Experimental Validation of Artificial Neural Network-Based Leak Detection System in Pipelines

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ABSTRACT: This paper describes the development and the validation through experimental data of a leak detection system for pipelines carrying hazardous materials. The system is based on artificial neural networks used to process measurements collected in the pipeline and coupled with a real time simulator of the flow in the line.

Though an accurate pipeline flow modelling code was developed, experimental data coming from real operating conditions are necessary to perform a reliable and all-around assessment of the detection system behaviour. In fact, field measured data are not easily available in the open literature, in particular those documenting the presence of leaks. Preliminary tests with field data relative to no-leak conditions were actually performed, yet, due to the unavailability of field operational data, a thorough activity of qualification against experimental data was necessary.

An experimental test rig for the simulation of a part an ammonia pipeline was designed and built in Consorzio Pisa Ricerche laboratory. Data collected by running the facility and reproducing typical flow conditions of pipeline have been then used for validation of the system developed.

This paper reports the development of the artificial neural network based leak detection system and its validation with data collected in the pipeline simulation facility. The system that was found extremely successful in leak detection and sizing even during heavy transients in the line.

As a general conclusion the activity performed has confirmed that artificial neural networks can be very effectively used for leak detection and location purposes in pipelines and have potentiality to be extended to analysis of different systems as networks and multiphase transportation systems.

KEYWORDS: Leak detection, pipeline, safety, transient flow, artificial neural networks.

INTRODUCTION

While transportation of fluids over long distances can be efficiently accomplished by means of pipelines, particular attention must be paid to prevention and detection of accidental releases from these facilities. Leaks in pipelines carrying toxic or hazardous fluids can give rise to serious environmental pollution and health hazards if not promptly detected and repaired.

Several leak detection systems have been developed up to now, but none of the present conventional leak detection methods has been shown to be universally applicable (Belsito, 1998). Furthermore present leak detection systems are developed without explicit consideration of the desired risk reduction; in order to define the optimum characteristics of the system, integration with risk analysis is necessary.

These considerations have led to the DEPIRE project aimed at:

1. developing, systematising and assembling risk analysis methodology for determining the characteristics of leak detection systems as a function of the desired reduction goals for a given pipeline.

2. developing leak detection system concept that can achieve the performance requirements arising from the risk studies at acceptable costs.
3. systematising techniques and software for reliability and unavailability analyses to confirm achievement of performance targets.

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In general, different systems apply for different leak sizes; this sometimes involves, at least on important pipelines, implementing more than one independent system at a time, (Stouffs, 1993). Detection and location of leaks by means of conventional methods can not be easily accomplished due to lack of adequate first principle or model based solutions. In addition high speed data processing is needed and system robustness to noisy signals is required.
Artificial neural networks, in principle, may meet many of the needed requirements, besides, thanks to their specific characteristics of learning from examples, deterministic models of the phenomena under analysis are not needed. A properly designed and trained artificial neural network-based system may provide improved performances compared with conventional leak detection techniques.
In this frame Consorzio Pisa Ricerche developed an innovative leak detection and location system based on artificial neural networks. The system was extensively tested with computer simulated data, proving itself as extremely effective in terms of minimum detectable leak size, speed of response and noise and instrumentation fault robustness (Belsito, 1997, 1998).
Though an accurate pipeline flow modelling code was developed, experimental data coming from real operating conditions are necessary to perform a reliable and all-around assessment of the detection system behaviour. In fact, field measured data are not easily available in the open literature, in particular those documenting the presence of leaks. Preliminary tests with field data relative to no-leak conditions were actually performed, yet, due to the unavailability of field operational data, a thorough activity of qualification against experimental data couldn’t be undertaken. To overcome this problem, an experimental test rig for the simulation of a real ammonia pipeline was designed and built.
The leak detection system concept that permits the development of an artificial neural network-based leak detection system was then validated against data collected running the facility. Data representative of the various operating conditions of a pipeline have been collected including steady state and unsteady flow patterns, with and without the presence of leaks of various sizes located in different sites along the line.
This paper describes the experimental rig construction, the data collection and the steps involved in developing and testing an artificial neural network-based leak detection and location systems for the pipeline simulation facility. The development, training and qualification activities carried out to test the performances of the neural network based leak detection and location systems, along with an in-depth description of the facilities used and of the database achievement testing activity, are illustrated and discussed.

