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Pipeline leak diagnosis based on wavelet and statistical features using Dempster–Shafer classifier fusion technique

Morteza Zadkarami, Mehdi Shahbazian, Karim Salahshoor*

Department of Instrumentation and Automation, Petroleum University of Technology, Ahwaz, Iran

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ABSTRACT

Leaks in hydrocarbon transporting pipelines cause major problems including environmental hazards and financial losses. Many leakage diagnosis methods try to detect the leaks with a small False Alarm Rate (FAR). However, they are not capable of identifying leakage location and size. In this paper, a novel leakage diagnosis method is introduced which not only detects the leakage occurrence, but also determines its location and size. The inlet pressure and outlet flow signals at different leakage conditions are generated using the OLGA software. Different feature extraction methods including statistical techniques and wavelet-based approaches are used to extract the features from the signals. The statistical and wavelet features are then individually used as inputs to a Multi-Layer Perceptron Neural Network (MLPNN) classifier to determine the leakage state. Finally, the outputs of two MLPNN classifiers are fused by the Dempster–Shafer (D–S) technique. The proposed leakage diagnosis method is applied to the first 20 km of the Golkhari to Binak pipeline located in the south of Iran. Simulation results show that the Correct Classification Rate (CCR) of the simultaneous detection and identification of the leakage location and size is about 95%.

1. Introduction

Because of the increased production and consumption of the petroleum and natural gas, pipelines play an important role in energy transportation. Therefore, being aware of the disturbing faults in the hydrocarbon transportation lines is concerned seriously (Meng et al., 2012). One of the most frequent and major faults is the pipeline leakage. Leaks occur mostly due to the pipeline erosion, faulty installation, material defects, digging and construction works near the pipeline (Boaz et al., 2014).

Several methods have been proposed for leakage detection. These methods can be divided into two main categories called the hardware- and software-based methods (El-Shiekh, 2010). Hardware-based methods employ special sensors to directly detect the occurrence of the leakage and determine its location. The fiber optic method, thermal infrared imaging, soil monitoring, ultrasonic and acoustic leakage detection methods are considered as the hardware-based category (Bai and Bai, 2014). Software-based methods, on the other hand, use the ordinary sensors which are embedded in the pipeline Supervisory Control and Data Acquisition (SCADA) system. Software-based methods are categorized into the model-based and measurement-based methods (Valizadeh et al., 2009b). Mass balance, Negative Pressure Wave (NPW), and Real Time Transient Modeling (RTTM) are examples of software-based leakage detection methods (Zhang et al., 2015).

Considering the importance of the leakage detection in lowering the environmental and financial damage and system maintenance, an appropriate method is one that is easily implemented and quickly detects the anomalies; it is able to identify the leakage location and size, and lastly it is cost-effective. Murvay and Silea (2012) compare different leak detection methods based on the aforementioned criteria.

The basic idea of the NPW method is as follows. When a leakage occurs, a rapid pressure drop appears at the leak point where a negative pressure waveform is produced. This wave propagates from the leak

* *Corresponding author*. Fax: +98 6135552709.
E-mail addresses: zadkarami@put.ac.ir (M. Zadkarami), shahbazian@put.ac.ir (M. Shahbazian), salahshoor@put.ac.ir (K. Salahshoor).
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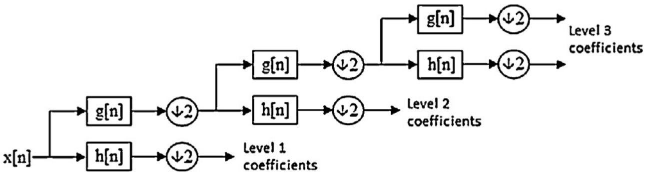

Fig. 1 – A three-level filter bank.

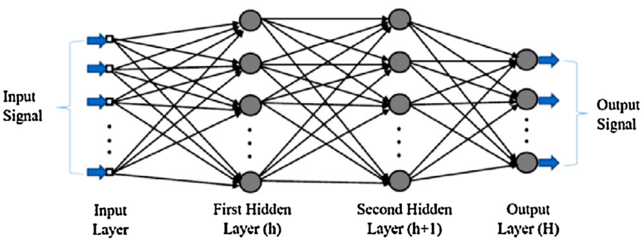

Fig. 2 – An MLPNN with two hidden layers.

point toward the sending and receiving terminals of the pipeline with the acoustic velocity; then, it changes the pressure of both terminals. This pressure change can be sensed by pressure transducers and be employed to identify the leak (Yi-Bo and Li-Ying, 2009). In addition to the leakage detection, NPW is able to specify the location of the leak. Using the advantages of the wavelet transform, NPW has been applied to a gas pipeline in Tianjin city, China. The results confirm an accurate detection of the leak locations (Yang et al., 2010). But, when the end pressure is fixed by a control system, NPW cannot detect the small leakages. To overcome this problem, a leakage detection method based on an integrated signal, which is a combination of the pressure and flowrate signals, has been introduced (Sun and Chang, 2014). Abdulla and Herzallah (2015) employ a Probabilistic Neural Network (PNN) that is fed with the inlet and outlet pressures and the outlet flow signals. The results obtained from this leakage detection technique were more robust.

