative of a commodity release. A commodity release is defined as being a loss of fluid from the pipeline which the monitoring tool is able to detect.

Leak detection can be accomplished by a variety of techniques such as: sensors, inspections, company staff, reports from SCADA monitoring, etc. The term CPM covers all of methods that use algorithmic tools.

This article focuses on the design, implementation, testing and operation of Computational pipeline monitoring system which use an algorithmic approach to detect anomalies in pipeline operation parameters.

The primary goal of this article is to provide a tool that assists the pipeline controllers in detecting commodity releases that are within the sensitivity of the algorithm. The purpose of this article is to aid pipeline operators in decision-making related to a possible leakage.

The CPM system described here is already running in a petroleum distribution company called PETROBRAS S.A., the biggest Brazilian company of the energy branch.

III. Problem Formulation

The pipeline system is the most economic way to move petroleum and its derivatives, establishing connection among maritime platforms, refineries and terminals.

The system integrity must be guaranteed constantly, in order to prevent leakages that, beyond the financial damage, can provoke ecological disasters and harm the image of the company before the public opinion.

A pipeline system of petroleum and its derivatives is formed of a pressurized net that has to send all fluid from the refinery to a new region called distributions companies. A typical distribution system can be seen at the fig *1*.

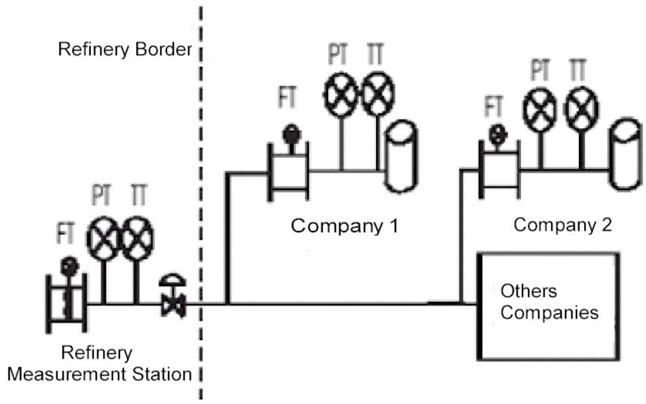

Fig. 1. Typical petroleum distribution system

The information available by the installed instrumentation is the following ones: pressure, volumetric flow rate, temperature in the entrance and output of the pipeline system.

In order to acquire these variables a driver has been developed.

The aim here is to detect and diagnosis a leakage among the refinery and the distribution companies using a “white box” concept model, built on an energy conservation equation, which is fully explained forward.

IV. Methodology Applied

Methods used to detect commode releases can be classified as externally or internally based.

Externally based systems which operate with non-algorithmic principal are not include in this article.

Internally based systems with use CPM techniques utilize field sensors to monitor internal pipeline parameter(s) such as: pressure, temperature, fluid viscosity, density, flow rate, etc. with are inputs for inferring a commodity release by computation. The Fig. *1.2* shows the structure available to achieve the proposed diagnostic.