DESCRIPTION OF THE EXPERIMENTAL FACILITY

FACILITY DESIGN

The rig design was based on a scaling analysis aimed at reproducing the pressure drops along the line. The scaling analysis is based on the steady state momentum conservation equation in order to preserve the pressure drops in the real pipeline. Water is used as operating fluid. The experimental rig has been equipped with pressure and flow rate transducers reproducing the pipeline instrumentation. The friction factor is then scaled using packed tubes. This solution permits to reproduce accurately the flow conditions in the line and the gravity head in the single tracts.

	EXPERIMENTAL RIG	SIMULATED LINE
Pipeline length	24 m	40567 m
Pipeline diameter	4” (0.1015 m)	8” (0.203 m)
Fluid carried	Water	Liquid ammonia
Number of monitoring stations	5	5
Operating flowrate (nominal)	5 kg/s	10.4 kg/s
Operating pressure drop (nominal)	0.3 MPa	0.3 MPa

Table 1: Pipeline characteristics.

Since the preserved parameter is pressure drop between the stations the absolute operating pressure can be different with respect to the reference line. It has been chosen to adopt an operating pressure of 4 bar, in order to be able to reproduce the maximum pressure drop occurring in the real pipeline. The resulting scaling factor for flow rate will be 0.45 corresponding to a maximum flowrate of about 5 kg/s. Table 1 reports the main characteristic of the reference ammonia pipeline, for the simulated tract of the line and for the experimental rig. It can be seen that the same pressure drop is simulated with a very short loop.

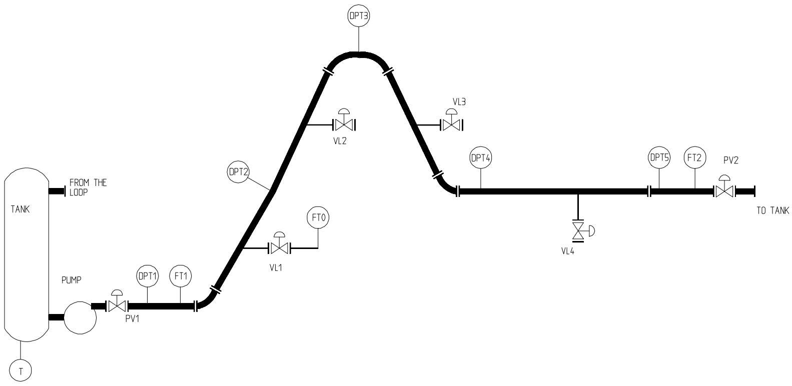

Figure 1: Sketch of the rig.

EXPERIMENTAL RIG LAYOUT

In Figure 1 a sketch of the facility is reported. The pipeline simulation facility reproduces the final part of the ammonia reference pipeline. The operating fluid (water) is contained in tanks and a pump provides the required pressure for the fluid to flow through the circuit. Variation of the boundary conditions are provided by a valve installed at rig inlet. Two flow rate transducers provide the values of inlet and outlet flow rates, while pressure transducers are installed at the end of each section. The gravitational head along the pipeline is reproduced by the elevation changes between the locations of the pressure transducers. Leaks can be simulated in each tract and can be obtained through small valves installed in intermediate positions between pressure tappings. Regulation of the area of the valves allows to obtain of leaks of different sizes.

EXPERIMENTAL DATA BASE ACHIEVEMENT

Several data sets reproducing typical operational pipeline flow patterns were created by running the experimental test rig. Steady state and time varying flow conditions in both cases of no leak and leak occurrence were investigated. Operational transients conditions were included in the simulations.
Tests were performed at different steady and transient flow rate conditions. As an example of the data collected Figure 2 reports trend of pressure and flow rate in the case of leak occurring when the flow rate makes steps between 3 and 3.6 kg/s. When flow rate reaches the higher value the leak is opened.

