Natural gas pipeline leak detection based on acoustic signal analysis and feature reconstruction

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ABSTRACT

The natural gas pipeline leakage detection task based on acoustic signal has some problems such as background noise coverage, lack of effective features, and low fault identification accuracy caused by small sample data. However, only one of these problems was usually studied in previous technologies. Almost no one has attempted to challenge multiple issues at the same time. In this study, a natural gas pipeline leak detection model that integrates acoustic feature processing techniques and feature reconstruction is proposed to resolve the above problems collaboratively. This model consists of two components. The first component is a feature processing technique of the acoustic signal that integrates frequency domain vector denoising and time domain associative function feature enhancement. The second component is a one-dimensional convolutional neural network with expanded structural feature encoder (FAE) feature reconstruction (FAE-1D-CNN). In the feature processing stage of the acoustic signal, firstly, the acoustic signal collected by the acoustic sensor is discretized into a digital signal. Secondly, the energy modal function is used to perform high/low energy modal clustering of digital signal features. The feature validity is enhanced by adding association factors to the low-energy modal features matrix. A low-pass filtering method is used in the high-energy modal features to remove the background noise coverage of the high-frequency components. In the fault feature extraction stage, a feature encoder (FAE) is introduced in the 1D-CNN network to extract effective fault features while performing secondary reconstruction of local spatial features, addressing the problem of small sample leakage signals with few effective fault characteristics. The global average pooling layer is used instead of the fully connected layer, and the Softmax function is adopted as the classifier for fault discrimination. The performance of the proposed method is evaluated on the GPLA-12 dataset, and the fault identification accuracy is up to 95.17%. Compared with other competing methods, the method in this paper exhibits optimal performance and has broad application prospects.

1. Introduction

Recently, the application proportion of natural gas as clean energy in buildings, factories, equipment manufacturing, and chemical products has been growing [1]. Pipeline transportation has become the preferred mode of transportation for liquid and gaseous energy sources such as oil and natural gas due to its wide range of transportation, high carrying capacity, fast delivery speed, and low economic cost [2–5]. However, pipeline leakage may inevitably occur because of some random factors such as imperfect pipeline materials, natural corrosion, welding defects, and third-party damage [6, 7]. And if the leakage caused an explosion near the pipeline infrastructure, it would be very serious, and bring many damages, i.e., human casualties, property damage, and environmental pollution. Therefore, an efficient leak detection algorithm with high recognition accuracy is needed to identify the fault types when the leak is not obvious for taking early emergency measures to prevent the escalation of natural gas pipeline leaks and ensure the safety of personnel and energy transportation.

Traditional natural gas pipeline leak detection techniques are mainly used to detect whether a pipeline is leaking by detecting changes in signal characteristics from pressure, flow, vibration, and acoustic waves, such as the fiber optic sensor method [8], negative pressure wave method [9], real-time model-based method [10], and ultrasonic flow meter method [11]. For the performance evaluation of these methods which are not restated in this paper, the reader is referred to [12–15]. However, the detection of unknown leakage points or the monitoring of the health status of long-distance pipelines is often a technical challenge in the industry. One feasible approach is to consider using sensor arrays to enhance the signal collection range, thereby ensuring accurate detection or localization of unknown or sudden leakage points [16, 17]. Although the above methods have good detection accuracy, they are long, costly, and require manual processing of fault characteristics. Acoustic methods are often used as the main choice for natural gas pipeline leak detection due to their advantages such as fast response time, high localization accuracy, and nondestructive detection [18, 19]. Most of the above methods are based on hardware implementation. While in the actual detection process, a large number of discrete digital signals generated by media changes are not fully utilized. If the fault characteristics contained in the above signals could be effectively analyzed, it would also improve the leak detection accuracy.

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With the continuous development of computer technology, more and more scholars have tried to use acoustic signals in combination with data-driven methods to monitor whether natural gas pipeline leaks [20–27]. To avoid the absence of useful fault characteristics and overcome the limitations of traditional pipeline leak detection methods that rely on expert experience to select signal features, a pipeline leak detection model based on integrated 1D-CNN-VAPSO-SVM was proposed from the perspective of adaptive learning of fault features in Ref. [28]. A dynamic risk probability analysis method based on a dynamic bayesian network (DBN) was developed to predict the probability and potential consequences of pipeline failure and leakage events in Ref. [29]. These methods usually use acoustic sensors to record a large number of acoustic signals near the leaks and use machine learning techniques (e.g., support vector machines, artificial neural networks, k-nearest neighbor) to select acoustic features to train classifiers, thereby characterizing pipeline status (e.g., normal/leakage) and fault factors (e.g., equipment health status/abnormal pressure) [30]. However, due to the self-propagation distortion and background noise coverage caused by acoustic attenuation, the feature extraction capability of the network model is seriously affected and the performance of the classifier is reduced, which easily leads to the incomplete robustness of leakage identification.