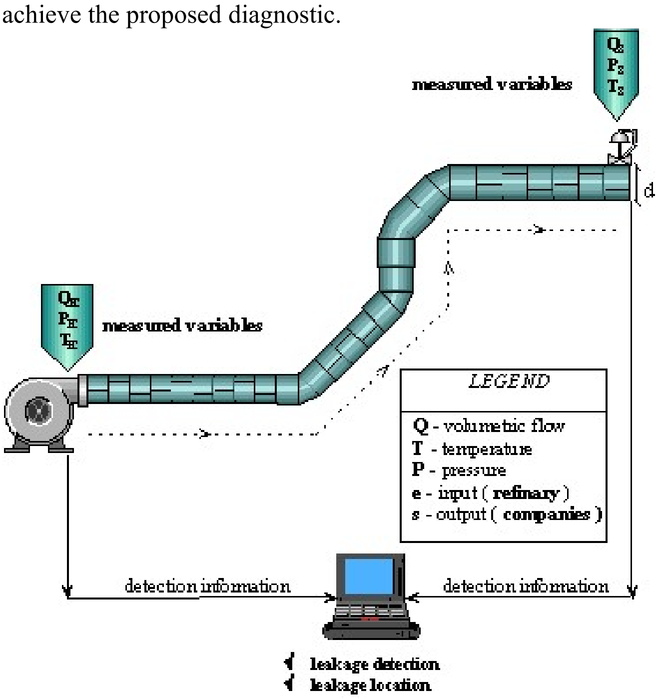

Fig. 2. Structure available to achieve the diagnostic

The type of CPM internally based methodology used here was the real time transient model (RTTM) of the pipeline system. This approach is perhaps the most sophisticated CPM method.

The fundamental improvement which RTTM provides over the others is that it models all the fluid dynamic characteristics (fluid, pressure, temperature). Extensive configuration of a physical pipeline parameters (length, diameter, route topology, etc.) are required to design a pipeline specific RTTM. The application software generates a real time transient hydraulic model. The model implemented is based on a finite elements approach. By using it, the pipeline may be viewed as a lot of blocks with certain length. Fig *3* illustrates the proposed approach.

The definition of the numbers of finite elements the pipeline has a very important effect on accurate a pipeline failure. If this parameter is too big a lot of computation effort is necessary. If this parameter is to low the system might not detect certain failure (position) successfully.

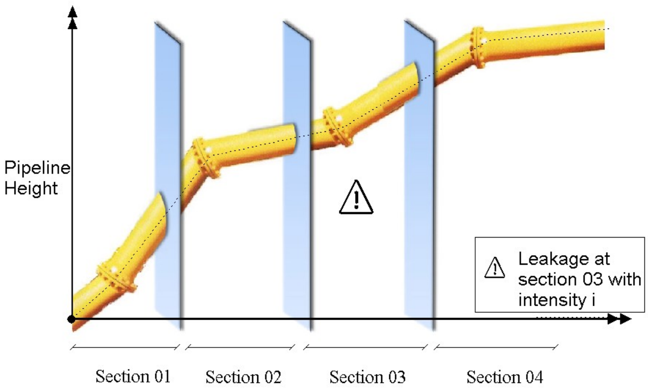

Fig. 3. Finite elements model approach

The proposed approach is to simulate data of pressure profile from a generic pipeline topology in order to create a database. Such database will contain information about all pipeline normal and fault behaviors. Once this database is available, a neural network based on Multi-Layer percepton (MLP) topology, is used to learn the pipeline system dynamic behavior.

Once this database is available, a neural network based on Multi Layer percepton topology, is used to learn the pipeline system dynamic behavior. The finite elements model described was developed using Matlab 6.0.

In order to implement the computational system responsible for the detection and diagnosis, a real time computation system was required. A data acquisition system driver had to be developed in order to get all process variables available at PETROBRAS system. All real time system was built using Visual C++.

The fig. *4* shows the methodology applied to achieve the Pipeline Leakage Detection and Diagnosis system.

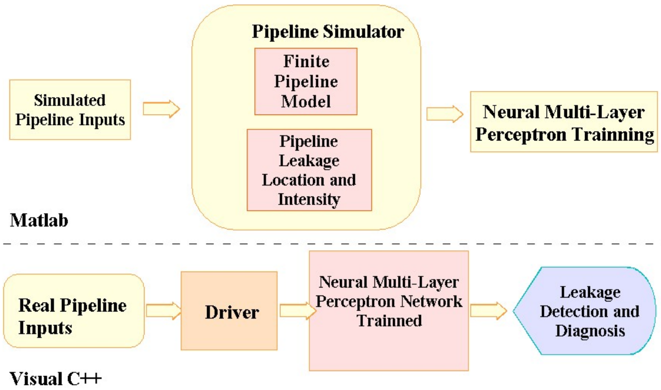

Fig. 4. Methodology applied to achieve the pipeline leakage detection and diagnosis system