DEVELOPMENT OF THE ANN-BASED LEAK DETECTION AND LOCATION SYSTEMS

The leak detection and location system is based on the analysis of real measurements coming from field instruments, performed by two neural networks, one for leak detection, the other for leak location, and numerical simulations performed by a specifically developed flow modelling code (Belsito, 1998).
Figure 3 shows the general flow-sheet of the global system for leak detection and location. Both measured and calculated data are used in the process. The neural networks make use of flow rate values calculated by a pipeline flow modelling code that uses the measured inlet flow rate and outlet pressure as boundary conditions.
The procedure for the design of leak detection system has been already applied for pipelines carrying ammonia (Belsito, 1998,1997) and LPG (Belsito, 1998B). In the next paragraphs all the steps composing this procedure will be briefly recalled.

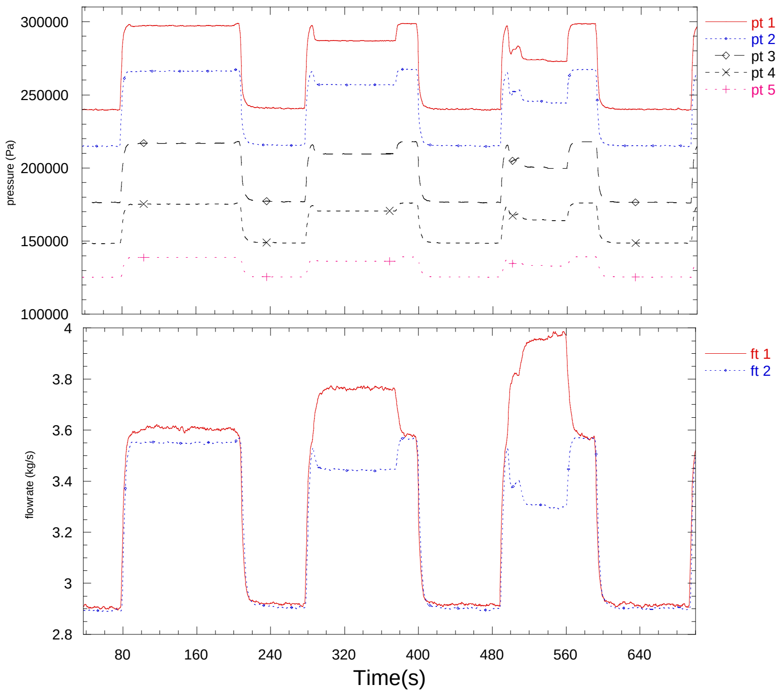

Figure 2: Leak test, unsteady flow: measured pressure and flow rate.

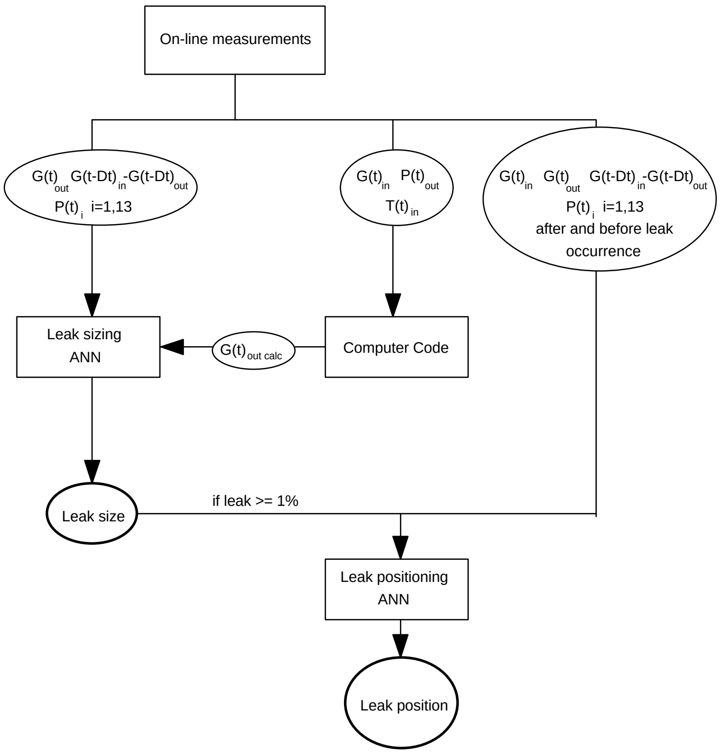

Figure 3: Logic diagram of the leak detection system.