In the signal feature processing stage, researchers consider more about removing the high-frequency background noise from the acoustic signal. Xu et al. [31] used wavelet transform denoising methods to improve the performance of leak identification, but the incorrect selection of wavelet parameters will greatly affect the denoising effect. Boudraa and Cexus [32] proposed to use continuous mean square error to distinguish the EMD decomposition to obtain low-frequency components. But EMD itself has disadvantages such as modal aliasing and endpoint effects. So the filtering effect tends to cause waveform distortion and cannot maximize the retention of the original characteristics of the signal. The variational modal decomposition algorithm (VMD) [33] does not have modal effects and endpoint effects. Liu et al. [34] proposed a denoising algorithm combining VMD and de-trended wave analysis, but the decomposition layer and penalty parameters of VMD have a large impact on the modal decomposition results. To effectively extract fault features, many scholars are using deep network models instead of traditional shallow networks to mine richer high-level features as a way to improve the fault recognition capability of network models. For example, convolutional neural networks (CNN) and autoencoders (AE) can mine high-level features through a hierarchical structure and have shown powerful feature extraction capabilities and good recognition performance in practical projects [35, 36].

However, in the complex industrial environment, the propagation process of acoustic signals of leaks from the leakage point to the acoustic sensor is easy to lead to the absence of inconspicuous fault characteristics and weakening the important features, due to the absorption and self-attenuation of sound waves in the pipeline media. To effectively solve this problem, researchers usually use multiple acoustic sensors with different acquisition modes (e.g., different acquisition locations, sampling frequencies, etc.) to obtain more acoustic signals, but the parallel use of multiple acoustic sensors tends to make the data differentially distributed, that is the data nonlinear and non-stationary problem. The non-stationary characteristics of the leakage acoustic signal directly affect the convergence ability of the leakage detection model and cause its generalization performance to deteriorate. In addition, although parallel sampling of multiple groups of acoustic sensors can enrich the fault features, there are still problems of missing inconspicuous fault features, weakened important fault features, and background noise coverage. More seriously, the amount of data samples available for collection is small due to the safety hazard relationship. Therefore, there are three main problems with the leak detection of natural gas pipelines based on acoustic signals, namely, high-frequency background noise coverage, lack of effective features, and small amount of data. However, the feature processing of leakage acoustic signals for practical industrial tasks cannot be only for a single problem. For example, wavelet transform, empirical modal decomposition, and variational modal decomposition methods can effectively remove the strong background noise of the leakage acoustic signal. However, it is difficult to overcome the problems of missing effective features and a small amount of data. Although some researchers have combined denoising techniques and data generation algorithms to address the noise interference and data deficiency of the leakage signal, such methods do not take into account the data discrepancy distribution and the absence of effective features. No technique has been reported in the previous literature that solves all the above problems simultaneously. In this study, we propose a natural gas pipeline leak detection model (two components) that integrates acoustic feature processing techniques and feature reconstruction to overcome all the above difficult problems in parallel and collaborative processing. The next part of this article will detail the inspiration for these two components.

In this paper, we propose an acoustic signal feature processing technique (viewed as the first component) integrating frequency domain vector denoising and time domain association function feature enhancement to solve the problem of missing effective features and strong background noise coverage in leaking acoustic signals. Specifically, the component first uses clustering and then modular feature processing. Inspired by the K-means clustering method [37], this paper tries to use the geometric distance between the means of data samples for clustering, where the closer the mean distance of different samples indicates the higher probability that the samples belong to the same type, and conversely, the farther the mean distance of different samples indicates the lower probability that the samples belong to the same type. Unlike the K-means clustering method, this paper is only concerned with the discrete distribution of the leakage acoustic signal, so there is no need to normalize the data. By using the sample mean distribution instead of the whole sample distribution without updating the clustering center, the classification results are not affected by the initial value and outlier point.

