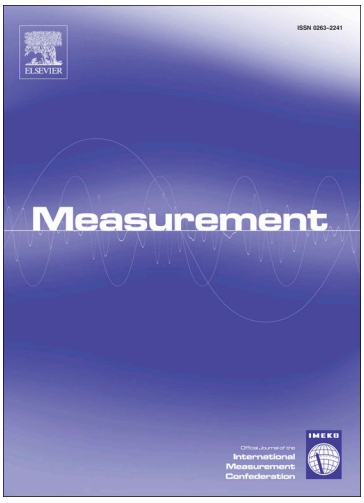
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PII: S0263-2241(21)01016-2
DOI: https://doi.org/10.1016/j.measurement.2021.110094
Reference: MEASUR 110094

To appear in: *Measurement*

Received Date: 15 January 2021
Revised Date: 24 August 2021
Accepted Date: 25 August 2021

Please cite this article as: W. Wang, H. Sun, J. Guo, L. Lao, S. Wu, J. Zhang, Experimental Study on Water Pipeline Leak Using In-Pipe Acoustic Signal Analysis and Artificial Neural Network Prediction, *Measurement* (2021), doi: https://doi.org/10.1016/j.measurement.2021.110094

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Measurement, Volume 186, December 2021, Article number 110094
DOI:10.1016/j.measurement.2021.110094

Experimental Study on Water Pipeline Leak Using In-Pipe Acoustic Signal Analysis and Artificial Neural Network Prediction

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Abstract: Water pipeline leakage is a common and significant global problem. In-pipe inspection based on hydrophone is one of the most direct, accurate, and reliable solutions for leak detection and recognition. In this study, a scheme of in-pipe detector was designed to pick up and identify acoustic signal due to leak. To investigate the characteristic of acoustic signal, an experimental platform was built to simulate the leaks and obtain acoustic signals under different leak conditions in an industrial scale water pipeline. Because a decreased pressure as leak has an unstable fluctuation in time domain, the frequency composition of the signal was analyzed in frequency domain, and then the change of frequency amplitude can be referenced to recognize the leaks. Moreover, the effects of leak size, pipeline pressure, and water flow rate on the characteristic of acoustic signal were investigated. The results show that the signal's intensity under leak conditions are significantly higher than that of no leak case, and it will increase as the increased leak size; the signal intensity under no leak case will increase with the growth of pipeline pressure; the flow velocity has little effect on the signal intensity. To increase the recognition accuracy, an artificial neural network model was developed for the leak prediction, and 18 cases through additional tests were selected to validate the accuracy of model. Comparing experimental and prediction results, maximum relative error is within 10.0%. It indicates that the prediction model has a reasonable accuracy for the leak recognition.

Key words: Experimental study; in-pipe leak prediction; water pipeline; artificial neural network model; time and frequency domain.

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The final published version (version of record) is available online at DOI:10.1016/j.measurement.2021.110094. Please refer to any applicable publisher terms of use.

1 Introduction

Urban water supply network is essential infrastructures for a city. Its normal and effective operations have become important prerequisites for the urban sustainable development [1]. However, with increase of service time, pipeline accidents caused by corrosion, aging, and third-party damage occur frequently. Once pipeline leaks, they will not only cause waste of water resources and huge economic losses, but also interrupt the normal industrial production and residential life. Therefore, the emergency operations including quickly detecting, locating and repairing pipeline leaks are significant to pipeline safety.

Researchers have developed numerous methods for detecting leaks, which generally divide into software-based and hardware-based methods [2]. The software-based approaches mainly rely on the acquisition and advanced processing of measurements along the pipelines, which require complex modeling and are less dependent on the pipeline hardware facilities [3]. They often incorporate pressure analysis method, flow rate and pressure change method, mass volume balance method, and dynamic model method [4]. The method is more effective and compatible for large and sudden leaks (the leakage is greater than 1.0% of the total flow rate), and but it is not sensitive to early small leaks as the attenuation causing by long-distance sound signal propagation [5].

Hardware-based methods rely on sensors device, such as acoustic sensors, optic sensors, magnetic induction sensors, ground-penetrating radar systems, and negative pressure wave sensing systems [6], which generally consist of outer-pipe and in-pipe detectors [7]. The outer-pipe detection can be conducted outside of the pipeline, which includes different detection methods such as audio-visual leak detection, correlation analysis leak detection, ultrasonic guided wave leak

detection, infrared photography, tracer gas detection, mass balance detection, negative pressure wave detection et al [8]. The in-pipe detector is pushed into a pipeline by carrying one or more sensors for detection and recognition, and automatically completes detection tasks. The sensors commonly include camera, acoustic, ultrasonic, leakage flux, and eddy current sensors [9]. Comparing to outer-pipe detection, in-pipe detection can be much closer to the leak, hence potentially able to pick up small leakages and can have higher detection accuracy.

Acoustic signal will be generated near the leak point as the leakage develops. Hence, one of conventional techniques is to detect abnormal sound waves using a hydrophone embedded in a recording device which can freely move in the pipe [10], which is considered as one of the most effective detection methods. For example the smart ball system developed by Pure Technology Ltd can detect leaks as small as 0.11 l/min [11]. The research team at MIT led by Prof. K. Youcef-Toumi designed a number of in-pipe detector prototypes and proposed the identification methods to differentiate leaks [12-14]. Tianjin University has developed an improved detection system based on ARM-Linux and micro electromechanical systems (MEMS), and an efficient support vector machine (SVM) classifier was employed to solve the leakage classification problem [15]. Another leakage detection system manufactured by GLD Company Ltd can move with the flow inside the pipe, which has a high sensitivity for small leakages below 1.0 l/min [16]. In above researches, the acoustic signals are mainly measured by a hydrophone mounting on the in-pipe detection, and then the system can detect the leaks based on the acoustic data analysis by the recognition algorithms.

For leak detection, the acoustic signal is often analyzed in both time and frequency domains. In the early 1990s, scholars of the Chinese Academy of Sciences (CAS) proposed a leak detecting

method by analyzing noise generated by pipeline leakage. Khalifa [17-18] reported experimental studies of acoustic wave propagation in a PVC pipeline, and the results showed that acoustic wave attenuation along the pipeline depends on the source frequency and line pressure. Xu [15] used the fast Fourier transform (FFT) to obtain spectral characteristics of sound signals, and then proposed a recognition algorithm based on frequency characteristics. Ben-Mansour [19] simulated pressure fluctuation and average power spectral density (PSD) of signal based on instantaneous separation eddy current simulation (DES). At present, the researches on the precise identification for micro leak which is lower than 1.0 l/min are still insufficient. In addition, the characteristics of acoustic signal are complicated under different pipe pressure, flow velocity, and leak orifice, which need further analysis [20].

Recently the leak detection using machine-learning techniques, such as artificial neural networks (ANN), is gradually becoming a research hotspot [6]. Wu [21] found that one-dimensional (1-D) Convolution Neural Networks (CNN) can extract the distinguishable properties of vibration signals. Waleed [22] used electronic pressure sensors with an ANN to detect leaks in a pipeline. However, the feasible scheme is deficient for the water pipeline's leaks detection, particularly the ANN method based on industrial scale experimental data.

The purpose of this study is to analyze situations of dynamic pressure distribution through experiments and predict the leak by the ANN. The acoustic signal was recorded through an industrial scale experiment platform built at Cranfield University, and then the effects of flow speed, leak size, and pipeline pressure on water pressure distribution were investigated. In addition, an ANN model was proposed to improve the prediction accuracy. The work will enrich the leakage recognition

theory for the urban water supply network.

2 Experiment setup

2.1 In-pipe detector system

The scheme of in-pipe detector is shown in Fig. 1. The detector can be pushed into the pipeline through a launcher. Meanwhile, leak acoustic signal is recorded by a hydrophone sensor which is embedded in the detector body. When the detector is near the leakage, the local pressure gradient variations can incur local acoustic signal variations which will be recorded by hydrophone to identify whether there is a leak [23-24]. A dead reckoning localization system usually including an inertial measurement unit (IMU) and three odometers [25] is used to locate the leak position. The system can adapt different diameter pipe through matching various support beams. When the operations are completed, the detector is recycled through a receiver.

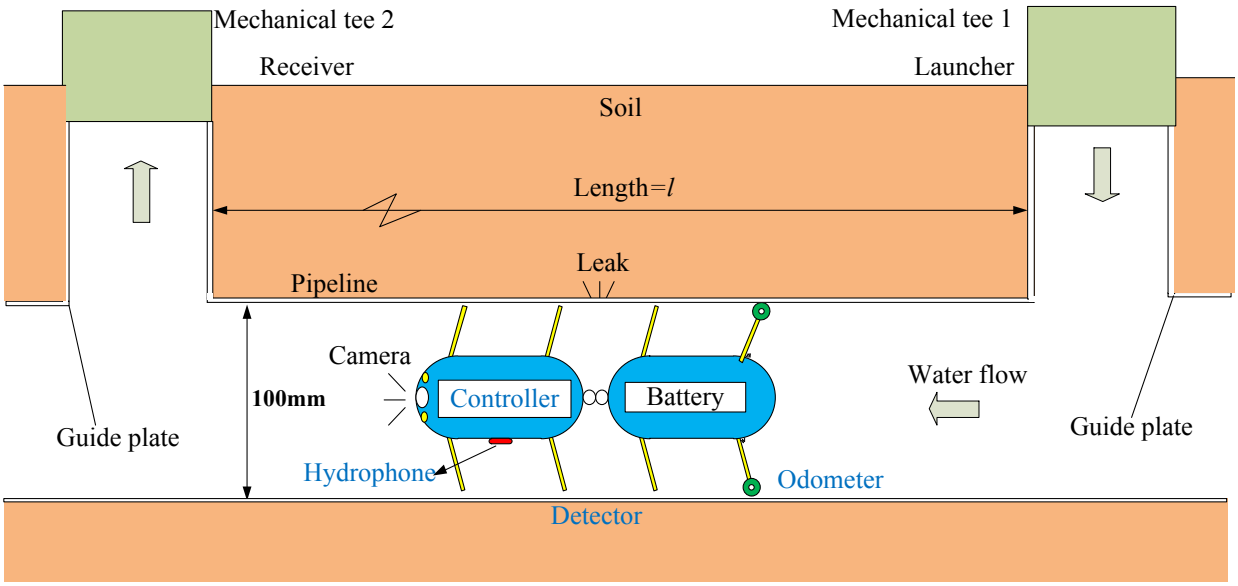


Fig.1 Scheme of the in-pipe detector.

