A hydrate blockage recognition technique for natural gas pipelines based on BP neural network

Yingchao Huang1,2, Shuo Jin1,2, Liqun Wu1,2*

1College of Electronic Information and Automation, Tianjin University of Science & Technology, Tianjin 300222, China
2Advanced Structural Integrity International Joint Research Centre, Tianjin University of Science & Technology, Tianjin, 300222, China
*Corresponding author’s email: wu_liqun@163.com

Abstract. In energy industry field, hydrate blockage in natural gas pipelines has become a critical issue with an increasing demand of natural gas in the world. In this paper, a hydrate blockage recognition technique has been proposed based on BP neural network, which can recognize leakage in natural gas pipelines as well. A monitoring system has been built for trials, which mainly includes a loudspeaker and a microphone for acoustic signals transmission and reception. This paper mainly introduces wavelet packet theory and BP neural network recognition algorithm for signal analysis and recognition purpose. The reflected signals are analyzed and extracted eigenvectors by using wavelet packet transform, then a three-layer BP neural network is built and trained. Experimental results show that this technique can recognize hydrate blockage and leakage effectively.

1. Introduction

Natural gas is a common energy source, which is widely used in households and industry fields [1]. It plays an important role in changing energy structure, reducing energy consumption and reducing air pollution [2]. The assurance of flow rate in pipelines is crucial, which ensures the safety of gas transportation in pipelines. However, an effective way to keep the natural gas pipeline smooth has always been a hot research direction in the field of natural gas industry [3]. Recently, pipeline hydrate blockage has become a critical issue for the natural gas industry, which may affect normal supplies of natural gas, resulting in serious environmental damage, huge economic losses and even loss of life. Therefore, the detection and localization of the pipeline hydrate blockage is significant for the industry [4].

In the past few years, a series of methods and research works have been proposed for hydrate blockage detection in natural gas pipelines. Bruno [5] from University of Perugia proved the reliability of pipeline anomaly detection technology through numerical and experimental tests based on transient testing. In addition, they diagnosed other abnormal (partially hydrate blocked or leaked) connection modes of pipelines through transient tests. Glidas Besancon [6] from the National Polytechnic College of Grenoble had carried out a study on the partial hydrate blockage in pipelines. This study mainly proposed a generalized method based on finite difference model, which can be used to detect and discuss the location and causes of the hydrate blockage.

In order to detect and locate hydrate blockage inside a pipeline, this paper presents a method based on the BP neural network, which is able to detect and recognize leakage as well.
2. Measurement principle
Fig. 1 shows the system measurement principle [7]. A loudspeaker is placed near the front end of a pipe to generate incident acoustic wave and transmit the acoustic wave inside the pipe. When the incident wave encounters an abnormal event such as a hydrate blockage or leakage, a reflected wave travels back and it is received by a microphone where is close to the loudspeaker. Then, the reflected signal is obtained by a data acquisition card (DAQ) and processed in PC. In addition to data acquisition, the DAQ is also used to generate driving signals. The driving signal is amplified subsequently by a power amplifier to drive the loudspeaker.

![Diagram of Measurement Principle](image)

Fig.1. Measurement principle

3. Laboratory experiment

3.1 Experimental setup
The experimental setup is shown in Fig. 2 [8]. A loudspeaker that is placed at the start point of the pipe, is used to generate the incident acoustic wave. A microphone is fixed closely to the loudspeaker to receive the reflection signals caused by the hydrate blockage. An NI-6366 DAQ card is used to receive the reflection signals and generate the driving signal. The driving signal is then amplified by a power amplifier to drive the loudspeaker. A 700-1100 Hz chirp signal is used as a driving signal frequency considered the attenuation and localization accuracy. To simulate an actual hydrate blockage, an ice block is used as a substitute, because of its similar physical properties with hydrate, especially acoustic properties [9].

![Experimental Setup Image](image)

Fig.2. Experimental setup

3.2 Location experiment and results
In the experiments, a cylinder ice block (50mm diameter, 100 mm long) is placed inside the pipe (as shown in Fig. 3(a)) at about 15.32m from the start point. The reflection signals by empty pipes are
shown in Fig. 3(b). The hydrate blockage reflection signal is shown in Fig. 3(c) after the subtraction difference between the hydrate blockage signal and the empty pipe signal. In the case of pipeline leakage, the leakage hole is at 14.39m (the aperture is 20mm). The detection signals in the leakage experiments are shown in Fig. 4 below.
Table 1. The comparison between the actual location and measurement result (m)

|                  | Actual location | Measurement result |
|------------------|-----------------|--------------------|
| Leakage          | 14.39           | 14.31              |
| Hydrate blockage | 15.32           | 15.26              |

4. Reflection signal analysis method based on wavelet packet

The “energy-pattern” method based on wavelet packet is employed to distinguish hydrate blockage and leakage [10]. Through the reconfiguration of decomposition coefficients within every frequency band on a certain scale, a new time sequence is constructed on each decomposition node. Time domain analysis is carried out to extract eigenvector, which contains the time-frequency characters of the reflection signal.