The mean values of the samples after clustering are distributed in different value ranges. If the mean value of a sample is in the high-value range, it means that the corresponding sample is rich in fault features, and if the mean value of a sample is in the low-value range, it means that the corresponding sample has unobvious fault features or there are missing features. In this paper, the above features are noted as high/low energy modal features. In pulsed neural networks [38], the neuron's membrane potential is activated only when it reaches a certain value. Inspired by this, this paper assigns the feature energy to the low-energy modal features, which can achieve the discrete value increase of the features to achieve the effect of feature activation, enrich the sample fault features and reduce the non-stationarity. The high-energy modal features have high-frequency background noise coverage, while the fault features in the leakage acoustic signal have low-frequency characteristics. So this paper adopts a low-pass filtering method to denoise the high-frequency components of the discretized leakage acoustic signal features. Meanwhile, this study solves the problems of feature missing, important feature weakening, and background noise coverage by integrated time-frequency analysis techniques with parallel cooperative processing.

In the fault identification link, the modeling methods based on deep learning have powerful feature representation and nonlinear approximation capability. They can solve large-scale unknown mechanism problems in parallel, which can deeply explore the advanced features in the leakage acoustic signal and improve the accuracy of fault identification. However, the premise of efficient fault feature identification and accurate detection is that sufficient data samples are needed to train the network model, because small sample data in the deep network model often faces the issue of overfitting or feature extraction difficulties due to the lack of effective fault feature information, which directly affects the fault discrimination ability of the classifier. To address the problem of insufficient data samples in the training process, a variational autoencoder-based conditional Wasserstein GAN with gradient penalty (CWGAN-GP-VAE) is proposed in Ref. [39] for generating faulty training samples to enrich the training dataset of the machine learning-based AFD method. In Ref. [40], a multi-labeled one-dimensional generative adversarial network (ML1-1D-GAN) was proposed to generate real damage data using an auxiliary classifier (GAN). Then the generated damage data and the actual damage data were used to train the fault classifier at the same time. The experimental results show that the data generated by ML1-1D-GAN is feasible. However, the above method is only for data generation, and while generating important information, redundant information is also generated, which will waste a lot of time for model training and classifier performance degradation. Therefore, in the fault feature identification segment, this paper focuses more on the effective extraction and reconstruction of fault features during model training. In Ref. [41], soft thresholding is inserted into the deep architecture as a nonlinear transformation layer to eliminate unimportant features and establish an adaptive denoising fault diagnosis model. Inspired by this, a one-dimensional convolutional neural network (viewed as the second component) with expanded structural feature encoder feature reconstruction is proposed in this study. Specifically, 1D-CNN is used as the base framework for feature extraction, and then the encoder of FAE is inserted into 1D-CNN. The effective reconstruction of fault features is achieved by parameter optimization of the training process. At the same time, the problems of low data volume and poor model generalization ability are solved.

Based on the above research and analysis, this paper proposes two parts components to solve the problems of background noise coverage, lack of effective features, and low accuracy of fault identification for small sample data in leakage acoustics. The first component is an acoustic signal feature processing technique integrating frequency domain vector denoising and time domain association function feature enhancement. The second component is a one-dimensional convolutional neural network with expanded structural feature encoder feature reconstruction (FAE-1D-CNN). The main innovations and contributions of this paper are as follows:

(1) For the problem of differential distribution of leakage acoustic signals, this paper proposes an energy modal clustering method.
(2) To effectively solve the problem of scarcity of effective fault features in low-energy modal features, this paper proposes a time-domain association function method to enhance the effectiveness of features by introducing association factors in the original leakage signal matrix.
(3) For the background noise coverage problem of high-energy modal features, this paper uses a Butterworth low-pass filter to eliminate the high-frequency background noise in the leakage signal.
(4) To effectively solve the problem that small sample data are prone to low model fault recognition accuracy, this paper proposes a leak detection model (FAE-1D-CNN) with a combination of feature extraction and feature reconstruction.
(5) FAE-1D-CNN is applied to natural gas pipeline leak detection, and the recognition performance is better than related mainstream techniques.