2.2 Experimental pipeline platform

To simulate different leak condition of water distribution network, an experimental pipeline

platform was assembled as shown in the Fig. 2. The pipeline is part of the Three Phase Flow Test Facility which is a near industrial scale pilot plant located in the Process Systems Engineering Laboratory of Cranfield University. The detailed description can be found in literature [26]. For this study the devices and facilities used for the tests included dynamic pressure transducer (DPT), flow valve, flow meter, pressure gauge, and pump, as shown in Table 1. In Fig.2 (a), the platform included a 56m long stainless steel pipe which has an inner diameter of 108.2mm. Water was used as the test fluid, which was supplied from the water tank to the experimental pipeline by a pump. If required, a metered air can also be introduced into the test section from a compressor via a tee to form a gas liquid two phase flow. After the test section, the gas liquid mixture flows to an 11,000 liter floatation separator where the air and water is separated, and the water is sending back the water tank for reuse. The opening of flow valve 1 and flow valve 2 were used to control the flow of water in the pipeline. The loop was fitted by adjusting automated flow controller and the pump to operate in different required test pressures and flow rates.

Table 1 Experiment hardware.

Equipment	Specifications/functions
Steel pipe loop	Build 56m length, 100 mm diameter of pipe loop
Pump	Provide different water flow rate at a pressure ranged from 0.1 to 0.3MPa gauge pressure
Valve 1	Control valve to regulate the water flow rate
Valve 2	Ball valve to open and close the flow loop
Gas/liquid Separator	Liquid (water in this study) and gas separation
1, 3 and 5mm orifice with a needle valve	Simulate leaks with aperture sizes of 1, 3 and 5mm
DPT 1	Measure the dynamic pressure of pipeline
DPT 2	Measure the dynamic pressure of pipeline

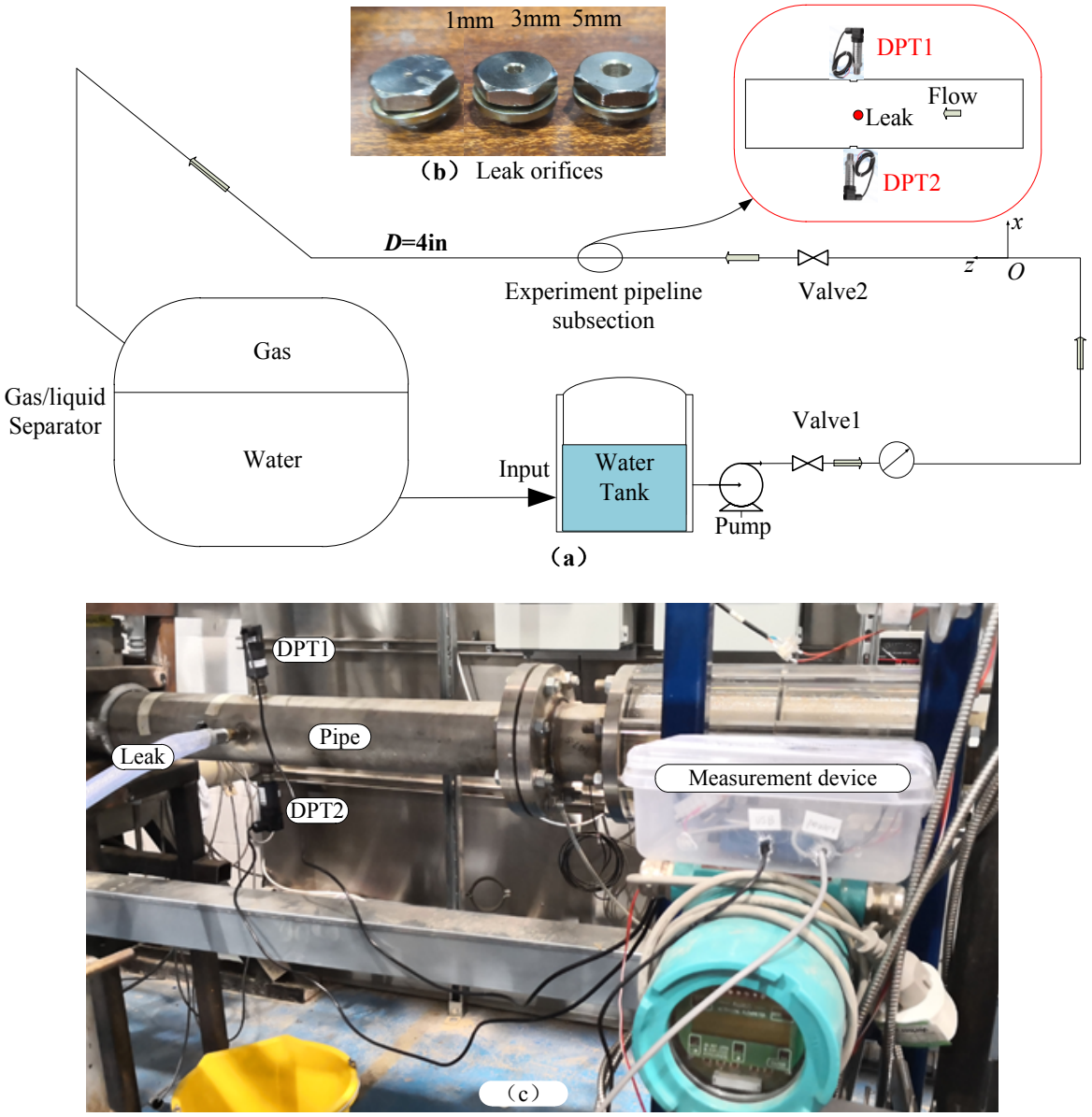


Fig.2 Experimental platform loop. (a) Schematic; (b) Leak orifices; (c) Experimental pipeline subsection.

A 12.7mm (1/2 inch) needle valve was used to simulate the different leakage through an orifice which the aperture size can be varied among 1mm, 3mm, and 5mm as shown in Fig.2 (b). Instead of the hydrophone, the DPT was used to catch the acoustic signals in the experimental pipeline as it has the similar characteristics with that of the hydrophone. This method was validated by Chatzigeorgiou [13]. The DPTs installed on the pipeline were selected to measure the acoustic signal as shown in Fig.2 (c). Two DPTs, with a pressure range of 0.01-10MPa, installed symmetrically regards to the

leak, one on the top and the other on the bottom of the pipe section. The sensors can pick up the water pressure fluctuations due to the leakage.

The parameters of measurement device and sensors are shown in Table 2. The DPTs used in the tests are identical in model and are manufactured by HBM Company Ltd, which are integrated with a low-noise amplifier. The accuracy level is 0.2%, the output voltage range is 0~5V, and the output current range is 4-20mA. A real-time data acquisition (DAQ) NI USB6009 was selected to collect the DPT outputs at 1000Hz sampling rate. A LabVIEW software was developed for test data recording and saving. The experimental platform can provide a water flow rate ranged from 0 to 10 l/s, and the pipeline pressure from 0.10 MPa up to 1.20MPa. A Coriolis flow meter Foxboro CFT50 was used to monitor the flow rate in the test pipeline.

Table 2 Parameters of measurement device and sensors.

Controller and sensors	Parameters
NI 6009	1000Hz sample rate.
DPT1	Pressure range is 0.01 to 10MPa, output current is 4-20mA.
DPT2	Pressure range is 0.01 to 10MPa, output current is 4-20mA.
Pressure transmitter	0.1 to 6.0MPa.
Flow transmitter	Foxboro CFT50 flow meter, 0 to 30 l/s, uncertainty 0.1%.

2.3 Experimental scheme

In this study, the experimental platform can test leak orifices of 1mm, 3mm, and 5mm, with line pressures of 0.1MPa, 0.2MPa, and 0.3MPa, and flow velocities of 0m/s, and 1m/s. There are totally 24 experimental cases were selected to investigate as shown in Table 3. The base case of no-leakage condition was used to compare with the cases of leakage conditions. Moreover, through comparing the leakage conditions, the effects of leak orifice size, pipeline pressure, and flow speed can be obtained. The characteristics of acoustic signal in the time and frequency domain which reflect the leak existence and even the recognition of leakage size are analyzed.

Table 3 Experimental cases.

In-pipe pressure	Flow velocity	Orifices
0.1MPa	No	no-leakage;1mm;3mm;5mm
0.2MPa	No	no-leakage;1mm;3mm;5mm
0.3MPa	No	no-leakage;1mm;3mm;5mm
0.1MPa	1m/s	no-leakage;1mm;3mm;5mm
0.2MPa	1m/s	no-leakage;1mm;3mm;5mm
0.3MPa	1m/s	no-leakage;1mm;3mm;5mm

3 Experimental results

The sound source because of leak radiates energy outward to form sound waves, which mainly include the friction sound of the water flow and the leak orifice, the impact sound, and the collision sound of the water flow and the air medium. To identify the characteristic of acoustic signal data, the experimental data under various leaked conditions were analyzed using the MATLAB software in the time and frequency domain.

3.1 Time domain analysis

To investigate the pressure distribution of inner pipeline collected by two DPTs, one experimental case is selected as an example, which has the pipeline inner pressure of 0.20 MPa, the leakage orifice of 5mm, and the flow velocity of 1m/s. Fig. 3 shows the pressure distribution results of two DPTs under the condition. Fig. 3 (a) and (b) are without leak, and Fig. 3 (c) and (d) are with 5mm leakage.

Fig. 3 shows that there is a decrease in the measured dynamic pressures as the appearance of leak. It can be seen that DPT1 signal (Fig. 3 (c)) fluctuates between 0.170 MPa and 0.210 MPa, which is lower than that of no leakage case as showed in Fig. 3 (a) fluctuating between 0.178 MPa and 0.218 MPa. Moreover, the DPT 2 has similar trend. It is noted that the noises originated from different sources could impose onto the acoustic signal and are picked up by DPTs during pipeline

inspection, and then the signal amplitude has the unstable feature, which can interfere with the leak recognition. It will increase the difficulty of the leak identification. Therefore, it is difficult to distinguish leak and even leakage size only through the signal analysis in time domain [13].

