An Intelligent System to Classify Leaks in Water Distribution Pipes

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***Abstract*—**Leaks in water distribution network are generally detected and located using conventional methods that is not able to give previously any idea about leak size. Current paper draw proposal plan to discriminate leaks according to its size, using a modular system in four blocs: 1) Signal preprocessing, 2) Representation using modified Mexican hat wavelet 3) Dimensionality reduction using random projection combined to principal component analysis and 4) Classification with artificial neural networks.

***Keywords*—** Leak signals, Signal representation, Dimensionality reduction, Artificial neural networks, Leaks classification.

I. INTRODUCTION

DRINKING water becomes a rare resource that water network managers have to save, indeed International Water Supply Association (IWSA), estimate the amount of lost or "unaccounted for" water is typically in the range of 20 to 30% of production. Unaccounted for water is usually attributed to several causes including leakage, metering errors, and theft – leakage is the major cause. In addition to environmental and economic losses caused by leakage, leaky pipes pose a public health risk as leaks are potential entry points for contaminants if a pressure drop occurs in the system.

Then, to reduce public health risk, to protect environment and particularly to preserve drinking water public, the ideal way is to implement a serious water system audit based on leakage control program such as Continuous network survey and Leak systematic detection.

Generally leak detection system is based on checking water network for leaks by using acoustic equipment which detects the sound or vibration induced by water as it escapes from pipes under pressure. Acoustic equipment include listening devices such listening rods, hydrophones, and geophones These are used to listen for leak sounds at contact points with the pipe such as fire hydrants and valve. Acoustic equipment also includes leak noise correlators. These are modern computer-based instruments that have a simple field setup and work by measuring leak signals (sound or vibration) at two points that bracket a suspected leak. The position of the leak is then determined automatically based on the time shift between the leak signals calculated using the cross-correlation method.

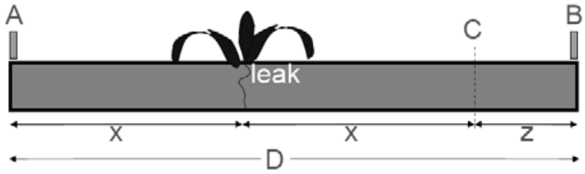

FIG.1: SCHEMATIC ILLUSTRATION OF THE LEAK SEEKING METHOD

If it exists, leak is located via time lag between leak signals that is found from the cross-correlation function, time corresponding to higher peak (τ_{max}) will correspond to the difference in arrival times between measured leak signals. In reference to Fig.1, the time delay between measured leak signals is related to the location of the leak by:

$$X = \frac{D - S.\tau_{\max}}{2} \tag{1}$$

where D is the distance separating acoustic equipments, and S is the velocity of sound.

Acoustic leak detection equipments using cross-correlation method are considered to be satisfactory especially to locate leak. however, they don't contain sufficient information about leak size.

To discriminate leak according to their size, current paper propose an intelligent modular system based on classification by multilayer perceptron network to deduce if that is large or small leak. System is presented as shown in Fig.2:

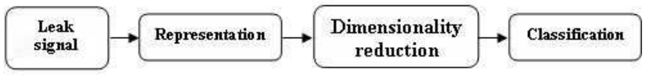

FIG.2: LEAK CLASSIFICATION MODULAR SYSTEM

II. COLLECTION AND PREPROCESSING OF THE LEAK SIGNALS

A. Leak Categorization

There are many ways to categorize leaks, it can be following pipes diameters, Pressure into canalization, hole area, etc. but the most significant parameter is the flow loss rate through the hole.

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For drinking water distribution in this case studied, depending on flow into pipe and on water use, we can build two categories:

- Small leak, where loss flow is below 5 l/min,
- Large leak, where loss flow represents at least 5 l/min.