The remaining work in this paper is organized as follows: Section 2 introduces 1D-CNN and autoencoder principles. Section 3 first describes the acoustic signal feature processing techniques integrating frequency domain vector denoising and time domain associative function feature enhancement, including high/low energy modal clustering methods, associative function feature enhancement methods, and Butterworth low-pass filtering noise reduction methods; and then describes how to construct a pipeline leak detection model (FAE-1D-CNN) based on feature extraction and local space feature reconstruction. Section 4 applies the above methods to natural gas pipeline leak detection, analyzes the FAE-1D-CNN model performance, and compares it with the existing mainstream methods (DRSN-CS, DRSN-CW). Finally, the work is summarized in Section 5.

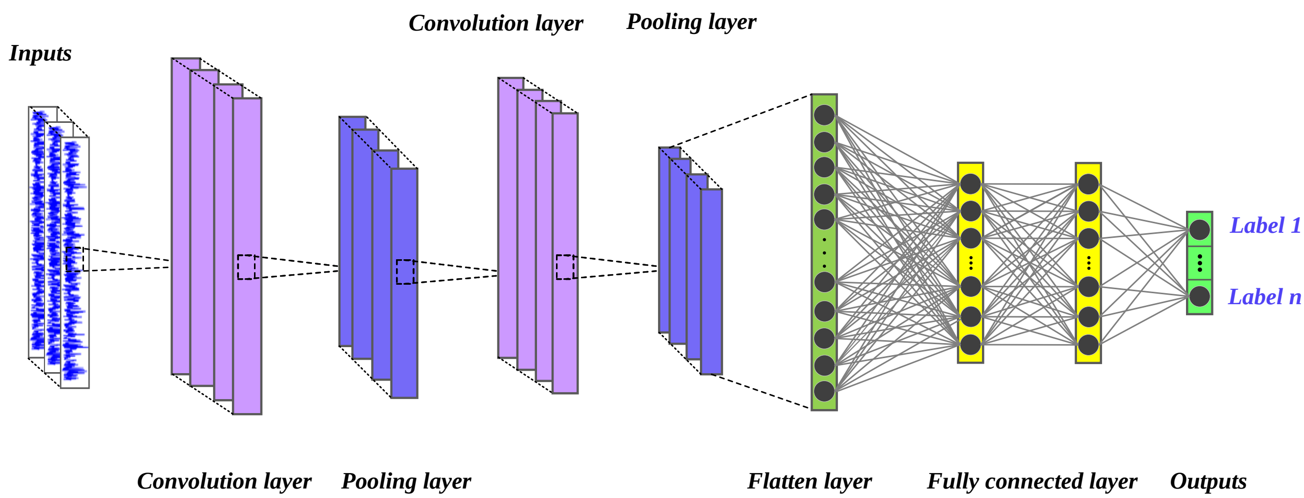

Fig. 1. 1D-CNN network model diagram.

2. Background

2.1. One-dimensional convolutional neural network

It is well known that convolutional neural networks (CNN) are commonly used in image recognition [42], natural language processing [43], speech recognition [44], and pipeline risk assessment [45]. In particular, 2D-CNN has become the main tool for image processing and video frame engineering applications. However, 2D-CNN is prone to robustness and generalization problems for sparse or single-application one-dimensional signals, such as pressure, vibration, and sound. To solve this problem, researchers developed 1D-CNN based on 2D-CNN. 1D-CNN also consists of a convolutional layer, pooling layer, fully connected layer, and output layer. The difference is that 1D-CNN focuses more on capturing the spatial structure inside the signal. It achieves the best recognition performance in biomedical data classification and early diagnosis, health state monitoring, and industrial equipment fault diagnosis. Therefore, in this paper, the natural gas pipeline leak detection task will be carried out on the 1D-CNN base framework shown in Fig. 1.

2.1.1. Convolution layer

The convolutional kernel in the convolutional layer achieves the purpose of extracting important feature information by performing sliding local convolutional operations on the input signal. The essence of the convolution kernel is a weight matrix. It uses local connectivity and parameter-sharing mechanisms in the feature extraction process. Therefore, compared with the fully connected neural network, the number of parameters in the 1D-CNN network is greatly reduced, which saves the memory space for running the program. Meanwhile, it makes the training speed significantly faster and also reduces the risk of overfitting. After completing the convolution operation, the activation function is used to transform the extracted effective features nonlinearly, thus enhancing the non-linear expressiveness of 1D-CNN. The operation of the convolution process is shown in Eq. (1).

$$x_j^i = f\Big(\sum_{i \in N_j} x_i^{l-1} w_{ij}^l + b_j\Big) \tag{1}$$

where N_j represents the input signal to be convolution operation, x_i^{l-1} represents the local area to be convoluted, w_{ij}^l represents the weight matrix, b_j is the bias coefficient, and $f(\cdot)$ is the activation function.