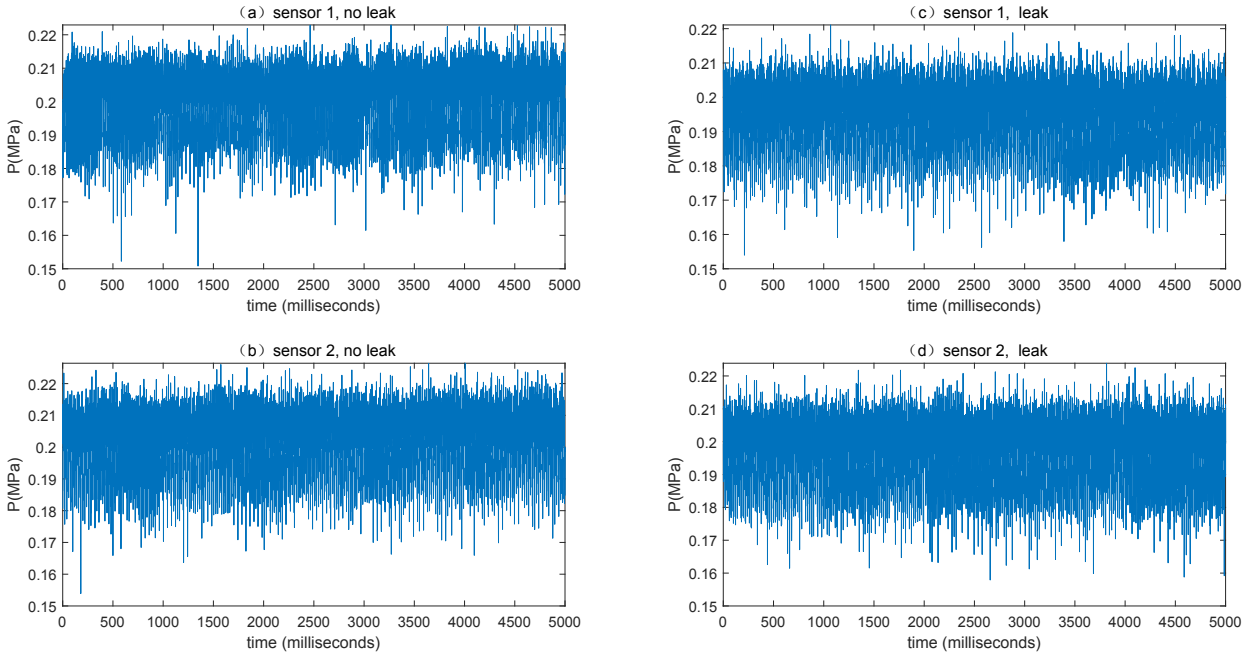


Fig. 3 Dynamic pressure of two DPTs（0.20MPa, 5mm, 1m/s）: (a)DPT 1, no leak; (b)DPT 2, no leak; (c)DPT 1, 5mm leak; (d)DPT 2, 5mm leak.

3.2 Frequency domain analysis

To eliminate interference, spectrum analysis is common applied in complex signal analysis, which has strong anti-interference ability. The FFT and PSD are two methods to obtain the frequency spectrum [19].

(1) FFT

The digital signals process by the FFT has very wide application in practical engineering. In this study, the sample frequency is 1000Hz, and the data quantity is 12000. The no leak results of case in Section 3.1 show in Fig. 4 (a) and (b), and the leak results show in Fig. 4 (c) and (d).

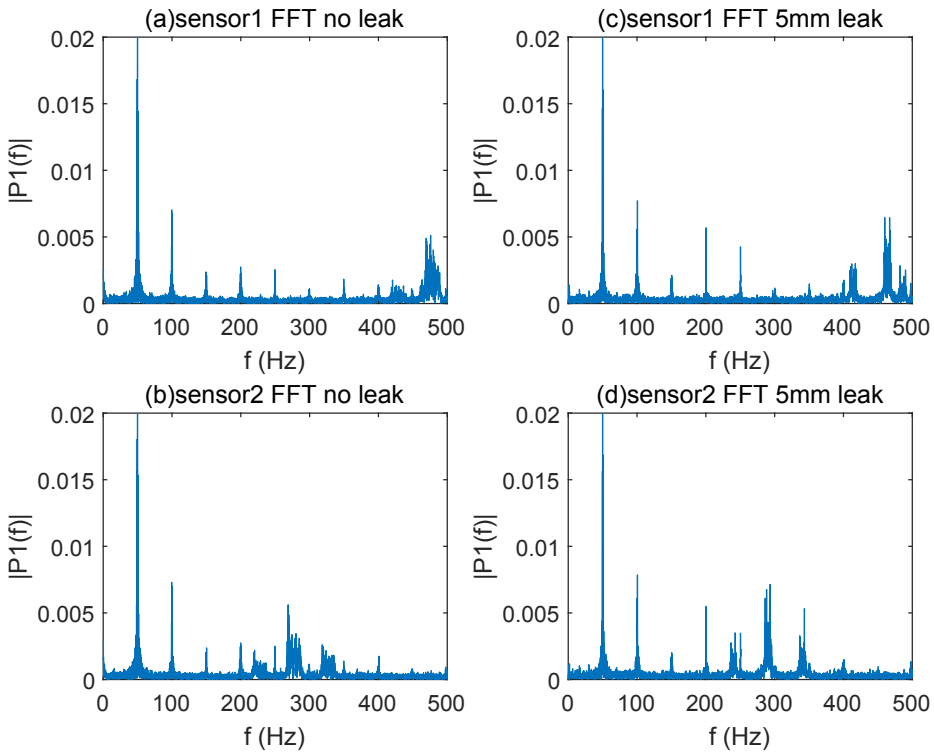


Fig. 4 FFT results of two DPTs' (0.20MPa, 5mm, 1m/s,): (a)DPT 1, no leak; (b) DPT 2, no leak; (c) DPT 1, 5mm leak; (d) DPT 2, 5mm leak.

Fig. 4 shows that the amplitude of a certain frequency will change due to the occurrence of leakage. Fig.4 (a) shows that distributional frequency as an acoustic background with no leakage has a wide range. Fig. 4 (a) and (c) show that curves between frequency 100Hz to 350Hz of DPT 1 caused by leakage has a remarkable increase than curves of no leak condition. Moreover, it is noted that the DPT 2 has similar trends. Comparing Fig.4 (a) and (b), it can be seen that the FFT curves of two DPTs have different characteristic at the different circumferential positions. Fig. 4 (c) and (d) indicate that the amplitude of frequency component caused by leakage in a certain extent has a relative increase than that of no leakage. In this case, the amplitude between 100Hz and 350Hz increases significantly, and the amplitude below 100Hz and up 350Hz frequency has little changes.

(2) PSD

Through the PSD, the relationship between signal power and frequency can be analyzed. Fig.5 shows the PSD curves of two DPTs' data. Fig. 5 (a) and (c) are the PSD of two DPTs with no leakage; Fig. 5 (b) and (d) are under 5mm leakage; Fig. 5 (e) and (f) is a merge of two DPTs' PSD curves.

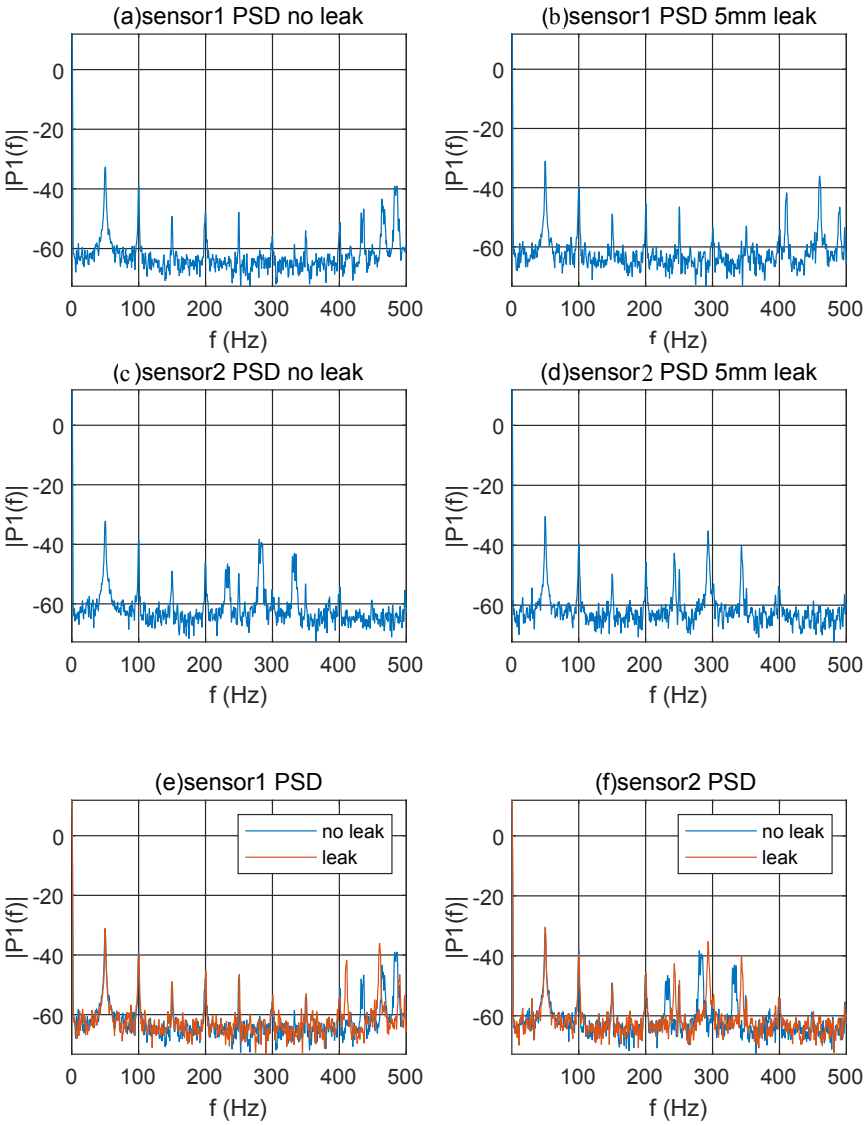


Fig.5 PSD of two DPTs (0.2MPa, 5mm, 1m/s):（a）DPT 1, no leak;（b）DPT 1, leak; （c）DPT 2, no leak;（d）DPT 2, leak; （e）DPT 1, comparison;（f）DPT 2, comparison.

