An Algorithm for Leakage Detection of the Heating Pipeline

Huijie Guo *, Yulong Li and Fan Yang
Beijing Institute of Radio Metrology and Measurement, Beijing, China

*Corresponding author e-mail: ghj203@126.com

Abstract. The existing heating pipeline in our country has the serious problem of bubbling, dropping and leaking, which causes the huge waste of energy and the loss of pipeline investment. An algorithm for leakage detection of the heating pipeline is proposed to solve the difficult problem of heating pipeline leakage monitoring by establishing the background noise database, capturing effective noise signals, screening suspected leakage noise signals and recognizing the leakage noise signal with an advanced coarse-to-fine process. Once the pipeline leakage is detected, professionals will be informed to locate and repair the leakage point to minimize the impact of the accident. Meanwhile, the background noise database and the parameters of leak detection algorithm are updated by using false alarm signals, which can continuously improve the accuracy of heating pipeline leakage detection.

1. Introduction
With the acceleration of urbanization in China, central heating has developed vigorously. However, the existing heating pipeline construction level is low, with serious leakage, which results in a huge waste of energy and pipeline investment loss [1]. Due to poor construction quality of heating network, it is difficult to find pipeline leakage. The detection of medium leakage fault in the pipeline basically relies on booster pressure, segmenting valve shutoff and other very inefficient and backward methods to find the leakage pipeline segment, and then find the leakage point through correlator, sound bar and ultrasonic detector [2].

Therefore, it is necessary to install simple leakage detection equipment, and use a method that can detect and identify the leakage of heating pipeline in real time, in order to conduct real-time monitoring of the leakage state of the pipeline, detect the leakage as soon as possible and repair it in time, so as to reduce the operation and maintenance cost of the pipeline, reduce energy loss and improve the service life of the pipeline.

2. Algorithm implementation
The purpose of the algorithm proposed is to provide a leakage detection method for heating pipeline. The noise recorder is used to collect the noise signal of the pipeline, and then the leakage noise of the pipeline is detected and identified in real time, in order to detect the leakage of the pipeline in time and alarm it, so as to provide a basis for scientific maintenance of the pipeline operation.

To achieve the above purposes, the proposed algorithm adopts the following technical scheme, with the specific implementation as follows.
2.1. Build the background noise database

The noise recorder will be installed on the outer wall of the pipeline in the key monitoring section before the heating season, and it is ensured that there is no leakage point in the pipeline to be monitored before installation. Background noise signals will be collected at regular intervals during 15 days before and 15 days after the beginning of heating season. The collection interval is 10 minutes and the collection duration is 10 seconds every time, with the sampling frequency of 6000 points per second [3]. The collection will last for 30 days.

Background noise database is built according to Manhattan distance. The Manhattan distance between signal X and signal Y is calculated as follows.

\[
(md(X,Y)) = \sum_{k=1}^{n} |x_k - y_k| \\
(\forall X = (x_1, \cdots, x_n), Y = (y_1, \cdots, y_n))
\]

Where, \(md(X, Y)\) is the Manhattan distance between signal X and signal Y. Given that the Manhattan distance threshold of background noise signals is \(T_{md}\), which is typically equal to 0.4. Given the newly acquired background noise signal \(N\), Manhattan distances between \(N\) and all signals in the background noise database are calculated respectively to obtain the maximum value \(M_{md}\). If \(M_{md} > T_{md}\), the signal \(N\) is added to the background noise database to update the database, otherwise, discard \(N\) and wait for the next time to collect the background noise signal, until the end of the background noise signal collection period, and then the background noise database is constructed [4].

2.2. Capture effective noise signals

The effective noise signal is captured in accordance with the maximum time-frequency vibromotive ratio of the background noise database.

First, the time-domain oscillation peak \(op(X)\) of signal \(X\) is defined as follows.

\[
(op(X) = \max(X) - \min(X) \\
(\forall X = (x_1, \cdots, x_n))
\]

Where, \(\max(\ )\) is the function to take the maximum value, and \(\min(\ )\) is the function to take the minimum value. The frequency domain energy density \(ed(X)\) of signal \(X\) is defined as follows.

\[
ed(X) = \frac{\text{sum}(|\text{FFT}(X)|^2)}{F_m}
\]

Where, \(\text{FFT}(\ )\) is the fast Fourier transform function, \(\text{sum}(\ )\) is the summation function, and \(F_m\) is the maximum frequency value of the spectrum of \(X\).

Then, the ratio of time-domain oscillation peak and frequency domain energy density of all signals in the background noise database are calculated respectively, by which the maximum time-frequency vibromotive ratio \(OM_{tf}\) of the background noise database is obtained as follows.

\[
OM_{tf} = \max \left(\frac{op(X_1)}{ed(X_1)}, \frac{op(X_2)}{ed(X_2)}, \cdots, \frac{op(X_n)}{ed(X_n)}\right)
\]

Where, \(X_k\) represents the \(k\)th signal in the background noise database, and \(n\) represents the number of signals in the database.

In practice, the noise signal \(Y\) of the pipeline is collected in real time, and \(op(Y)/ed(Y)\) is calculated. If \(op(Y)/ed(Y) > \alpha \times OM_{tf}\), \(Y\) is determined to be an effective noise signal and subsequent discrimination is required. Otherwise, \(Y\) is discarded and noise signals are collected again for detection [5]. Where, \(\alpha\) is the weighted decision coefficient. Typically, the value of \(\alpha\) is from 0.6 to 0.75.