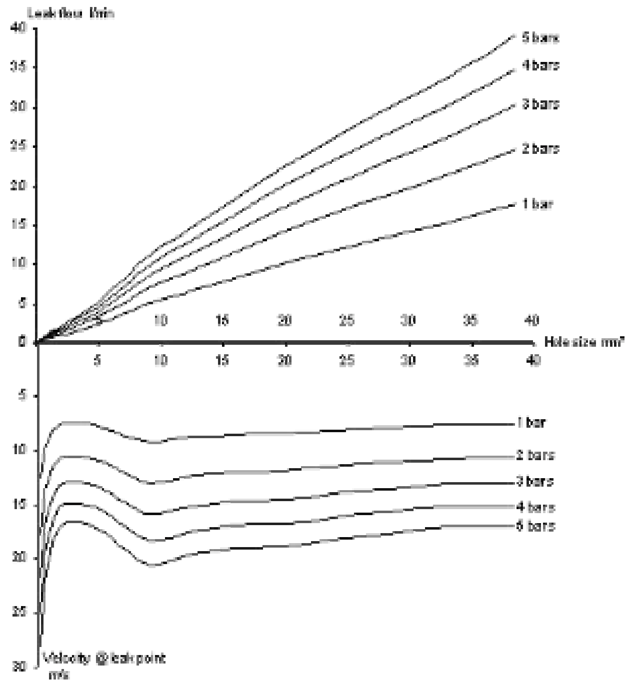

FIG.3: LEAK SIZE DEPENDING ON PRESSURE AND HOLE AREA [1]

As shown in Fig.3, leak flow increase with hole area and total head into pipe. Signal magnitude is related to speed at leak point, according to Fig.3, small leak can sound like a large one if there is a tiny hole. Consequently we note two confusion zones for leak discrimination. First one is in the boundary between two categories and the second one is in the range of tiny holes (about 2mm²).

B. Signals Collection

To apply our automatic recognition pattern to classify leaks, we collected a set of signals relating to leaks happened in Marrakech drinking water pipes. We selected for each leak only the powerful signal detected by hydrophones placed in two points that bracket the leak.

We collected 55 signals, 21 of them were related to leaks that happened in Iron pipes, leaks collected concern the two categories and are shared following next table:

TABLE I
LEAK SIGNAL COLLECTION BY CATEGORIES

Leak size	Iron Pipe	PVC Pipe	*Total*
Large	14	21	35
Small	7	13	20
Total	21	34	**55**

C. Leak signal Preprocessing

Like in cross-correlation method, leak signals were digitally recorded played back off site in analog form and stored using personal computer. The signals were first passed through anti-aliasing filters with a cutoff frequency set at 200Hz for plastic pipes and 1000Hz for iron pipes. Then, each signal was segmented for intervals of 60s with sampling frequency of 500Hz. Signals obtained were stored on the hard disk of a personal computer.

Digitized leak signals were analyzed using digital filtering and spectral analysis software on a personal computer. The signals were first digitally filtered as necessary using high- and low-pass filters of the fourth-order Butterworth type. [2]

In order to avoid magnitude effect due to sound wave propagation conditions such as distance between leak and acoustic sensor, pipe material, pipe diameter, pressure into pipe, etc. and we normalized signal by reducing magnitude scale: $\mathbf{I}/I_{max}$.

III. LEAK SIGNALS REPRESENTATIONS

Because leak signal bearing depends on propagation condition and noise signal, it can't be directly comparable even if we consider frequency representation, so it is better to adopt a representation that take into its account simultaneously both time and frequency. For this reason, we employ the modified Mexican hat wavelet that is used for the first time to represent seismic signals [3]:

$$\psi(t) = \frac{2}{\sqrt{3}} \pi^{-1/4} \left(1 - t^2\right) e^{-t^2/2} e^{-i\omega_0 t} \qquad (2)$$

This representation is a continuous wavelet transform, that profits at the same time of the intrinsic properties of the Mexican hat wavelet and Morlet wavelet. On the one hand, Mexican hat wavelet is a real function that is useful to detect discontinuities in signals. On the other hand Morlet wavelet is complex valued, it is enabled one to extract information about the amplitude and phase of the signal being analyzed [4].