V. Finite Elements Model

The finite element model is generated by using real fluid Bernoulli's equation. The eq. 1 enables the model to make use of all physical pipeline parameters and some of internal pipeline parameters.

$$z_1 + \frac{p_1}{\gamma} + \frac{U_1^{\ 2}}{2g} = z_2 + \frac{p_2}{\gamma} + \frac{U_2^{\ 2}}{2g} + h_{p12} \qquad (1)$$

Since a real fluid is considered the eq. 1, the Hagen-Poiseuille equation is used to calculate the power loss in the pipeline system in a laminar flow on circular pipelines. The Hagen-Poiseuille equation is detailed by eq. 2.

$$h_{p12} = \frac{128}{\pi g} \frac{|(l_1 - l_2)| * Q}{D^4} \qquad (2)$$

By using these equations it's possible to build a new equation that allows the calculus of the pressure profile through de pipeline system. The eq. 3 shows exactly that equation.

$$\Delta p = \gamma(\Delta z + \frac{\Delta U^2}{2g} + h_{p12}) \qquad (3)$$

The inputs and outputs of the finite elements model applied are shown at fig. *5*.

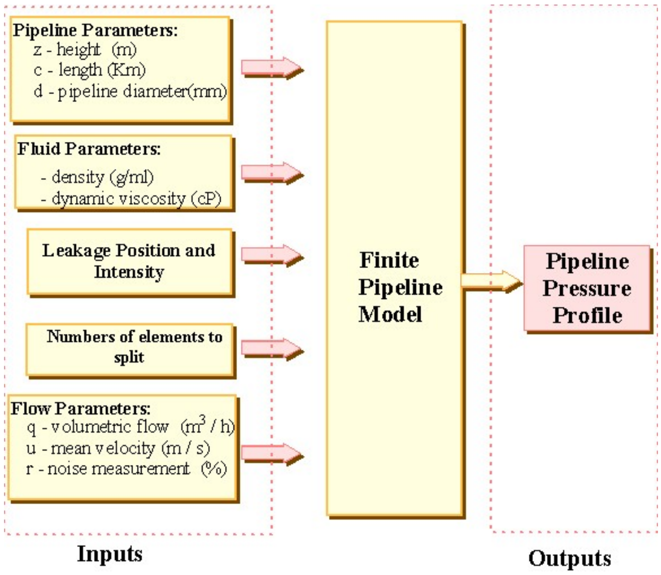

Fig. 5. Inputs and outputs of the finite elements model applied

The output pressure from the model was used to generate a database containing the behavior of normal and faulty pipeline condition. The built database was used to train the neural network.

VI. Multi Layer Perceptron Training

The MLP network was composed by 2 hidden layers with 3 nodes in each hidden layer. The activation function was the sigmoid.

The back-propagation method was used to adjust the neural network weights. The input output model of the neural network is shown at fig. *6*.

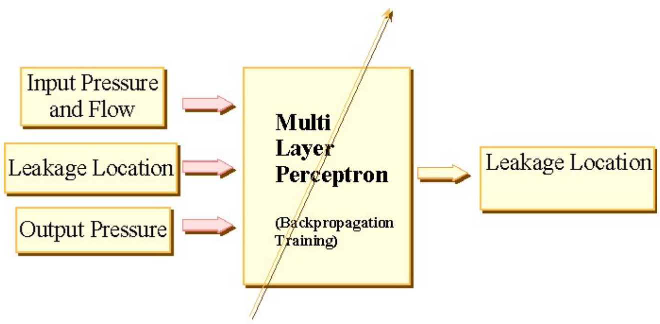

Fig. 6. Input output model of the neural network

The network was trained by a set having 7 faults (leakages) and 7 normal operational conditions at a certain flow (180 m^3/h).