REFERENCE PIPELINE

Geometry and flow characteristics of the facility for which the leak detection system must be realised are needed to make an accurate simulation of it through the pipeline modelling code. In the present case the reference line is the Consorzio Pisa Ricerche test rig previously illustrated.

DEVELOPMENT OF THE PIPELINE FLOW MODELLING CODE

A large range of data, covering the whole range of operating and faulty conditions (i.e. in presence of a leak) should ideally be available for a successful training of artificial neural networks, but field data measured in the presence of leaks in pipelines are generally not available in the open literature. Due to the lack, in many cases, of such data for artificial neural network training, the database used for the present work was derived from computer simulator. This necessitated development and validation of a code, followed by testing of the neural networks based on the data generated by the code against field data, to the extent available.

The equations solved by the code are the classical balance equations for mass, momentum and energy, solved by means of a finite difference scheme. It simulates both single- and two-phase flow and it is written in C++ in order to allow modularity and relative ease in change of models (Belsito, 1998). The physical model is one-dimensional in space and transient in time. It is able to simulate transient behaviour of a pipeline after a leak occurs or upon changes of the boundary conditions. The code is based on a homogeneous two-phase flow model, i.e. liquid and vapour phase are well mixed and are essentially at the same velocity and temperature.

CODE VALIDATION

Validation against experimental data is needed to assess the reliability of the pipeline flow modelling code. The extent of the validation activity depends on the availability of experimental data. Both no-leak and leak situations have been analysed and assessed. The flow patterns recorded during this research activity (steady state, non-steady, with leak, without leak) have been used for pipeline flow modelling code validation and tuning.

DATA BASE SETUP

The pipeline flow modelling code was used to generate a database for training the artificial neural networks. Each case in the data set consisting in the time evolution of inlet and outlet flow rate and pressure calculated in the positions corresponding to the 5 measurement stations along the line. The database includes cases calculated without leaks.

The pattern database described above does not contain instrumentation noise, which needs to be superimposed *a-posteriori*. In order to do this, the measurement system used in the reference pipeline was first characterised.

DEVELOPMENT OF THE LEAK DETECTION SYSTEM

The problem has been tackled by using two different units for leak detection and sizing, and leak location. The first system works on-line monitoring pipeline status and giving an alarm if a leak is detected, thus firing the second system that enable location of the leak along the line. For leak sizing, both data with no leak and data with leak are used for network training. For leak location the leak is known to have occurred and therefore data without leaks are not needed.

Development of the leak sizing network

The basic configuration of the leak sizing artificial neural network, i.e. choice of the architecture, learning parameters, and scaling of the input parameters, was set up using patterns with noise being superimposed. The patterns used here were subdivided into a training set and a test set (2/3 and 1/3 of the total number of patterns, respectively) utilised for verifying the predictive capability of the network. Field data have then been utilised for validation.

As a result of this activity, a feedforward multilayer perceptron, using sigmoidal curves as activation functions was derived as the first version of the leak detection and sizing network. Such an artificial neural network consists of three layers: the input layer has 8 nodes, each of them corresponding to one signal measured in the pipeline; the hidden layer has 6 nodes and the single output gives the size of the leak. The input nodes of the network receive the signals, appropriately scaled, coming from the two flow meters and the 6 pressure meters installed along the reference pipeline.

The prediction of the network for the test set was very accurate. The artificial neural network was able to satisfactorily predict both leak occurrence and sizes. It was seen that the alarm threshold in this system should be about 1.2% leak in order to not give rise to spurious alarms.