Fig. 5 shows that the characteristic of the PSD is similar trends with that of the FFT curves. Fig. 5 (e) and (f) shows that the signal power between 100Hz and 350Hz has increased relative to the case

of no leakage, the signal power corresponding to its low-frequency component hardly changes, and the signal power corresponding to the high-frequency component fluctuates to a certain extent. It is noted that the recognition metric in the PSD curves can be identified and but it is not clear.

4 Effects of influence factors

In the Section 3, the experimental results only are preliminarily analyzed. Many factors such as orifice size, pipeline pressure, and liquid flow speed, can affect signal characteristic in frequency domain. Thus, the experimental data is investigated from above three aspects to reveal leak signal characteristics.

4.1 Effects of leak size

To analyze the effects of leak sizes, three orifices of 1mm, 3mm, and 5mm were used. Other parameters shown in section 3.1 are unchanged. The detail discussion about the FFT and PSD curves is provided in appendix.

To quantify above phenomenon, the signal power P as shown in equation (1) is introduced to analyze the variation of FFT data [19]. The calculation results are shown in Table 4, and the effect of the overall signal intensity against the leak size is shown in Fig.6.

$$P = \frac{\sum_{n=1}^{N} |x[n]|^2}{N} \tag{1}$$

Where, $x[n]$ is vector of the discrete time signal, N is the total number of elements in $x[n]$.

Table 4 Power of discrete signal.

Leak condition	Power of DPT 1 [V²/s]	Power rate of DPT 1	Power of DPT 2 [V²/s]	Power rate of DPT 2
no-leakage	5.37e-04	1.00	5.84e-04	1.00
1mm	5.99e-04	1.12	6.52e-04	1.12
3mm	7.91e-04	1.47	8.60e-04	1.47
5mm	8.03e-04	1.50	8.80e-04	1.51

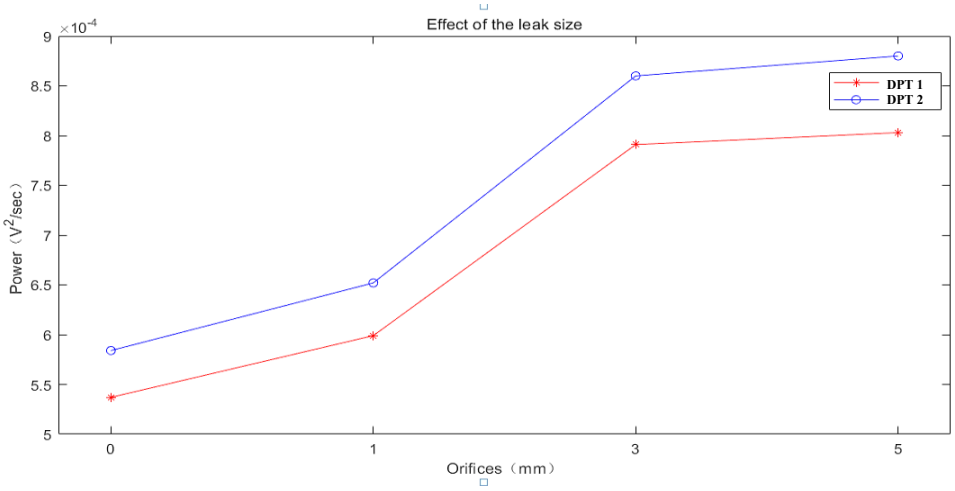


Fig.6 signal intensity against the leak size.

Table 4 shows that powers of DPT 1 and DPT 2 under leak conditions are higher than that of no leak case. For 5mm leak, it is 1.51 times than that of no leak case in DPT 2. However, the power as shown in Fig.6 is not simple increase with the growth of the leak size, which is not a linear relation between power and orifice size. It is noted that there is similar power when the leak orifices are 3 mm and 5 mm. The results show that power of DPT 2 installing on the bottom of pipeline is bigger than that of DPT 1 installing on the top of pipeline. It should be noted that signal distributions are subtle different at different recording position.

4.2 Effects of pipeline pressure

To investigate the influence of pipeline pressure, the pressures of 0.10MPa, 0.20MPa, and 0.30MPa are selected. Other pipeline condition parameters of DPT 1 are that the flow velocity is 1 m/s, and the leakage orifice is 1mm, 3mm, and 5 mm. The power of DPT 1 is calculated as shown in Table 5, and the overall signal intensity against the pressure is described in Fig.7.

Table 5 Discrete signal power of DPT 1.

Leak condition	0.1 MPa, power [V^2/s]	Power rate	0.2 MPa, power [V^2/s]	Power rate	0.3 MPa, power [V^2/s]	Power rate
no-leakage	3.91e-04	1.00	5.37e-04	1.00	5.77e-04	1.00
1mm	4.60e-04	1.18	5.99e-04	1.12	6.01e-04	1.04
3mm	8.60e-04	2.20	7.91e-04	1.47	6.03e-04	1.05
5mm	9.57e-04	2.45	8.03e-04	1.50	10.00e-04	1.73

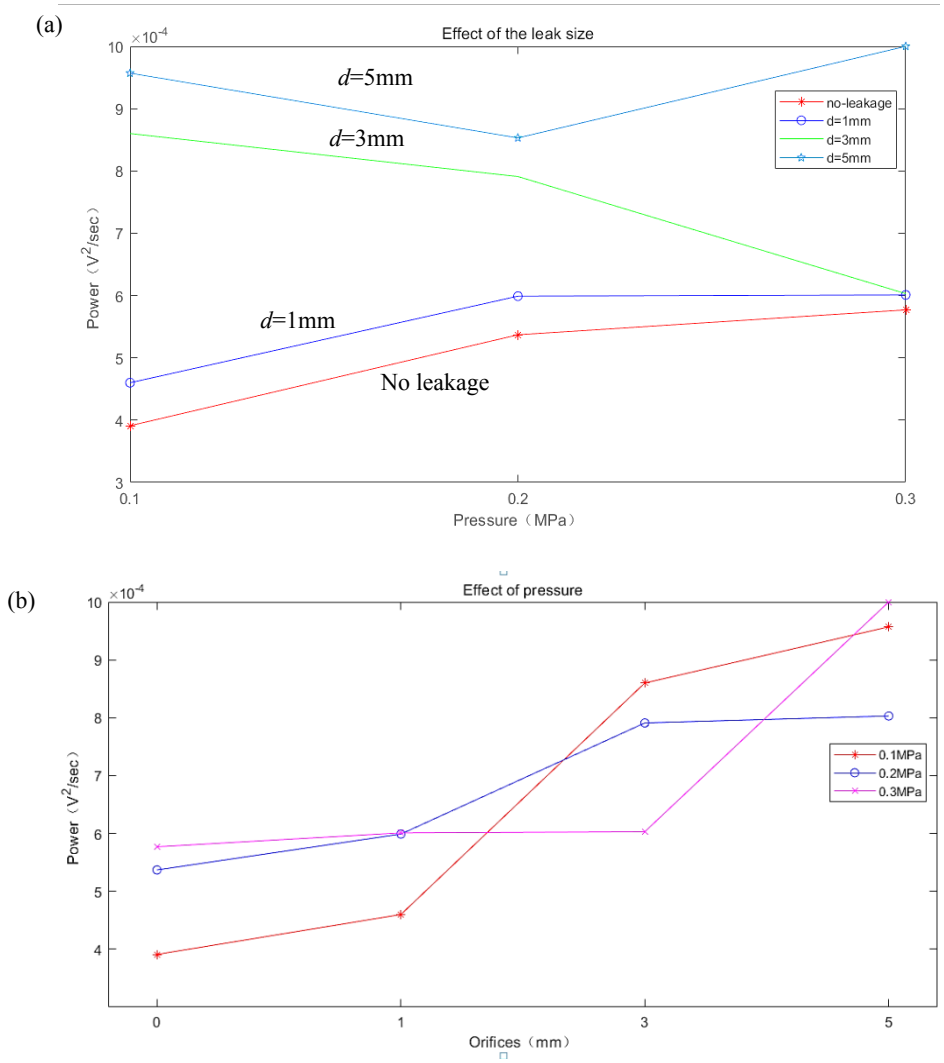


Fig.7 Effects of pipeline pressure. (a) Signal intensity against the pressure; (b) Power of DPT 1 in different pipeline pressure.

Fig.7 (a) shows that the not all powers under different leakage conditions have increased trends against pressures. The power of no-leakage and 1mm leakage increases with the growth of pipeline pressure. However, there is not a stable increase change for the 3mm and 5mm leakages along the

growth of pressure. The phenomenon likes whistling. The stronger sound wave is related to three aspects of the opening size of the lips, pressure, and gas flow speed and has not always increase with the higher pressure. Moreover, Fig.7 (b) shows that the power is a basic increase trend as the growth of leak orifice sizes in a certain pipeline pressure, and the increase rate is non-linear. For 5mm leak, it is maximum power in various leak cases under each pipeline pressure, which is 9.57e-04 V^2/s, 8.03e-04 V^2/s, and 10.00e-04 V^2/s, respectively.

4.3 Effects of flow velocity

To study the influence of flow velocity, the static condition and the flow velocity 1m/s are selected. Other pipeline conditions parameters of DPT 2 are unchanged which is the pressure of 0.20MPa. The power results of DPT 2 are calculated as shown in Table 6, and the overall signal intensity against flow velocity is shown in Fig.8.