2.1.2. Pooling layer

The pooling layers are often used after convolutional layers to extract representative features from the previous convolutional layer, which helps to reduce the dimensionality "curse" and prevent the occurrence of overfitting. The commonly used pooling methods are max pooling and average pooling. In this paper, the max pooling method is used, and its operation formula is as follows.

$$y^{l(i,j)} = \max_{(j-1)M+1<t<jM} \{x^{l(i,t)}\} \tag{2}$$

where $x^{l(i,t)}$ represents the value of the t neuron in the i channel of the l layer, M is the pooling kernel size, and $y^{l(i,j)}$ represents the output value of the j neuron in the i channel of the l layer.

2.1.3. Global average pooling layer

The global average pooling layer (GAP) can spatially average the channel feature map and spread the high-dimensional spatial feature vector into a one-dimensional vector, which has the same effect as the fully connected layer. Meanwhile, GAP enhances the correlation of fault features and label information, reduces the number of network training parameters, speeds up model convergence, and effectively prevents the overfitting phenomenon. Therefore, this paper uses the global average pooling layer instead of the fully connected layer, which is calculated as follows.

$$y^l = \frac{1}{K} \sum_{i=1}^{K} x_i^l \tag{3}$$

where y^l represents the global average of the l channel of the input feature map, K represents the number of features for each channel, and x_i^l represents the i eigenvalue of the l channel.

2.2. Autoencoder(AE)

The autoencoder is essentially a neural network with a symmetric structure and efficiently reconstructs the data. It is mainly composed of two basic units, i.e., an encoder and a decoder as shown in Fig. 2. The working process of the autoencoder is divided into the pre-training phase and fine-tuning phase. In the pre-training phase, firstly, representative features of the input data are captured and mapped to the potential space by the encoder. Secondly, the representative features are decoded by the decoder and the input data are reconstructed. Adding a classification or regression layer to the autoencoder network transforms AE into a deep neural network (AE-DNN) based on the AE base framework. The squared error or cross-entropy error is commonly used as a loss function in the fine-tuning phase to update parameters for the pre-training process. Autoencoders have shown good performance in image processing, detection, and fault diagnosis of industrial processes [35].

2.2.1. Encoder

The encoder maps the input vector $x \in R^d$ to the potential space $s \in R^n$, and its calculation process is shown in Eq. (4).

$$s = \sigma(Wx + b) \tag{4}$$

where s is the latent space that the encoder extracts representative features, and σ is the activation function such as ReLU or Tanh activation function. W is the weight matrix, and b is the bias coefficient.

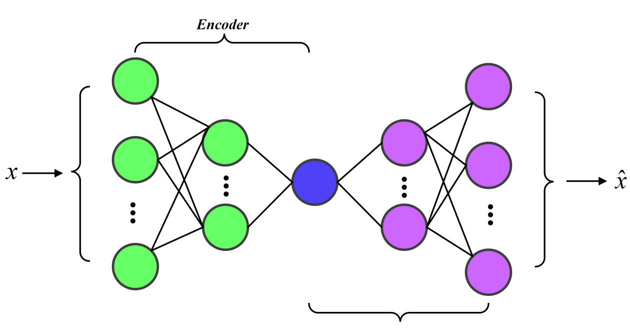

Fig. 2. Autoencoder structure diagram.

2.2.2. Decoder

The decoder attempts to map the potential space s into the reconstructed output data $\tilde{x}$, and its calculation process is shown in Eq. (5).

$$\tilde{x} = \sigma'(W's + b') = \sigma'\left\{W'(\sigma(Wx + b)) + b'\right\} \tag{5}$$

where σ' represents the activation function, and W' and b' represent the weight matrix and bias coefficient respectively. It should be emphasized that W' and b' are different from the encoder.

3. Proposed method

The natural gas pipeline leak detection method based on acoustic signal analysis and feature reconstruction consists of the following two parts: (1) Feature enhancement and noise reduction based on the acoustic signal. (2) Spatial feature reconstruction and fault classification by FAE-1D-CNN. Fig. 3 shows a simplified flow chart of the above method, which will be explained in detail in the remaining subsections of this chapter.