Development of the leak position network

Leak positioning is achieved by means of a neural network monitoring every single tract of the pipeline under analysis. Each tract is delimited by sectioning valves and equipped with pressure transmitters at both ends. The output layer of the location artificial neural network consists of several neurons, one for each of the tracts in which the pipeline is divided. The neuron with the highest activation determines the leak location. The artificial neural network for location of the leak is intended to work in cascade with the artificial neural network for leak detection. When a leak is located then the artificial neural network for location is "fired" and the prediction of position is done.
Leak location systems was conceived to use as inputs the pressure drop due to a leak measured by the transducers along the line. The leak occurrence causes a pressure drop in the various positions where transducers are located and in addition a drop in the outlet flow rate. The combination of the amplitude of pressure drops contains the information on leak position. The calculation of the pressure drop due to the leak from field data requires that the time of leak occurrence is well identified. As a consequence, provided a definition of the response time of the system for leak detection, the time of leak occurrence must be estimated. This task is performed by the artificial neural network for leak detection that provides the dimension of the occurred leak as well. The developed artificial neural network was trained with signals without noise using the steady state pressure drops (5 signals) and flow rate drops (2 signals). The output is the tract where leak is located (4 outputs). The performance of the network is errorless: 100% of the patterns are correctly classified in test and in training sets. It is worthwhile to note that this performance refers to steady state conditions. A degradation of the performance of the leak location system is expected in the case transient conditions occur in the line.

COUPLING OF THE ANN WITH THE CODE FOR DATA PREPROCESSING

So far, a leak sizing ANN has been successfully trained using noisy, steady-state, numerically generated patterns. Designing a system to be operated in the field requires that routine, relatively slow transient operations be treated by the system without giving rise to spurious alarms. The main difference from such transient operations and steady-state conditions previously utilised, is that while during steady-state conditions the input and output flow rate differ only by the leak flow rate and the noise, in the case of transient conditions, the "packing effect" due to liquid compressibility is responsible for one more contribution to flow rate unbalance. Such contribution must be included during training of the network or during pre-processing of the transient data. In this phase of the work, then, the leak sizing network was fed with real field data. The performance of the artificial neural networks fed with the field data was to give rise to many spurious alarms. The actual (measured) outlet flowrate and code-predicted outlet are then fed to the ANN together with the usual pressure signals (see Figure 3). This allows compensation for the packing effect of the fluid that would otherwise be present in case both measured inlet and outlet flow rates are directly compared. Apart from noise and modelling approximations, measured and calculated outlet flow rates would differ only by the contribution given by the leak as in the steady-state case. This is the main reason for the improved behaviour obtained from the neural network.
The code that has been developed must run on-line with the artificial neural network producing one of the inputs. Indeed, this is possible owing to the computational simplicity and efficiency of the C++ computer code that has been developed (Belsito, 1997, 1998, 1998B). The new output given by the leak sizing artificial neural network showed a behaviour that is fairly robust vis-à-vis transient field signals.
In the coupling of the artificial neural networks with the code it was found that the dynamics of the instrumentation, must be considered while processing field data. In fact, flow meters may have different dynamics that give rise to spurious alarms.

ASSESSMENT OF THE ANN AGAINST FIELD DATA

All the data that have been collected in the test campaign have been analysed by the leak detection and location system in order to validate the capabilities of the system against experimental data. The main results of the validation activity are presented.

NO LEAK CASES

The data recorded in no leak conditions have been used in order to validate the leak detection system capabilities against spurious alarms. Both steady flow data and unsteady flow data have been used. Steady flow data have been fed to the

leak detection system for various values of the flow rate. In all these cases no spurious signals have been generated by the leak detection system. In the case of stepwise variation of the flow no spurious alarms are generated by the system.
In the tests with flow rate oscillating around a reference value the leak sizing system gives sometime rise to spurious alarms. These alarms occurs for very short periods of time and corresponds to strong transients in the line. The spurious alarms occurs only at the lowest value of the flow rate in the loop.
False alarms are not generated if the flow in the loop increases. Anyway if a slightly higher threshold is used (for instance 1.5% leaks) no spurious alarms are generated. These results are in agreement with those obtained in the development of the leak detection system for LPG pipeline (Belsito, 1998B): the higher the flow rate and the pressure in the loop, the easier the leak detection and location.