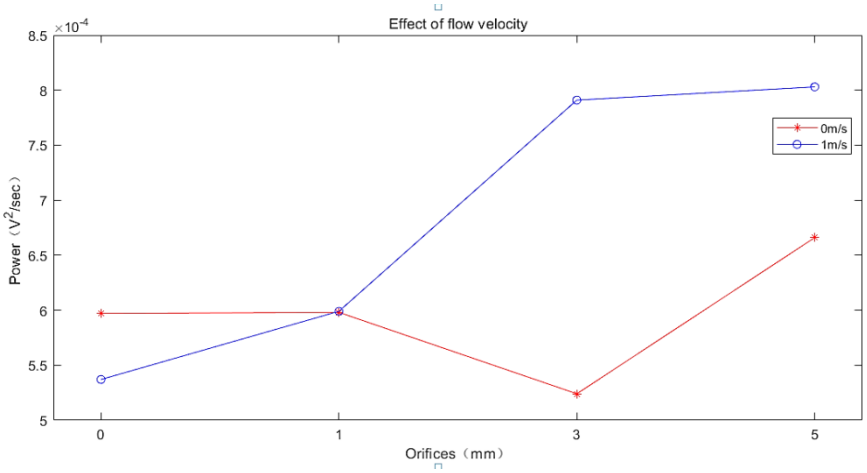


Fig.8 Signal intensity against the flow velocity.

Table 6 Power of the DPT 2 discrete signal.

Leak condition	0 m/s, power [V^2/s]	Power rate	1 m/s, power [V^2/s]	Power rate
no-leakage	5.97e-04	1	5.37e-04	1
1mm	5.98e-04	1	5.99e-04	1.12
3mm	5.64e-04	0.95	7.91e-04	1.49
5mm	6.66e-04	1.12	8.03e-04	1.50

Table 6 and Fig.8 show that power of 1m/s condition has a basic increase trend as the growth of leak orifice size, and power of 0m/s has not the similar rule because of smaller power of 3mm leakage than other conditions. It means that power has an increase trend against the leakage size when there is flow velocity, and however flow velocity has little effect on the power when the water is static. Fig.8 shows that power of 5mm leak is larger than other cases under each flow velocity, which are 6.66e-04 V^2/s and 8.03e-04 V^2/s, respectively.

5 ANN prediction

The scenarios presented above researches can determine whether a leak in the pipeline exists by observing the pressure data in time and frequency domain. However, it is difficult to build signal recognition database for various actual cases and is difficult to identify leaks quantitatively. To increase the recognition accuracy, an ANN model is performed to predict leaks in this section [27]. The ANNs are capable of learning, storing and recalling information based on a given training dataset and provide an unconventional approach for many engineering problems that are difficult to describe or solve using normal methods [28].

The multilayer back propagation (BP) neural network is a widely used ANN in many research fields, which can handle the complicated nonlinear relationships between inputs and outputs in many systems. Waleed [22] proposed a neural network based framework, which the operator can use to verify whether the identification of a leak is valid. Ribeiro [29] developed a BP neural network for the prediction of two-phase and three-phase pressure drop. Therefore, the BP neural network is suitable for the leak recognition.

The ANN analysis steps are generally uniform, which includes: (1) collect database; (2) define

the neurons of the input; (3) define the hidden layer and prediction layer; (4) define the loss expression; (5) train the model; (6) validate the model. In this study, it is conducted according to the above steps.

5.1 ANN Model

The structure of BP neural network constructed by MATLAB artificial neural network toolbox is shown in Fig. 9 (a). The ANN input is the data detected by the DPTs under the experimental conditions. As the FFT and the PSD transformation, 1000 amplitude values are obtained as the input feature quantities for the neural network, and it is 1000 neurons in the input layer. The output is leak orifice size of pipeline, and the number of neurons in the output layer is 1.

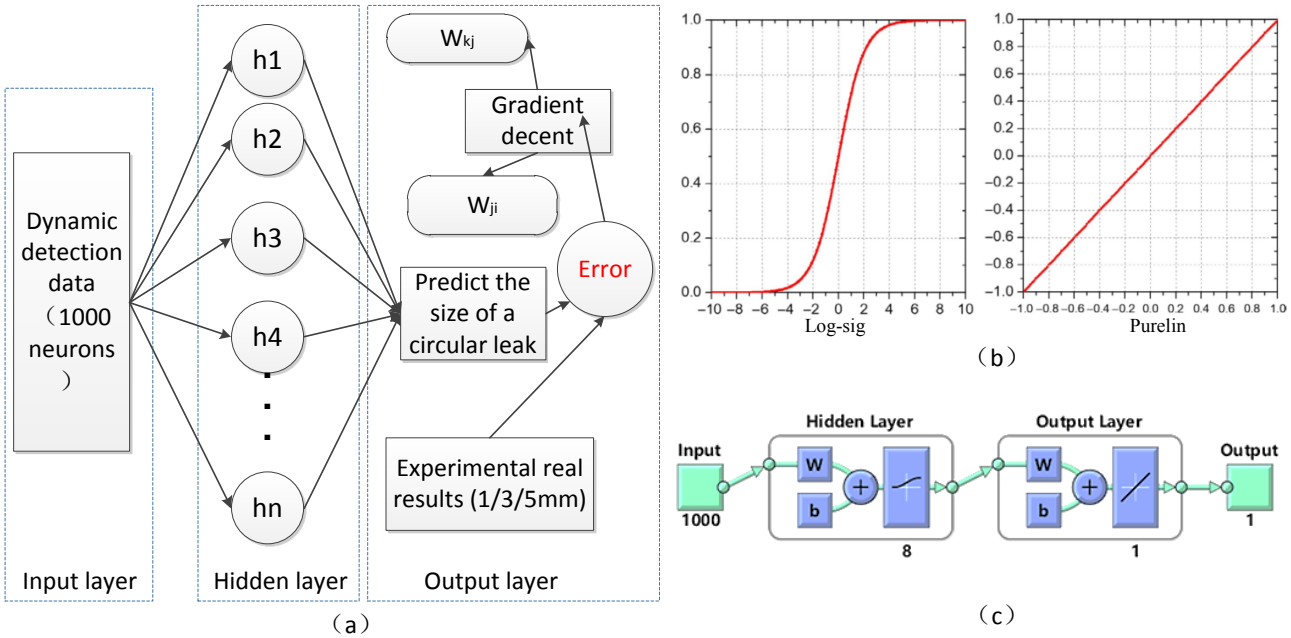


Fig. 9 Artificial neural network. (a) structure for leak detection; (b) activation functions; (c) neural network.

The activation function between the input layer and hidden layer is set to ‘logsig’, and the activation function between the hidden layer and output layer is set to ‘purelin’ as shown in Fig. 9(b). Moreover, the Levenberg-Marquardt (LM) algorithm was adopted due to its capacity which train

rapidly and efficiently and increase the convergence speed of the ANN [29]. The LM algorithm is an iterative algorithm for finding the extreme value of a function, which combines the features of the Newton method and the gradient method.

Neurons numbers of hidden layers can determine the quality of the network. Hence, eight artificial neural network structures are compared to obtain a suitable network for the prediction of leakage diameter. The prediction accuracy results obtained through different network structures are listed in Table 7. The prediction accuracy of case 3 can reached 98.95%. It indicates that the hidden layer with 8 neurons is the best choice for the constructed network. Therefore, the ANN structure with 1 hidden layer and 8 neurons are selected for the ANN model of the pipeline leakages prediction as shown in Fig. 9 (c).

Table 7 Prediction accuracy rate of different hidden layer nodes.

No.	Hidden layer nodes	Training error	Iteration times	Prediction accuracy (%)
Case 1	6	0.00906	19	93.74
Case 2	7	0.00472	9	89.03
Case 3	**8**	**0.00591**	**6**	**98.95**
Case 4	9	0.00461	8	98.52
Case 5	10	0.00634	5	87.68
Case 6	11	0.00459	7	84.76
Case 7	12	0.00674	7	84.68
Case 8	13	0.00227	7	89.88

The experimental cases shown in Table 3 were repeated 6 times, and then 144 cases can be obtained for collecting database. In the ANN, the cases were divided into 3 sets for network training. The percentages of training data set, verification data set, and test data set were set as 70%, 15%, and 15%, respectively. After initialize the network and input the parameters and data sets, network weights and thresholds are continuously modified to make error function decrease in the direction of negative gradient. It selects the mean squared error (MSE) as the loss function. Fig. 10 shows the

results of trained artificial neural network in training, verification, testing, and all process with leak defects.

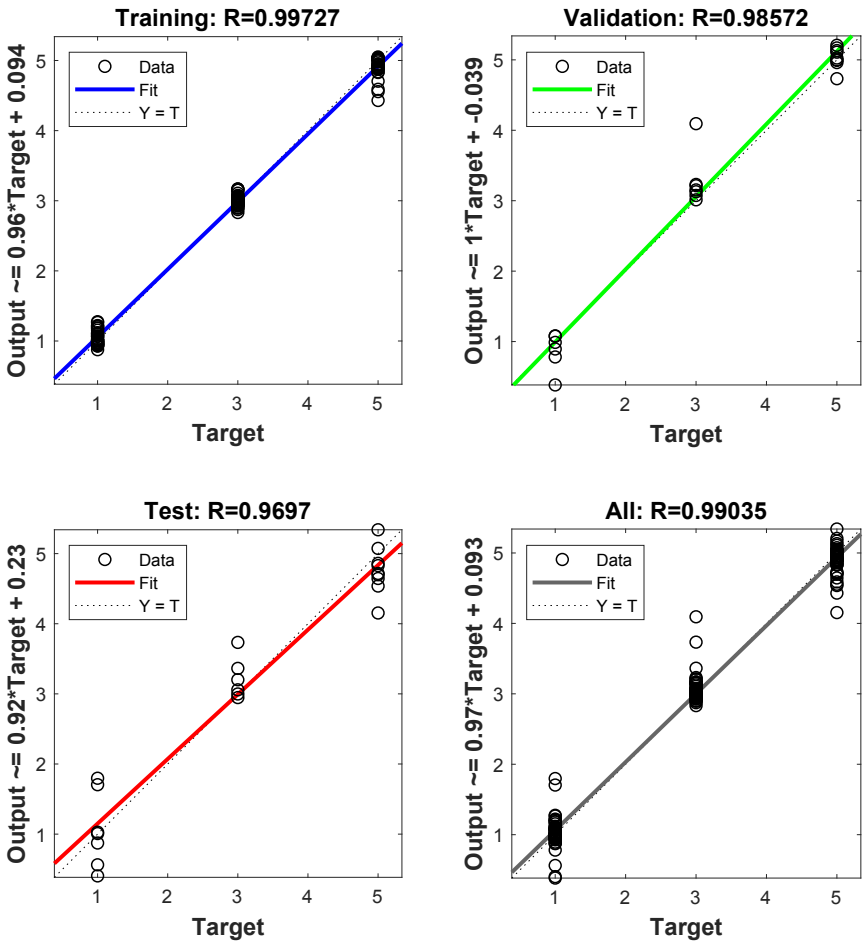


Fig. 10 Neural network target to output fitting curve.