3.1. Acoustic feature processing technology

Since the small sample leakage acoustic signal inevitably has the problems of missing effective features and strong noise, it is important to enhance the effective features and eliminate the background noise in the acoustic signal in the data processing stage. Therefore, in this paper, we propose an acoustic feature processing technique. The technique includes the following three methods: (1) an energy modal clustering method for leakage acoustic signals(E). (2) Low-energy modal features using association function to enhance the effective feature method(A). (3) A method for removing background noise from high-energy modal features using Butterworth low-pass filtering(B). The above technique is called EAB in the following study. Next, we will elaborate on the acoustic feature processing technique for this time-frequency analysis method.

3.1.1. Energy modal clustering

The acoustic signals of leakage points are collected by multiple sets of sensors, and are then converted into a digital signal matrix. Due to the factors such as the placement of sensors, different parameter settings, and complex environment, it is easy to cause data differential distribution. Typically, this kind of data exhibits the following characteristics: (1) strong background noise coverage [46–48]; and (2) data with missing fault features or weakened important fault features [49, 50]. Therefore, a numerical clustering method is needed to separate the data that includes high-frequency background noise and missing important features. Inspired by the K-means clustering method, this paper proposes an energy modal clustering method. An energy modal set EM is constructed by Eq. (6), which includes high-energy modal features EM^{he} and low-energy modal features EM^{le}. In this case, high-energy modal features correspond to data containing background noise, while low-energy modal features correspond to data with missing important features. This represents the relationship between acoustic signals and energy modal clustering described in this paper.

$$EM = (EM^{le}, EM^{he}) \tag{6}$$

Calculate the sample mean value $\bar{\beta}_i$ of each row element in the two-dimensional digital acoustic signal matrix x_{mn}(see Eq.(7)), and use $\bar{\beta}_i$ to represent the corresponding sample. Then find the matrix mean λ_{mean} as shown in Eq. (8) again.