LEAK CASES

All the recorded trends have been used to test the whole system. The time evolution of pressure and flowrate have been provided to the leak detection system and the evaluation of the leak size is done. When a leak larger than 1% is detected the system for location is fired and the location is predicted.

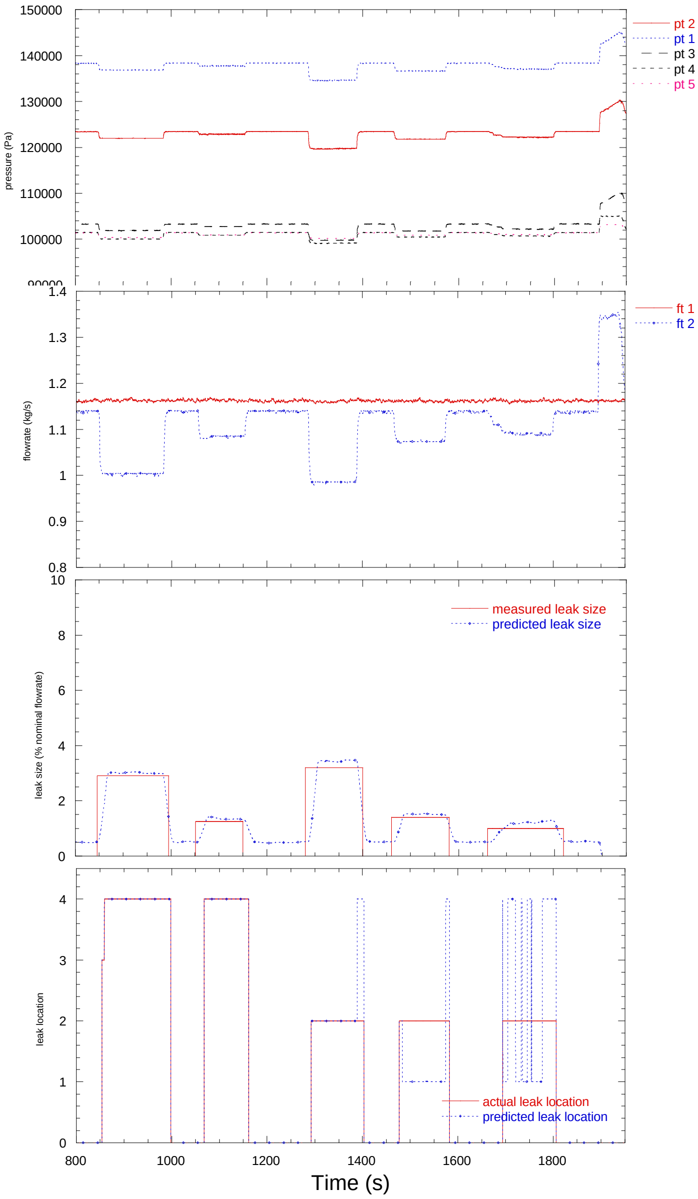

Figure 4: Pressure, flow rate, leak size and position for leak test, steady flow rate.