Fig. 10 shows that the accuracy between network output value and actual value of this model is 0.99035. Moreover, to prove the accuracy of the proposed model, the MSE is introduced as a metrics to evaluate the prediction model. The network is iterated 12 times to reach the best model, and the MSE reached 0.0079379 when the model performance reached the best, which shows that the training results are better. The above results show that the constructed BP neural network can accurately predict the pipeline leakage under different experimental conditions.

5.2 Model validation

To validate the accuracy of proposed ANN framework, the additional 18 cases listed in Table 8 were adopted for the comparison analysis. The relative error δ_t between the experimental results and the predicted results through the proposed ANN model is as following [30-31]:

$$\delta_t = \frac{r_e - r_p}{r_e} \times 100\% \tag{2}$$

Where, r_e is the experimental result; r_p is the predicted result.

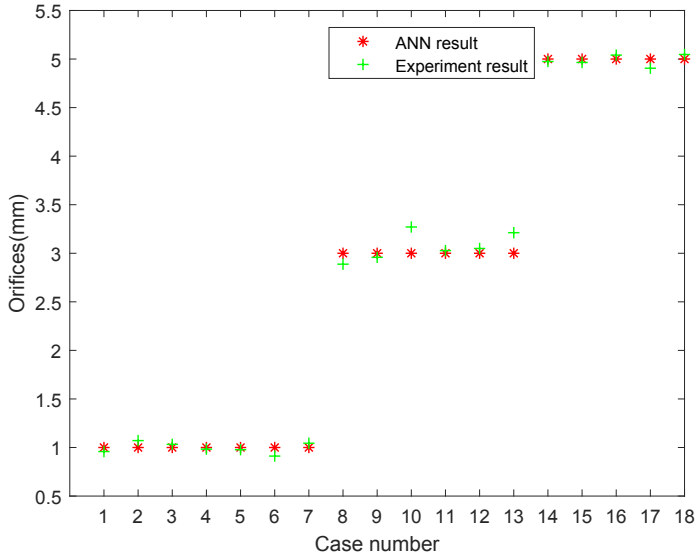
Moreover, the prediction results and the relative errors [32] in Table 8 are shown in Fig. 11.

Table 8 Validation cases.

No.	Pressure	Velocity	Orifice	No.	Pressure	Velocity	Orifice
Case 1	0.10MPa	0m/s	1mm	**Case 10**	**0.10MPa**	**1m/s**	**3mm**
Case 2	0.20MPa	0m/s	1mm	Case 11	0.20MPa	1m/s	3mm
Case 3	0.30MPa	0m/s	1mm	Case 12	0.30MPa	1m/s	3mm
Case 4	0.10MPa	1m/s	1mm	Case 13	0.10MPa	0m/s	3mm
Case 5	0.20MPa	1m/s	1mm	Case 14	0.20MPa	0m/s	5mm
Case 6	0.30MPa	1m/s	1mm	Case 16	0.30MPa	0m/s	5mm
Case 7	0.30MPa	0m/s	1mm	Case 16	0.10MPa	1m/s	5mm
Case 8	0.20MPa	0m/s	3mm	Case 17	0.20MPa	1m/s	5mm
Case 9	0.30MPa	0m/s	3mm	Case 18	0.30MPa	1m/s	5mm

Noted: the case 10 is the maxium relative error.

(a)



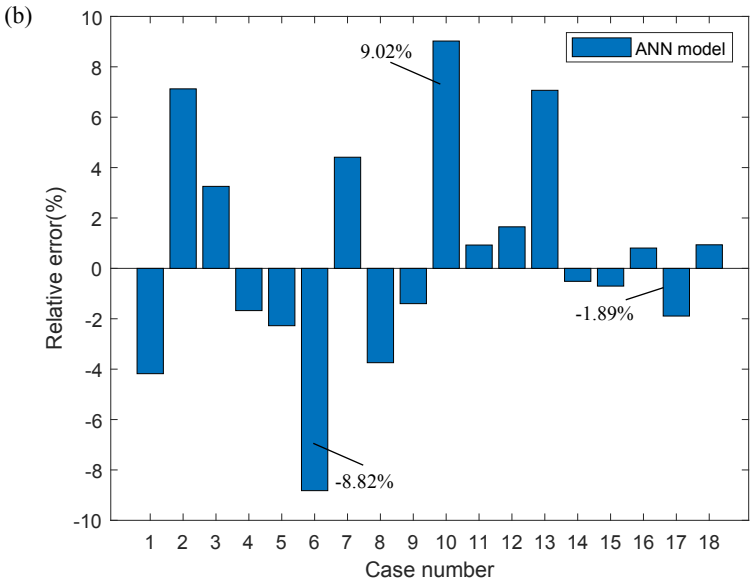


Fig. 11 Comparison of the leak diameter obtained by experiment and ANN model. (a) the prediction results;(b) the relative error.

Fig.11 (a) shows that 5mm leak and 1mm leak have the smaller difference between prediction and experimental results and the 3mm leak has the maximum value. To quantify the error, the relative error can be distinguished in Fig.11 (b). It shows that the relative error of 5mm leak with the maximum error of -1.89% has the better accurate precision than 3mm and 1mm leak. Moreover, the maximum relative error of the artificial neural network occurring at case 10 is 9.02% [27]. It indicates that the established model can be used to predict the size of leak diameter.

6 Conclusions

In this study, an experimental platform was built to record the signal of water pipeline leak. The experimental data was analyzed using the time and frequency domain analysis, and then an ANN model is proposed for the intelligent leaks judgment.

In time-domain, when there is a leak, the pipe pressure would decrease. However, the signal is unstable. It is difficult to distinguish leak only through the signal analysis in time domain. In

frequency domain, the frequency component will change due to the occurrence of leakage, and the signals captured by the two DPTs at different position are different. Moreover, the signal powers of the experimental data are investigated from three aspects including the orifice size, the pipeline pressure, and the liquid flow speed. The results show that the signal powers under leak conditions are higher than that of no leak case, which has a basic and non-linear increase trend as the growth of leak orifice size; the signal powers under no leak case would increase with the growth of pipeline pressure, and there is a basic increase trend as the growth of leak orifice size under different pipeline pressures; meanwhile, the flow velocity has little effect on the signal power.

To improve the detection accuracy of the leak, an ANN model is selected to analyze the experimental data. The frequency domain signal data is import into the BP neural network model, and the output can obtain the orifice size. The maximum relative error is within 10.0% through comparing the experimental results and the prediction results of 18 validation cases, and it indicates the proposed ANN model has a reasonably good accuracy for the leak recognition.

In the future, more data under different conditions should be acquired, and other intelligent algorithms should be compared to improve the inspection precise. Moreover, in order to expand the application field of technology investigated in this study, it will consider to be used for the oil and gas pipelines.

Acknowledgement

This work was supported by National Natural Science Foundation of China (No. 51309237) and Science Foundation of China University of Petroleum, Beijing (No. 2462020XKJS01).

Appendix

There are three aspects including the orifice size, the pipeline pressure, and the liquid flow speed for revealing the leak signal characteristics in following discussion.

(1) Effects of the leak size

To analyze the effects of the leak size, the signal FFT conversions of two DPTs are shown in Fig. 12, and the PSD curves of two DPTs are shown in Fig. 13.

