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Leak location of pipelines based on characteristic entropy

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ABSTRACT

The leakage of oil/gas pipelines is one of the major factors to influence the safe operation of pipelines. So it is significant to detect and locate the exact pipeline leakage. A novel leak location method based on characteristic entropy is proposed to extract the input feature vectors. In this approach, the combination of wavelet packet and information entropy is called "wavelet packet characteristic entropy" (WP-CE). The combination of empirical mode decomposition and information entropy is called "empirical mode decomposition characteristic entropy" (EMD-CE). Both pressure signal and flow signal of low noise and high noise of pipeline leakage are decomposed to extract the characteristic entropy. The location of pipeline leak is determined by the combination of the characteristic entropy as the input vector and particle swarm optimization and support vector machine method (PSO-SVM). The results of proposed leak location method are compared with those of PSO-SVM based on physical parameters. Under the condition of high noise, the results of proposed leak location method are better than those of PSO-SVM based on physical parameters.

1. Introduction

Pipeline transportation has been widely used in every walk of life because of its special merits in transporting liquid, gas, slurry. However, more and more serious leak problems have not only affected the natural run but also made huge loss to human life and wealth.

Currently, some methods and systems for pipeline leak detection have been developed. Ostapkowicz (2014) presented an improved method based on negative pressure wave detection which used median filtering of the calculating deviations of pressure signals. Yang, Wen, Li, and Wang (2013) extracted the sound signal of pipe and presented the neural-network approach for identification of pipeline leakage. Srirangarajan et al. (2013) used multiscale wavelet method to detect and locate pipe burst events in water distribution system. Molina-Espinosa, Cazarez-Candia, and Verde-Rodarte (2013) established the transient model of an incompressible flow of pipes with leaks. The finite differences technique was used to resolve the model. Lazhar, Hadj-Taïeb, and Hadj-Taïeb (2013) studied a single viscoelastic pipe by the transient analysis and the viscoelastic factor was considered by a generalized KelvinVoigt model. He also considered the presence of the two leaks in a pipe.

In the above methods of pipeline leak location, intelligent algorithm and pattern recognition was one of the main methods. In this method, the extraction of input vector was very important. Belsito, Lombardi, Andreussi, and Banerjee (1998) proposed a leak-detection method based on artificial neural networks (ANN), which can detect and locate leak down to 1% of flow rates. This method could compensate for the operational variations and prevent spurious alarms by combining with adequate preprocessing of those data. The input feature vectors of this method were inlet and outlet flow rate, and the fluid pressures.

Da Silva, Morooka, Guilherme, Da Fonseca, and Mendes (2005) used fuzzy system to classify the running mode and identify the operational transients. The fuzzy system could identify the leakage better because of adjusted thresholds. It was adequate to evaluate a small-scale LPG pipeline monitoring case. The input feature vectors of this method were transient measured through average volumetric flow (Transqm) and transient measured through the origin–destination differential pressure variation (Transdp). But it was difficult to determine the thresholds of the input feature vectors.

The Interactive Self-organizing Data Analysis Technique Algorithm (ISODATA) method was used to classify the normal pipeline and abnormal pipeline by Jinqiu, Laibin, Zhaohui, and Wei (2007). The abnormal pressure waves of pipeline leakage were detected by pressure transducers. Ten features extracted from samples are mean, effective value, peak value, root amplitude, mean square, root-mean-square, variance, and skewness in time-domain, peak

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amplitude and corresponding frequency point infrequency-domain.

Izquierdo, López, Martínez, and Pérez (2007) proposed a neuro-fuzzy approach to detect the pipeline leakage. The flow rate and piezometric heads of pipeline were extracted to the input feature vectors. Tylman, Kolczyński, and Anders (2010) proposed a leak-detection method based on neural networks and Bayesian network to detect leaks of dielectric fluid in underground high-pressure and fluid-filled (HPFF) cables. The input feature vectors of this method were pressure, temperature and electric value. Laurentys, Bomfim, Menezes, and Caminhas (2011) proposed a leak-detection method based on expert system. The input vectors of this method were flow, pressure and temperature. Mandal, Chan and Tiwari (2012) proposed a novel leak-detection method based on rough set theory and support vector machine (SVM). The input vectors were the normalized pressure and flow rate. Arsene, Gabrys, and Al-Dabass (2012) proposed a leak-detection method based on neural networks and graphs theory. The input vectors were head and flow.