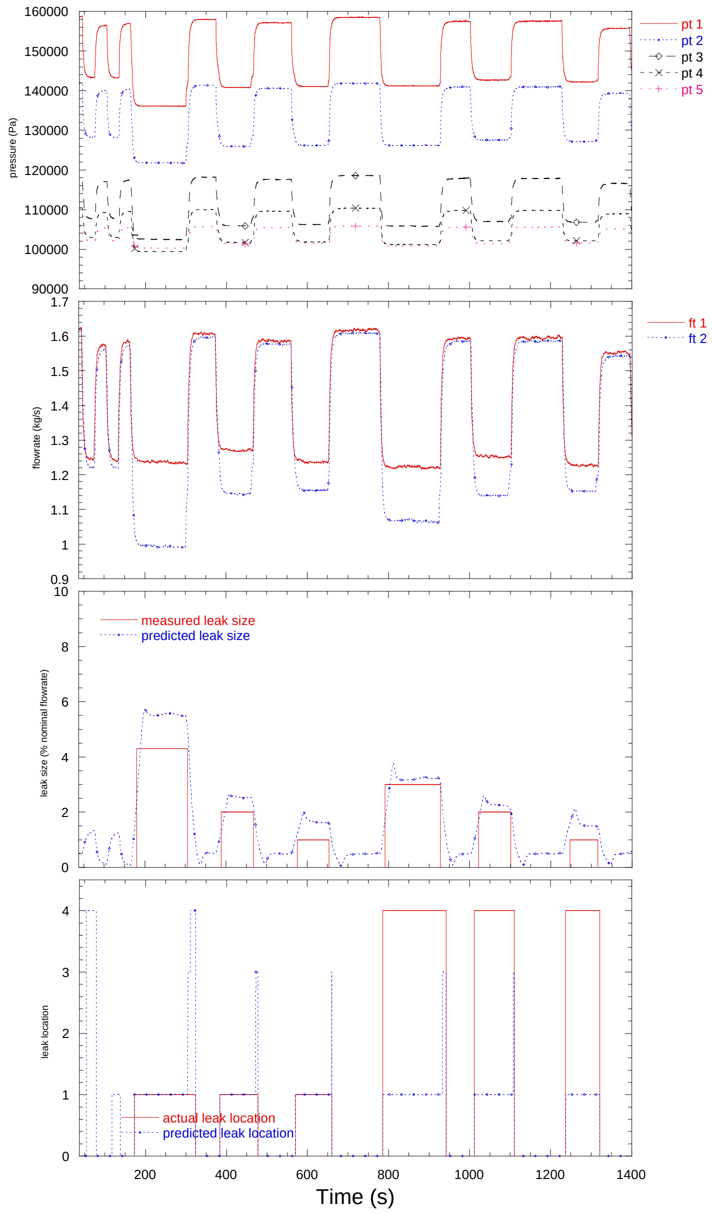

Figure 5: Pressure, flow rate, leak size and position for leak test, step in flow rate.

Steady flow cases

An example of the results obtained by testing the leak detection system against steady flow rate is reported in Figure 4. The trend of pressure and flow rate are reported together leak size and position estimated by the ANN-based system. It can be seen that the leak sizing is always quite accurate, while some errors are present in the location of the leak. This is particularly evident in the event of small leak and low loop flow rates even if the error are quite small. This result is quite general: in steady state conditions leak detection is quite accurate while limited errors can be found in leak location prediction.

Unsteady flow cases: step in flow rate

Results obtained in the analysis of steps in flowrate with leak occurrence can be found in Figure 5. The figure refers to a case in which flowrate is changed from 1.6 to 1.3 kg/s and the leak is open. It can be seen that leak size is calculated with good accuracy. Some spurious alarms are generated confirming that the sensitivity of the system, if spurious alarms are to be completely avoided, is about 1.5%. Discrepancies can be found in the results of the leak location system. In fact the leak is predicted to occur always in position 1 while actually it occurs in location 4 in some cases. It should be noted that the step in flow rate considered in the present case (0.3 kg/s) are very fast. They occur in time of the order of few seconds while in the real pipeline they are much slower .

Unsteady flow cases: oscillating flow rate

Results similar to the previous case are found in the case of oscillating flow rates (Figure 6). Flow rate is varied around a reference value and leak are opened during the transient. Again leaks are easily detected, even if with delay compared to the previous cases, but errors in location are present.