In order to improve the leakage detection performance, knowledge-based techniques with different optimization approaches have been considered (Lou et al., 2011). A leakage detection approach has been introduced that encompasses the rough set theory and Support Vector Machines (SVMs) in association with the Artificial Bee Colony (ABC) optimization algorithm. This system indicated low levels of FAR (Mandal et al., 2012). Fuzzy systems are also used to decrease the FAR in a small-scaled Liquefied Petroleum Gas (LPG) pipeline monitoring system (Da Silva et al., 2005).

The idea of solving the leakage detection problem as a classification problem has been applied to the Iranian Seraje pipeline (Valizadeh et al., 2009a). In the research done by Valizadeh et al. (2009a), the inlet and outlet pressures, and the temperature and flowrate signals are obtained by the OLGA software. The statistical features were extracted and set as the inputs of a classier to detect the leak. Different classifiers including the Artificial Neural Network (ANN), fuzzy, and linear classifiers were studied. The CCR of each classifier was calculated. The results showed that the fuzzy classifier had the best performance with a CCR of about 96%. The main disadvantage of this approach was its incapability in identifying neither the leakage location nor the leak size.

In order to obtain more accurate results, multi-sensor data fusion techniques may be applied. Multi-sensor data fusion is usually performed at three different levels including the signal level, the feature level, and the decision level. At the signal level, the signals are combined from different sensors to create a new signal with a lower Signal-to-Noise Ratio (SNR) than the original signals. At the feature level, different features extracted from the signals are integrated. At the decision level, the results are merged from multiple classifiers using methods such as the D–S and Bayesian inference to make the final decision (Liu, 2011; Hall and Llinas, 2001). Jiang et al. (2013) introduce a leakage detection method in which the time-based features and wavelet packet features are extracted from the NPW signal. These features are then fed into an MLPNN classifier as the input vector. The CCR

Table 1 – Statistical features.

Statistical characteristics	Formula
Mean	$\bar{x} = \frac{1}{N}\sum_{k=1}^{N} x_k$
Standard deviation	$\sigma = \sqrt{\frac{1}{N-1}\sum_{k=1}^{N}(x_k - \bar{x})^2}$
Skewness	$\frac{1}{(N-1)\sigma^3}\sum_{k=1}^{N}(x_k - \bar{x})^3$
Kurtosis	$\frac{1}{(N-1)\sigma^4}\sum_{k=1}^{N}(x_k - \bar{x})^4$

for two classifiers with the time-based and wavelet packet features are reported as 95.36% and 94.45%, respectively. The fusion of both features, however, can yield a CCR of 98.32%. Another leakage detection method has been applied to a natural gas pipeline (Gao et al., 2013). The authors have used acoustic, flowrate and NPW signals at the two ends of the pipeline. In their method, the noises are omitted using the wavelet transform. D–S classifier fusion has been used to identify the leakage location.

To diagnose the leaks of the Golkhari–Binak pipeline, located in Iran, Zadkarami et al. (2016) employ the input pressure and outlet flowrate signals. They utilize various feature extraction methods such as the wavelet transform, statistical techniques, and a fusion of both methods to feed an MLPNN classifier. They found that the feature-fusion based classifier was more accurate in terms of the leakage detection, localization, and its size determination.

The aim of this article is to identify the leakage location and its size in a studied pipeline as well as decreasing the FAR through the ANN classification. The end pressure of the pipeline is assumed to be fixed. The input pressure and output flowrate signals for different leakage scenarios are generated by the OLGA software. To approximate the real-world conditions, a normal noise is added to the signals. The statistical and wavelet features are extracted from the noisy signals and are individually employed as the inputs of two MLPNN classifiers. To obtain more accurate results, the aforementioned classifiers are fused by the D–S technique. The approach is then compared with the methods which only employ the statistical or wavelet features as their inputs. The results confirm the effectiveness of the proposed method in detecting the leak and identifying its location and size.

The rest of this paper is organized as follows. Section 2 presents the theoretical background. The novel leakage diagnosis methodology is described in Section 3. The results of the proposed method are discussed in Section 4. Finally, Section 5 concludes the paper.

2. Theoretical background

2.1. *Wavelet transform*

One of the most practical and widely used techniques in signal processing is the Fourier transform. This technique is capable of demonstrating the signal frequency characteristics. However, it cannot reflect the local information in the time domain. To eliminate the limitation of the Fourier analysis, Short-Time Fourier Transform (STFT) was introduced. The main principle of the STFT is to split the signal into many small time blocks. Then, it analyzes each time block using the Fourier transform to determine the block frequency (Gao et al., 2013).

The time-frequency partitioning of the STFT is constant over the entire time-frequency plane. Considering the uncertainty principle or the Heisenberg inequality which states that the multiplication of the time (Δt) and frequency ($\Delta\omega$) resolutions should be greater than 0.5, resolutions are bounded and cannot be chosen arbitrarily small at the same time ($\Delta t\Delta\omega \geq 0.5$) (Wei, 1995). The wavelet transform follows the above ideas and has the capability to obtain a multi-resolution analysis by varying the resolutions Δt and $\Delta\omega$ in the time-frequency plane.