Supposing the sampling frequency of the signals is \(2f\), and then if \(j\) layer wavelet packet decomposition is carried out on the signals, \(2^j\) frequency bands of equal width can thus be formed. The frequency width of every interval is \(f/2^j\). After the decomposition, the coefficient of \(j\) layer wavelet packet is \(C_{jk}^m\), \(k = 0, 1, \cdots, 2^j - 1\) and \(m\) is the location in the wavelet packet space [11].

According to Parseval energy integral equation,

\[
\int_{-\infty}^{\infty} |f(x)|^2 dx = \int |C_{j,k}|^2
\]

which demonstrates that the coefficients of wavelet packet have energy quantity.

\(E_{j,k}\) is the signal energy of the frequency band at the node \(k\) of \(j\) layer, and then

\[
E_{j,k} = \sum_m |C_{jk}^m|^2
\]

And energy \(E_{j,k}\) is normalized when

\[
E = \sum_{k=0}^{2^j-1} E_{j,k} (k = 0, 1, \cdots, 2^j - 1)
\]

Then,

\[
\hat{E}_{j,k} = E_{j,k} * 100% / E
\]

Where \(\hat{E}_{j,k}\) is the energy obtained after normalization.

The driving signal used in the experiment is a 700-1100Hz chirp signal. The eigenvector based on normalized energy is extracted by five-layer wavelet packet decomposition [12]. According to the frequency distribution characteristics of the reflected signals, 8 relatively sensitive frequency bands are selected.

Typical eigenvectors for hydrate blockage and leakage are shown in Fig. 5 (a) and (b) respectively, which clearly shows that the eigenvectors for the two cases are different from each other.
Table 2 shows the eigenvectors of reflected signals. E1-E8 are the first eight typical eigenvectors for hydrate blockage and leakage.

|         | E1    | E2    | E3    | E4    | E5    | E6    | E7    | E8    |
|---------|-------|-------|-------|-------|-------|-------|-------|-------|
| Hydrate | 62.95 | 26.37 | 5.25  | 2.59  | 1.41  | 0.57  | 0.12  | 0.05  |
| Leakage | 67.48 | 22.70 | 4.65  | 2.57  | 1.25  | 0.58  | 0.12  | 0.04  |

After extracting eigenvectors of reflected signals of detected signals, BP neural network is employed to recognize the reflected signals.

5. **BP neural network and recognition results**

5.1 **BP neural network**

BP neural network is a multi-layer feed-forward neural network that uses the algorithm of error back propagation to adjust the weight. The BP network topology model includes the input layer, the hidden layer and the output layer [13].

The most basic three-layer BP artificial network structure is shown in Fig. 6. BP algorithm can be used for recognition, which consists of training and target recognition two stages. In the training stage, the back-propagation algorithm is applied repeatedly to adjust the weight and deviation of the network. When the square error of the network output layer is less than the set error, the training is completed, and the weight and deviation of the network are saved. In the recognition stage, the actual target data is loaded into the trained BP network. The output of the BP network represents the type of target data [14].
In this paper, a three-layer BP neural network is selected. The eigenvector extracted above is used as input of the neural network [15]. The number of nodes in the input layer is 8, the number of neurons in the hidden layer is 3, and the number of nodes in the output layer is 1. Seventy samples of blockage and leakage are selected as learning training data, and the remaining 10 samples are used for recognition.

5.2 Recognition results

After eigenvectors are trained by BP neural network, the eigenvectors extracted from 10 test data are recognized as shown in Table 3, in which a hydrate blockage signal should be denoted as 0, and the leakage signal should be denoted as 1.

| E1   | E2   | E3   | E4   | E5   | E6   | E7   | E8   | Results |
|------|------|------|------|------|------|------|------|---------|
| 62.64| 26.53| 5.20 | 2.73 | 1.45 | 0.59 | 0.12 | 0.05 | 0       |
| 63.03| 26.34| 5.28 | 2.54 | 1.40 | 0.57 | 0.12 | 0.05 | 0       |
| 63.01| 26.35| 5.28 | 2.55 | 1.40 | 0.57 | 0.12 | 0.05 | 0       |
| 62.99| 26.36| 5.28 | 2.56 | 1.40 | 0.57 | 0.12 | 0.05 | 0       |
| 62.95| 26.37| 5.27 | 2.57 | 1.40 | 0.57 | 0.12 | 0.05 | 0       |
| 62.92| 26.39| 5.24 | 2.61 | 1.42 | 0.57 | 0.12 | 0.05 | 0       |
| 62.81| 26.45| 5.22 | 2.66 | 1.43 | 0.58 | 0.12 | 0.05 | 0       |
| 62.72| 26.50| 5.22 | 2.68 | 1.44 | 0.58 | 0.12 | 0.05 | 0       |
| 66.79| 23.45| 4.77 | 2.41 | 1.27 | 0.55 | 0.11 | 0.04 | 1       |