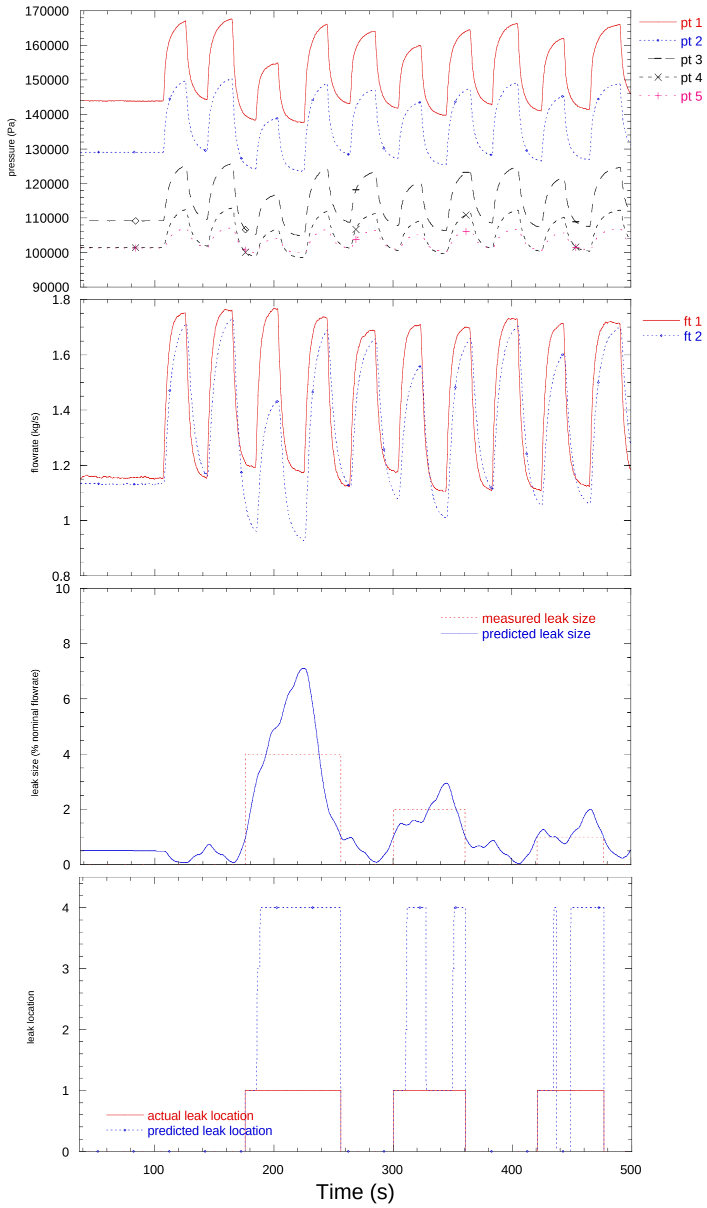

Figure 6: Pressure, flow rate, leak size and position for leak test, oscillating flow rate.

CONCLUSIONS

An artificial neural network-based system for leak detection and location has been developed. The neural network for leak detection have been trained and successfully tested with noisy signals. It was found that it is necessary to compensate the effect due to fluid compressibility to avoid spurious alarm as a consequence of a simple transient flow condition in the line. The coupling between the code and the artificial neural network allows data pre-processing and compensation of the compressibility effect due to variations in the boundary conditions in the system.

The experimental activity described in this paper and the following development and testing activity of ANN-based leak detection system permitted to assess the capabilities of the system against experimental data. A vast experimental campaign has been carried out and various typical conditions of the pipeline have been simulated: steady state flow, steps in the flow rate and oscillating flow conditions have been measured. Both cases with and without leak have been recorded.

The data that have been collected were used to test the system that was found extremely successful in leak detection and sizing even during heavy transients in the line. All the leak have been detected and sized correctly.

The system is able to detect leaks as small as 1.5% of the flow rate without generating spurious alarms. The location of large (5%, 10%) leaks is predicted with high accuracy. This is particularly interesting because, for such a leak, fast location is more important. Performance in location are quite good for steady state cases while it is still acceptable in transient analysis of small leaks. Robustness of the system has been proven against spurious alarms under transients in the line has been proven. As a general conclusion the activity performed has confirmed that ANN can be very effectively used for leak detection and location purposes in pipelines and have potentiality to be extended to analysis of different systems as networks and multiphase transportation systems.

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