The fig. *7* shows some of the training set, generated by the finite elements models, supplied to the neural network.

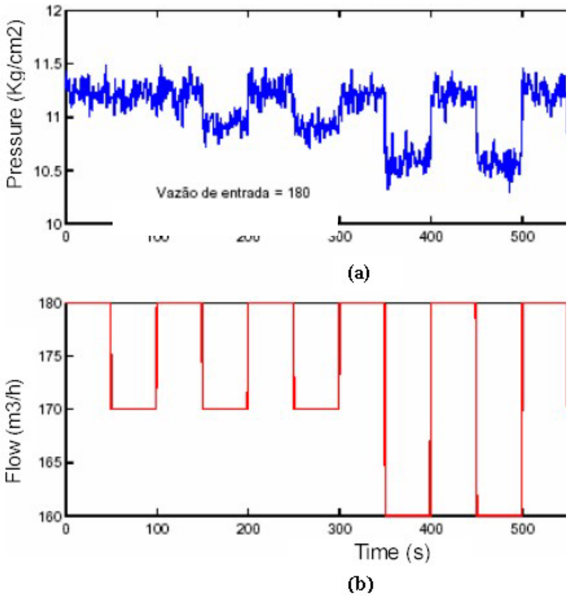

Fig. 7. a) Pipeline Output Pressure versus time b) Output flow versus time

The fig. *7* shows that in t=150s a leakage was generated with 10 m^3/h intensity, in t=300s a new leakage was generated with 20 m^3/h intensity.

VII. Results

The trained network was implemented in Visual C++. A real pipeline profile was used to validate the proposed leakage methodology.

The fig. *8* shows the network errors during the detecting and locating phase.

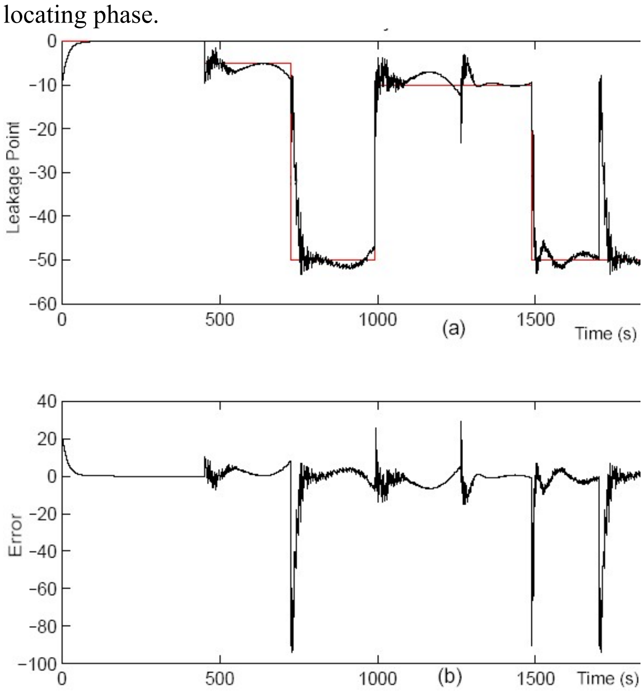

Fig. 8. (a) In red is shown leakage generated and in black is shown the neural network output (b) neural network validation error

The fig. 8 shows that the implements network was able to detect a leakage point after a little interval time (in average 3 minutes after the leakage occurrence).

This system is current in use by PETROBRAS to detect and estimate a leakage position.

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IX. Biographies

A technical biography for the main author is included below.

Carlos Laurentys de Almeida: Born in Belo Horizonte, Minas Gerais, on 11 feb., 1980. Graduated by the *Universidade Federal de Minas Gerais* in Automation and Control Engineering (2003) in honors, best student in September 2003. At present attending the Master Degree Course at the Federal University of Minas Gerais.