| E1   | E2   | E3   | E4   | E5   | E6   | E7   | E8   | Results |
|------|------|------|------|------|------|------|------|---------|
| 68.54| 21.58| 4.49 | 2.77 | 1.21 | 0.62 | 0.12 | 0.03 | 1       |
| 68.42| 21.73| 4.51 | 2.74 | 1.21 | 0.61 | 0.12 | 0.03 | 1       |
| 68.11| 22.00| 4.55 | 2.72 | 1.22 | 0.61 | 0.12 | 0.03 | 1       |
| 68.03| 22.10| 4.56 | 2.69 | 1.23 | 0.60 | 0.12 | 0.03 | 1       |
| 66.98| 23.22| 4.73 | 2.47 | 1.26 | 0.56 | 0.11 | 0.04 | 1       |
| 66.95| 23.26| 4.74 | 2.45 | 1.27 | 0.54 | 0.11 | 0.04 | 1       |
| 66.67| 23.58| 4.79 | 2.37 | 1.27 | 0.54 | 0.11 | 0.04 | 1       |
| 66.64| 23.63| 4.80 | 2.35 | 1.27 | 0.54 | 0.11 | 0.04 | 1       |
| 62.54| 26.56| 5.19 | 2.79 | 1.46 | 0.59 | 0.12 | 0.05 | 0       |
| 62.56| 26.57| 5.20 | 2.76 | 1.45 | 0.59 | 0.12 | 0.05 | 0       |

According to Table 3, it can be concluded that the correct recognition rate of hydrate blockage is 90% and that of leakage is 80%. The results indicate that BP neural network can effectively recognize hydrate blockage and leakage.

6. Conclusion

As currently hydrate blockage is a big issue for the industry, a natural gas pipeline safety monitoring technique is studied in this paper, which is based on BP neural network. According to the experiment results, the technique is able to monitor both hydrate blockage and leakage effectively in pipelines. The “energy-pattern” method, based on wavelet packet, is confirmed by the results of experimental data to be able to extract eigenvectors for hydrate blockage and leakage. The BP neural network is
used to train and recognize the hydrate blockage and leakage signals for pipelines, which proves the validity of proposed recognition method. This cost-effective and eco-friendly technique could enable people to identify the type of an abnormal sector inside a pipeline (blockage or leakage) and its location so that a series of operations can be taken in time to assure the safety of natural gas pipelines.

Acknowledgments
This work was funded by the Tianjin Research Program of Application Foundation and Advanced Technology (No. 15JZDJC39200).

References
[1] Farzaneh Gord, Mahmood. (2013) Investigation of hydrate formation in natural gas flow through underground transmission pipeline. Journal of Natural Gas Science & Engineering., 15:27-37.
[2] Yuan, Zongming, Z. Deng, M. Jiang. (2015) Extended partial blockage detection in a gas pipeline based on Tikhonov regularization. Journal of Natural Gas Science & Engineering., 27:130-137.
[3] Xiao Sen Li, Chun Gang Xu, Yu Zhang. (2016) Investigation into gas production from natural gas hydrate. Applied Energy., 172: 286-292.
[4] Cuiwei Liu. (2014) Study on leak-acoustics generation mechanism for natural gas pipelines. Journal of Loss Prevention in the Process Industries., 17:174-181.
[5] Brunone, Bu. Effectiveness Assessment of Pipe Systems by Means of Transient Test-based Techniques. Procedia Environmental Sciences., 19:814-822.
[6] Ignacio Rubio Scola, Glidas Besancon, Didier Georges. (2015) Frequency-model-based obstruction detection and location in a pipeline by output error minimization. Journal of Natural Gas Chemistry., 20: 210-225.
[7] Qu, Zhigang. (2016) Online monitoring method of hydrate agglomeration in natural gas pipelines based on acoustic active excitation. Measurement., 92:11-18.
[8] Qu, Zhigang. (2017) Study on the natural gas pipeline safety monitoring technique and the time-frequency signal analysis method. Journal of Loss Prevention in the Process Industries., 47:1-9.
[9] Licence, Peter. (2008) Clathrate Hydrates of Natural Gases. Chemical Industries Series., 87:158-164.
[10] Hariharan M, Fook C Y, Sindhu R. (2013) Objective evaluation of speech dysfluencies using wavelet packet transform with sample entropy. Digital Signal Processing., 23:952-959.
[11] Wei Z, Gao J, Zhong X. (2011) Incipient fault diagnosis of rolling element bearing based on wavelet packet transform and energy operator. Wseas Transactions on Systems.,10 :81-90.
[12] A. A. Kassem, M. H. Chaudhry, P. K. Mohapatra. (2006) Detection of Partial Blockage in Single Pipes. Journal of Hydraulic Engineering., 132: 200-206.
[13] Yu F, Xu X. (2014) A short-term load forecasting model of natural gas based on optimized genetic algorithm and improved BP neural network. Applied Energy., 134:102-113.
[14] Song, Mengmeng, H. Song, S. Xiao. (2017) A study on Fault Diagnosis Method of Rolling Bearing Based on Wavelet Packet and Improved BP Neural Network. Materials Science and Engineering., 15:12-16.
[15] Barros J, Diego R I. (2008) Analysis of Harmonics in Power Systems Using the Wavelet-Packet Transform. IEEE Transactions on Instrumentation and Measurement., 57:63-69.