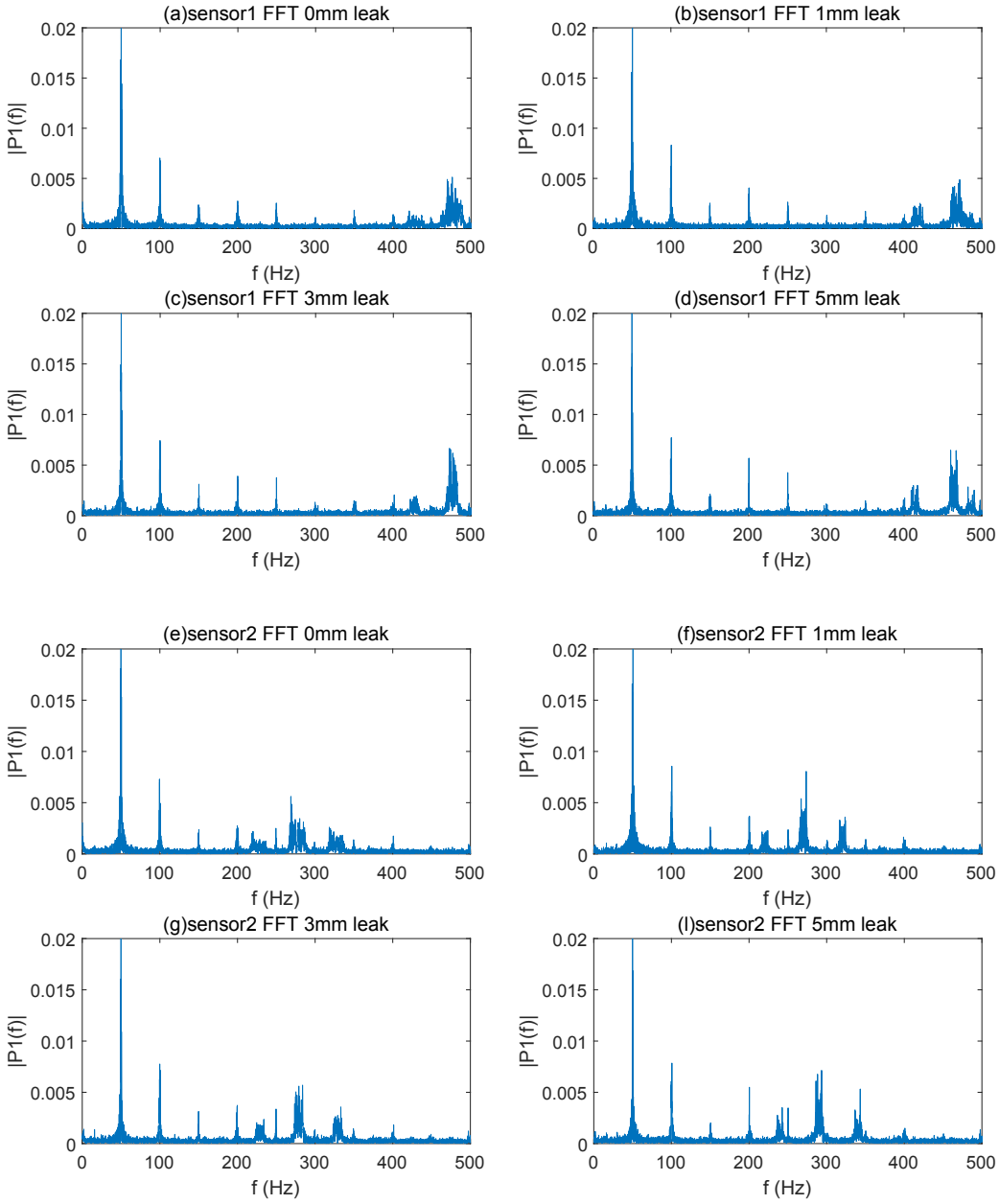


Fig. 12 DPT 1 and DPT 2, FFT (0.20MPa, 1m/s). (a) DPT 1, no leak; (b) DPT 1,1mm; (c) DPT 1,3mm; (d) DPT 1,5mm; (e) DPT 2, no leak; (f) DPT 2,1mm; (g) DPT 2,3mm; (o) DPT 2,5mm.

Fig. 12 shows that the amplitude corresponding to 150Hz-300Hz change significantly and amplitude of other frequency have little changes. The increments of 150Hz-300Hz do not increase as the leakage diameter increases. Moreover, DPT 2 has similar phenomenon. The amplitude change of certain frequency component caused by leakage can be used to recognize the leak.

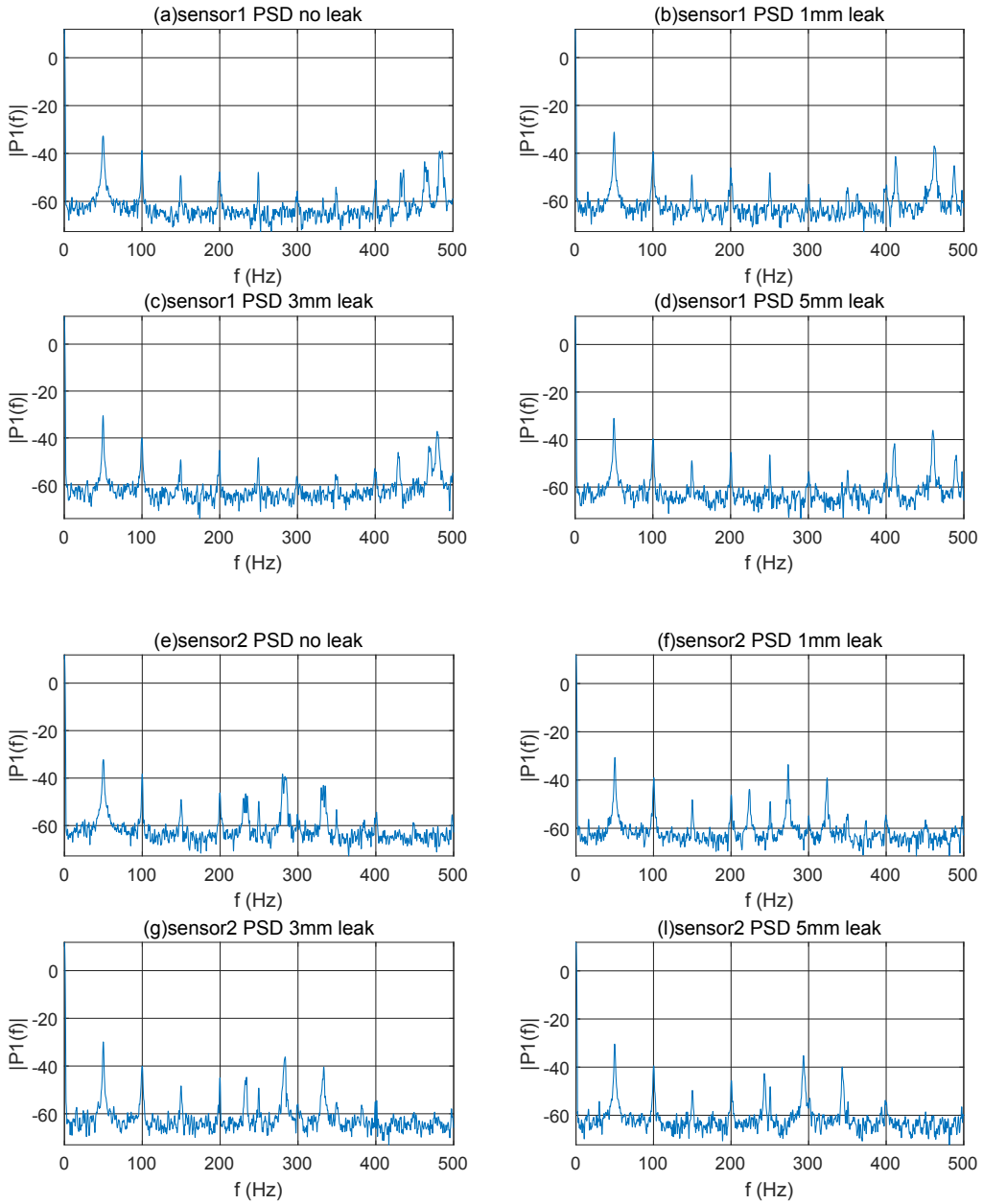
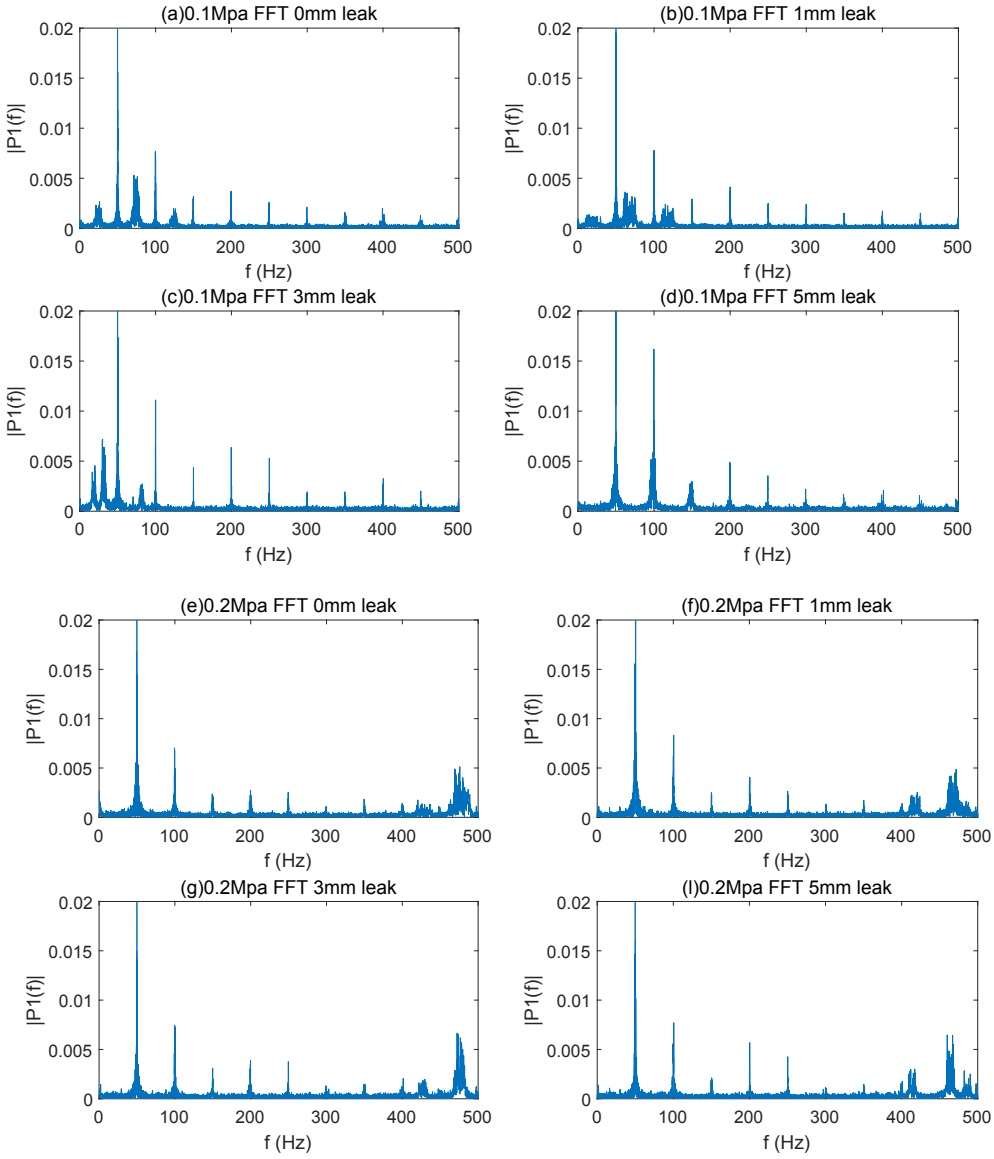


Fig. 13 DPT 1 and DPT 2, PSD (0.20MPa, 1m/s). (a) DPT 1, no leak; (b) DPT 1, 1mm; (c) DPT 1, 3mm; (d) DPT 1, 5mm; (e) DPT 2, no leak; (f) DPT 2, 1mm; (g) DPT 2, 3mm; (l) DPT 2, 5mm.