2.3. Screen suspected leakage noise signals

The suspected leakage noise signal is screened by noise clustering and category enclosing.

First, the mean deviation algorithm is used to aggregate all signals in the background noise database into \(m\) classes, and the Euclidean distance between the centroid of every two classes of signals is denoted
as $D_k$. Thus, there are $K = m (m-1)/2$ class spacing in total, that is $k = 1, 2, \ldots, K$. Therefore, the minimum category spacing $D_{mi}$ of the background noise database is calculated as follows.

$$D_{mi} = \min(D_k), k = 1, 2, \ldots, K$$  \hspace{1cm} (5)

Then, the Euclidean distances between the effective noise signal $Y$ obtained in the previous step and the centroid of signals of $m$ classes in the background noise database are calculated respectively, and the maximum value among them is denoted as $D_e$. If $D_e > D_{mi}$, $Y$ is determined to be a suspected leakage noise signal, and subsequent discrimination is required. Otherwise, $Y$ is determined as background interference noise to discard, and noise signals are collected again for detection [6].

2.4. Recognize leakage noise signals

According to the Mahalanobis distance of joint feature similarity in time-frequency domain, the noise signal is classified as a leakage noise signal or a background noise signal.

First, empirical mode decomposition is performed for the suspected leakage noise signal $Y$ obtained in the previous step.

$$\text{emd}(Y) = \sum_{k=1}^{n} \text{imf}_k + \text{ref}$$  \hspace{1cm} (6)

Where, $\text{emd}(\ )$ represents the empirical mode decomposition function, $\text{imf}_k$ represents the natural mode components with number of $n$, and $\text{ref}$ represents the residual component [7].

Then, the time-frequency joint feature vector $\text{tf}(Y)$ of signal $Y$ is defined as follows.

$$\text{tf}(Y) = \text{cat}([\text{mean}(\text{imf}_k), \text{median}(\text{imf}_k), \text{fem}(\text{imf}_k), \text{fim}(\text{imf}_k)], l)$$  \hspace{1cm} (7)

Where, $k = 1, 2, \ldots, l$, $\text{mean}(\ )$ represents taking the mean function, $\text{median}(\ )$ represents taking the median function, $\text{fem}(\ )$ represents the function of taking the frequency value of maximum spectrum energy, $\text{fim}(\ )$ represents taking the maximum frequency spectrum value function, and $\text{cat}(\cdot, l)$ represents concatenating $l$ vectors [8].

And then, the time-frequency domain joint feature vectors of all signals in the background noise database are calculated respectively to form the time-frequency domain joint feature sample set $\text{TF} = (\text{tf}_1, \ldots, \text{tf}_n)$ of the background noise database. Given the mean vector $\mu$ of $\text{TF}$ and the covariance matrix $\mathcal{S}$, the Mahalanobis distance $M_i$ between the two vectors in $\text{TF}$ is calculated as follows.

$$M_{ij} = \sqrt{(\text{tf}_i - \text{tf}_j)^T \mathcal{S}^{-1} (\text{tf}_i - \text{tf}_j)}$$  \hspace{1cm} (8)

Where, $(\ )^T$ represents the vector transpose operation, $i, j = 1, 2, \ldots, n$, and the maximum of $M_i$ is denoted as $M_S$. The Mahalanobis distance $MD$ of signal $Y$ to $\text{TF}$ is defined as follows.

$$MD = \sqrt{(Y - \mu)^T \mathcal{S}^{-1} (Y - \mu)}$$  \hspace{1cm} (9)

If $MD > \beta \times M_S$, $Y$ is identified as the leakage noise signal, and immediately sent an alarm to inform professionals to locate and repair the leakage point in the current monitoring section. Otherwise, $Y$ is identified as background interference noise to discard, and noise signals are collected again for detection [9]. Where, $\beta$ is the weighted classification coefficient. Typically, the value of $\beta$ is from 0.9 to 1.15.

2.5. Update the database and model

In practical application, in order to improve the accuracy and robustness of the aforementioned leak detection algorithm and reduce the disturbance caused by a large number of background noise, the dynamic updating mechanism of the model should be added to gradually reduce the detection error rate of the algorithm, so as to adapt to different detection environments.

In a real system, if background interference noise is identified as leakage noise signal, the background interference noise is added to the background noise database to update the database, and then $OM_{i1}, D_{mi}$, $M_S$ and other discriminant parameters are updated accordingly, so as to optimize the above leakage detection algorithm of the heating pipeline [10].
The above steps can effectively solve the difficult problem of heating pipeline leakage monitoring through the establishment of background noise database, collection of effective noise signals, screening of suspected leakage noise and determination of leakage noise signals by the coarse-to-fine process. At the same time, the background noise database and parameters of leakage detection algorithm are updated by using false alarm signals, which can continuously improve the accuracy of heating pipeline leakage detection.

3. Summary
The above algorithm starts from the background noise of heating pipeline which is easy to collect, and gradually discriminates whether the noise signal collected in practice is leakage noise signal from coarse to fine by establishing background noise database. Moreover, with the continuous updating of background noise database, the accuracy of the leakage detection model of heating pipeline will get higher.

The algorithm proposed in this paper has a strong applicability for the leakage detection of the heating pipeline, and can monitor the leakage status of the pipeline in real time and give a timely alarm when the leakage occurs, which is conducive to improving the operation and maintenance level of the heating pipeline.

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