According to above analyses, the artificial neural network had practical limitations for small numbers of samples. The hyper-parameters of SVM were determined through experiences. At the same time, the pressure and flow rate of pipeline were chosen as the most used input vectors. They had definite physical meaning. In fact, the signal of pipeline leakage was an unsteady signal and easy to be interfered by its ambient noise. Besides, the correlation between input feature vectors and output values was poorer. In order to solve these problems, in this research, the input vectors of pressure and flow of pipeline leakage are extracted by information entropy (Cui, Zhang, Kang, & Lan, 2009). The information entropy combined with wavelet packet (WP) forms the wavelet packet characteristic entropy (Bokoski & Juricic, 2012) (WP-CE). While the information entropy combined with empirical mode decomposition (EMD) forms the empirical mode decomposition characteristic entropy (Huang, Hu, & Geng, 2011) (EMD-CE). The methods of particle swarm optimization and support vector machine (PSO-SVM) (Ni, Jiang, & Pan, 2013)are employed as the location method in the system, which can recognize the different locations along with a pipeline effectively.

The remainder of this paper is organized as follows: In Section 2, overview of WP, WP-CE, EMD EMD-CE and PSO-SVM algorithms is presented. Section 3 is the simulation study of pipeline leakage. Section 4 is the analysis of the performance of applied algorithms. Section 5 is the conclusions.

2. Basic theory

2.1. Wavelet packet

Wavelet analysis can be used in multi-resolution analysis of time domain and frequency domain because of its good sense of localization. But the resolution of wavelet analysis is very poor when frequency is high. Wavelet packet decomposition can make multi-layer division for the frequency band of the fault signal and then can be further decomposed high frequency part of signal, which makes it more accurate in signal analysis as shown in Fig. 1. Wavelet packet transform can decompose signals into different frequency bands to choose adaptive frequency bands to overcome the disadvantages of wavelet transform (Qu, Feng, Zeng, Zhuge, & Jin, 2010).

Wavelet packet decomposition has the following relationships:

$$S = AAA3 + DAA3 + ADA3 + DDA3 + AAD3 + DAD3 + ADD3 + DDD3.$$

Wavelet packet decomposition can decompose the press and flow signal of pipeline leakage with the following recursion.

$$\begin{cases} u_{2n}(t) = \sqrt{2}\sum_k h(k)u_n(2t-k) \\ u_{2n-1}(t) = \sqrt{2}\sum_k g(k)u_n(2t-k) \end{cases} \quad (1)$$

where, $h(k)$ is high-pass filter and $g(k)$ is low pass filter.

2.2. Wavelet packet characteristic entropy (WP-CE)

Signal is decomposed into j layer wavelet packet coefficients. $S_{(j,k)}$ is wavelet packet decomposition sequence. $K = 0 \sim 2^j - 1$. The wavelet packet decomposition of signal is regarded as a division of signal. The measure of the division of signal (Bokoski & Juricic, 2012) is defined as:

$$\varepsilon_{(j,k)}(i) = \frac{S_{F(j,k)}(i)}{\sum_{i=1}^{N} S_{F(j,k)}(i)} \quad (2)$$

where, $S_{F(j,k)}(i)$ is fourier transform value of $S_{(j,k)}(i)$. N is original signal length.

According to the basic theory of entropy, wavelet packet characteristic entropy is defined as:

$$H_{j,k} = -\sum_{i=1}^{N} \varepsilon_{j,k}(i)\log \varepsilon_{j,k}(i) \quad \left(k = 0\sim 2^j - 1\right) \quad (3)$$

$H_{j,k}$ is the j layer and the k-th wavelet packet characteristic entropy of signal.

2.3. Empirical mode decomposition

EMD (Wu & Huang, 2004; Yu, YuDejie, & Cheng 2006), an adaptive method to decompose any data into a set of intrinsic mode function (IMF) components, is considered to be a breakthrough in the field of signal analysis in recent years. EMD is ideally suitable for analyzing data from non-stationary and nonlinear processes, while the non-stationary of press signal in pipeline leakage is obvious. So the EMD method can grasp the information of the signal characteristics more accurately and efficiently.

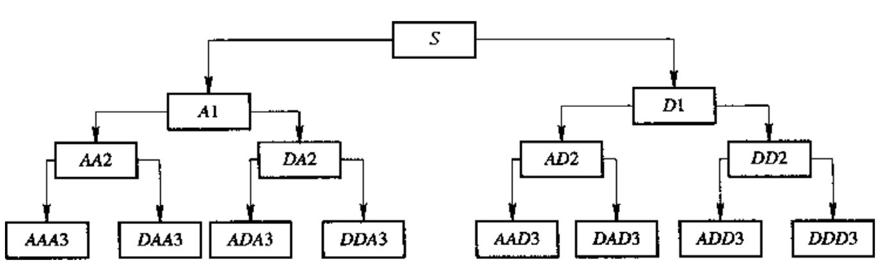

Fig. 1. Schematic of three layer wavelet packet decomposition.