Fig. 13 shows that the PSD curve of each DPT has similar trends with the FFT curves, and the PSD of two DPTs are different with that of no leak. Therefore, the PSD curve or the FFT curve can used to distinguish leaks.

(2) Effects of the pipeline pressure

The PSD curves or the FFT curve of the cases are similar with the analysis of the section of "Effects of the leak size". Therefore, the FFT curves under different pipeline pressures are only analyzed in following content, and they are shown in Fig.14.



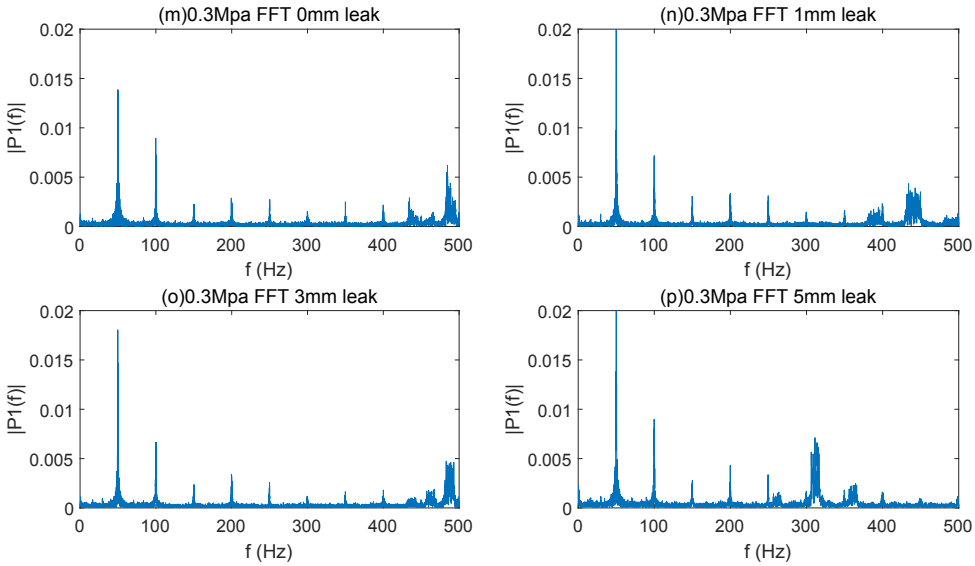


Fig. 14 DPT 1, FFT（1m/s）: (a) 0.10MPa, no leak; (b) 0.10MPa, 1mm; (c) 0.10MPa, 3mm; (d) 0.10MPa, 5mm; (e) 0.20MPa, no leak; (f) 0.20MPa, 1mm; (g) 0.20MPa, 3mm; (l) 0.20MPa, 5mm; (m) 0.30MPa, no leak; (n) 0.30MPa, 1mm; (o) 0.30MPa, 3mm;(p) 0.30MPa, 5mm.

Fig. 14 (a), (e), and (m) show that the FFT curves under no leak are different as the pressure effects. It is because that the internal pressure of pipeline becomes larger, and then the amplitude of the FFT curve under no leak conditions has increased significantly. When the leak occurs, different pipeline pressures have clear effect on the frequency distribution of the leakage signal, and main changes of the signal frequency components are different along the leak orifice diameter. It indicates that the maximum discrete signal power occur different orifice diameter under different pipeline pressure.

(3) Effects of the flow velocity

The FFT curves under different flow velocity are shown in Fig.15.

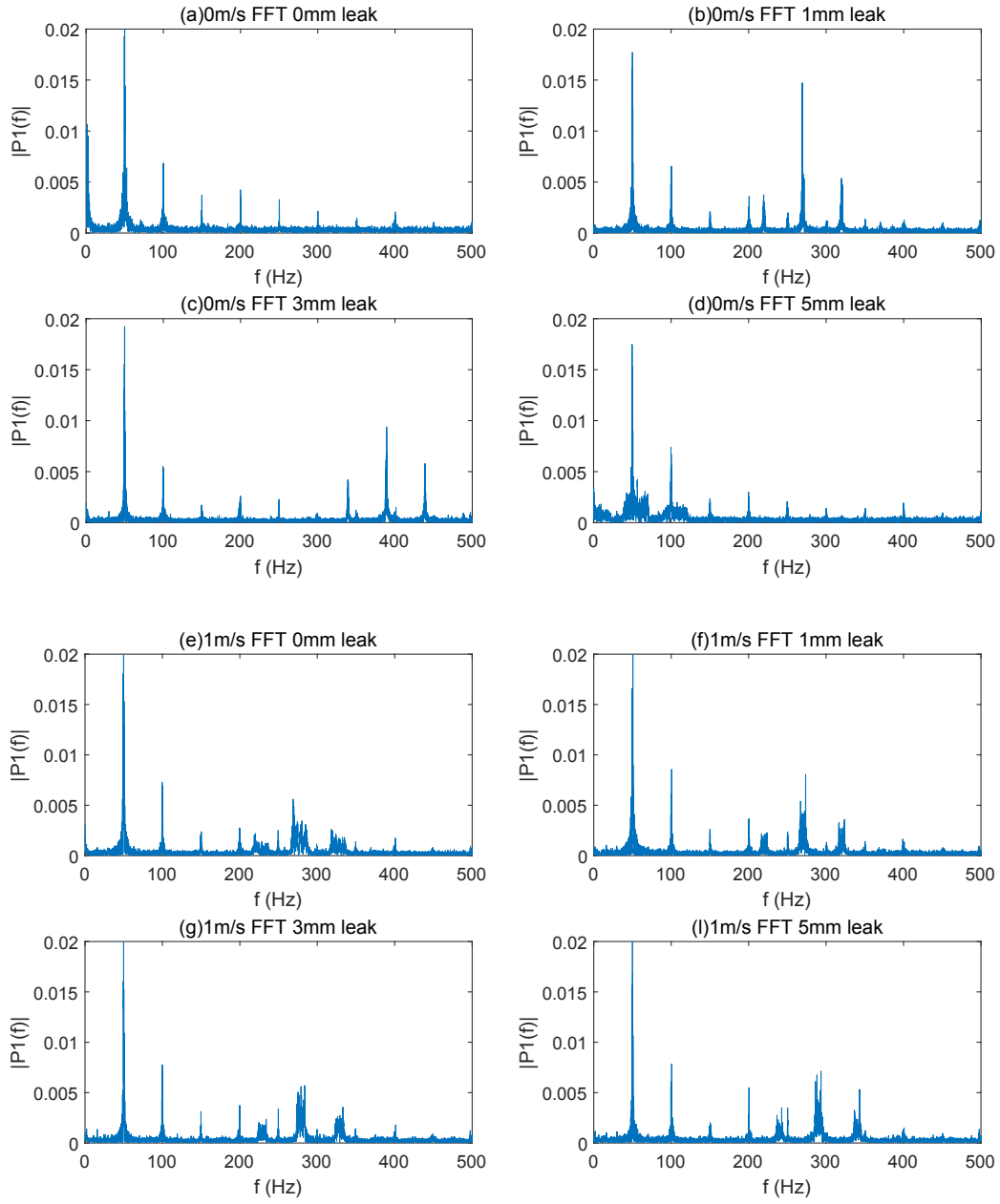


Fig. 15 DPT2, FFT (0.20MPa). (a) 0m/s, no leak; (b) 0m/s, 1mm;(c) 0m/s, 3mm; (d) 0m/s, 5mm; (e) 1m/s, no leak; (f) 1m/s, 1mm;(g) 1m/s, 3mm; (h) 1m/s, 5mm.

Fig. 15 shows that with the increase of the water velocity in the pipeline, the amplitudes corresponding to 100 Hz-450 Hz occur clear fluctuating. Different water flow velocities in the pipeline have certain effect on the frequency distribution of the leakage signal.

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(1) An experiment was built to simulate leaks in an industrial scale experimental

pipeline.

(2) The effects of orifice size, pipeline pressure, and liquid flow speed were investigated.

(3) An artificial neural network model was developed for leaks prediction.

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AUTHORSHIP STATEMENT

Manuscript title: Experimental Study on Water Pipeline Leak Using In-Pipe Acoustic Signal Analysis and Artificial Neural Network Prediction

All persons who meet authorship criteria are listed as authors, and all authors certify that they have participated sufficiently in the work to take public responsibility for the content, including participation in the concept, design, analysis, writing, or revision of the manuscript. Furthermore, each author certifies that this material or similar material has not been and will not be submitted to or published in any other publication before its appearance in the Hong Kong Journal of Occupational Therapy.

Authorship contributions

Please indicate the specific contributions made by each author (list the authors' initials followed by their

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Liyun Lao	Writing; Visualization
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Acknowledgements (AUTHORSHIP STATEMENT)

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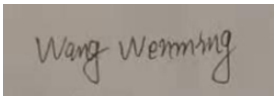
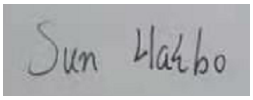
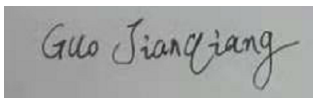
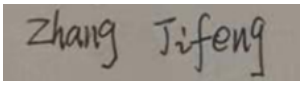
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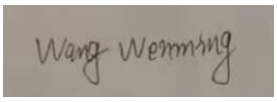
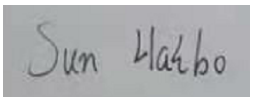
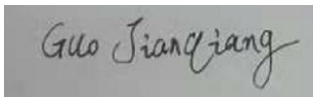
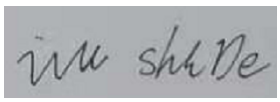
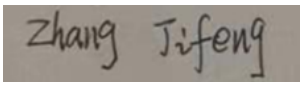
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Wang, Wenming; Sun, Haibo; Guo, Jianqiang; Lao, Liyun; Wu, Shide ...

2021-08-30
Elsevier
https://doi.org/10.1016/j.measurement.2021.110094
Wang W, Sun H, Guo J, et al., (2021) Experimental study on water pipeline leak using in-pipe acoustic signal analysis and artificial neural network prediction. Measurement, Volume 186, December 2021, Article number 110094.

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