IV. DIMENSIONALITY REDUCTION

The bidimensional representation of Leaks signals by the modified Mexican hat wavelet gives high dimensional images. For a system of automatic classification and in order to eliminate the problems due to high dimensional data such as the curse of dimensionality [5], the dimensionality stage must be integrated in the system.

In this studied case we use similar procedure using to reduce dimensionality image for seismic signal. [3]

A. Random Projection

In random projection, the original d-dimensional data is projected to a k-dimensional (k<<d) subspace through the origin using a random k×d matrix *R* whit unit lengths columns. The random mapping arises from the Johnson-Lindenstrauss lemma [6]: If points in a vector space are projected onto a randomly selected subspace of suitable high dimension, then the distances between the points are approximately preserved.

B. Principal Component Analysis

Abridged PCA, which is commonly technique in data analysis field used to reduce dimensionality because it is the optimal linear scheme for compressing a set of high dimensional vectors into a set of lower dimensional vectors. Also model parameters can be computed directly from the data.

C. Algorithm

Algorithm, for dimensionality reduction is sit up in four steps:

- Step1: Normalization of the scalogram image,
- Step2: Reduction of dimensionality of each image corresponding to each leak signal,
- Step3: Power mean Calculus for each scale level,
- Step4: Feature extraction by principal component analysis.

V. CLASSIFICATION

A. Methodology

To classify leak signals, we use Multilayer perceptron networks (MLP) that are artificial neural networks formed of cells simulating the low level functions of neurons and used where signals can not be defined mathematically.

MLP network responds to an input by producing an output. This is a result of the transmission of the input through the network of neurons linked by weights. The output of the MLP network is a combination of outputs of each of the neurons in the output stage of the MLP.

Before the MLP can be used for classification, it has to be trained during the time when it learns of the input/output relationship for training vector set. During the learning cycle, MLP is given sets of input patterns and corresponding target outputs representing the training vector.

B. Classification set up

Mathematically, Leak signals can be defined as chaotic signals, therefore it is appropriates to be classified using artificial neural networks.

In order to train our intelligent agent able to discriminate leaks according to its size, we consider a set of 34 signals that are carefully selected to ensure pattern efficiency and we use scaled conjugate gradient algorithm as a learning method.

TABLE II
LEAK SIGNAL CLASSIFICATION SET UP

Cycle	Iron Pipe	PVC Pipe	*Total*
Learning	13	21	34
Testing	8	13	21
Total	21	34	**55**

C. Neural network architecture

MLP network used like artificial neural network have architecture of 30-5-2 (mean 30 input nodes, 5 hidden nodes and 2 output nodes). The learning rate was set to η=0.001.

VI. RESULTS AND DISCUSSION

At the end of the learning cycle, we tested system recognition ability using the signal test set, we obtained following results:

TABLE III
RECOGNITION PERFORMANCES

Test	Iron Pipe	PVC Pipe	*Total*
Tested	8	13	21
Correct	7	9	16
Percentage	87,5%	69%	**76%**

We note the low recognition rate, especially for plastic pipes. It can be due to following reasons:

- leaks signal set for iron pipes is insufficient to build reliable pattern,
- several leaks are happened in confusion zones,
- Recognition rate is lower for plastic pipes; it is true, because of its characteristics concerning acoustic wave propagation: signal attenuation, low speed of sound, etc.
- External noisy sources, generally leak seeker have to choose convenient time to listen to pipes.

VII. CONCLUSION

At the end of this paper, we can conclude that the artificial neural networks method is appropriated to classify leaks size in spite of low recognition rate. To improve this method, it will be advised to study signals in confusion zones. Also, result can be better; if we increase signals set of the training cycle.

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