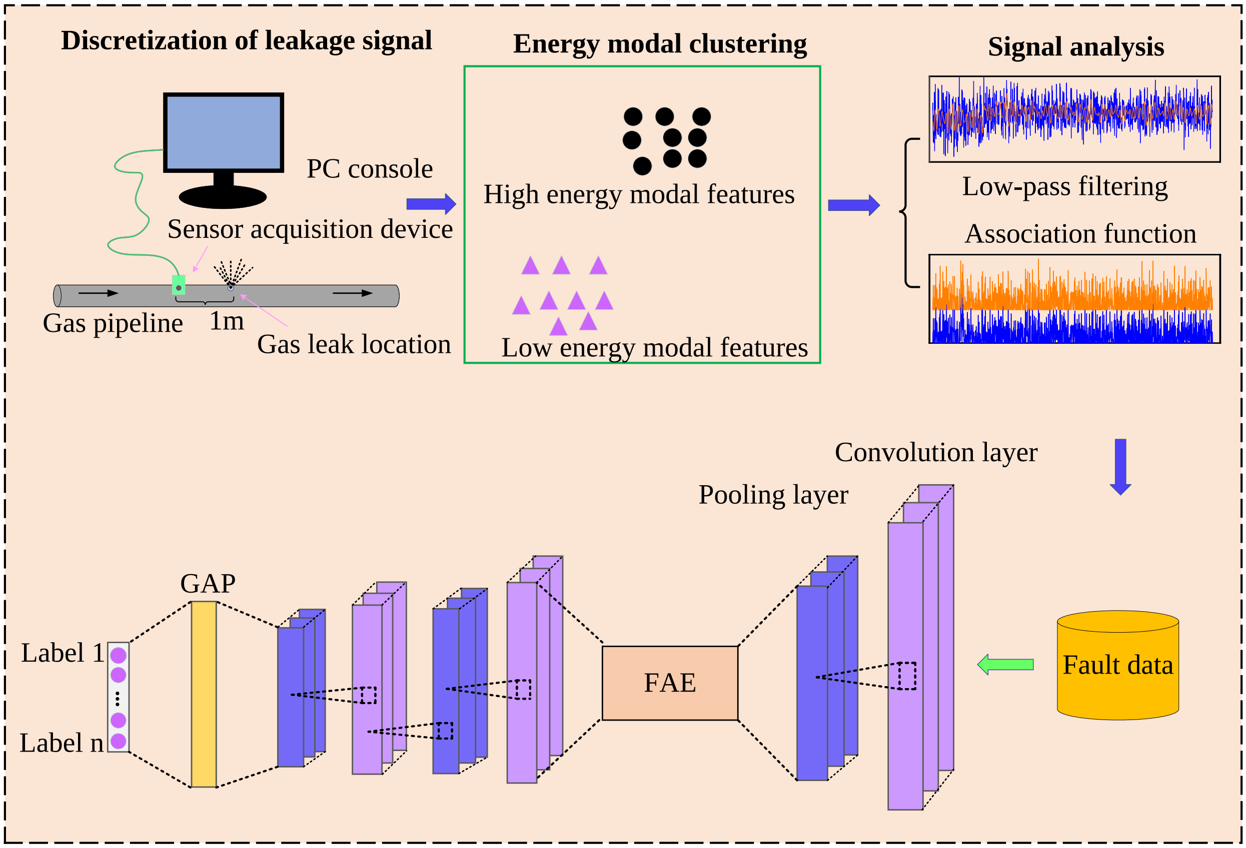

Fig. 3. Flow chart of the method in this paper.

$$x_{mn} = \begin{pmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{m1} & \cdots & a_{mn} \end{pmatrix} = \begin{pmatrix} \beta_1 \\ \vdots \\ \beta_m \end{pmatrix} \tag{7}$$

where x_{mn} is a two-dimensional matrix, and m, n are the row and column, respectively. For this industrial study, x_{mn} represents the input signal matrix of the leakage model.

$$\lambda_{mean} = \frac{1}{m}\sum_{i=1}^{m}\bar{\beta}_i = \frac{1}{m*n}\sum_{i=1}^{m}\sum_{j=1}^{n}\beta_i[j] \tag{8}$$

where λ_{mean} is the matrix mean, $\bar{\beta}_i$ is the sample mean, and i is the index of samples.

We propose to use Eq. (9) as the clustering constraint for each sample mean, by which the fault features of acoustic signals can be effectively clustered into high-energy modal features and low-energy modal features.

$$EM = \begin{cases} \beta_i \in EM^{le}, if\, \bar{\beta}_i < \lambda_{mean}(1-c) \\ \beta_i \in EM^{he}, if\, \bar{\beta}_i \geq \lambda_{mean}(1+c) \end{cases} \tag{9}$$

where EM is the energy modal set, EM^{le} is the low-energy modal feature, EM^{he} is the high-energy modal feature, β_i is the data sample, the value of c ranges from (0,1), and the superscript "*le*" and "*he*" respectively represent low energy and high energy.

3.1.2. *Association function*

In classification recognition detection, effective features can make the classifier play an excellent fault recognition performance. However, there are inconspicuous features or missing important features in the low-energy modal features after the above-mentioned clustering, which brings challenges to the feature extraction of the convolutional layer and the fault discrimination of the classifier. Therefore, we adopt an analysis method in the time domain and propose to add an association factor to each element in the low-energy modal feature matrix, so that the feature missing or not obvious in the original signal is endowed with feature energy. In this paper, this method is recorded as an associative function, and its calculation process is shown in Eq. (10). In addition, EM^{le} updated using Eq. (10) can not only enhance the effective features but also approach EM^{he} to reduce the difference in data distribution. It needs to be emphasized that in each group of samples, the corresponding tag information remains unchanged. The low energy modal feature EM^{le} to get the association factor carries out the overall update of the feature matrix, and then gets the EM^{le}_{update}.

$$EM^{le}_{update} = EM^{le} + \gamma \tag{10}$$

where γ is the association factor.

In this study, acoustic signals with missing or weakened important features caused by sensors or complex factors are considered as weak signals. After performing energy modal clustering (Eqs. (7-9)), such weak signals are categorized as low-energy modal features. To enhance the validity of the fault features and reduce the data variance distribution, Eq. (10) is used to add association factors to the low-energy modal features and perform an overall numerical update.

3.1.3. Butterworth low-pass filter

The acoustic signals of pipeline leaks are often contaminated by equipment noise and environmental noise, which can easily cause convergence oscillations and low accuracy of fault identification in leak detection models. Therefore, having clean, high-quality data sets is crucial for industrial process detection and fault diagnosis. The Butterworth low-pass filter is better for digital signal denoising due to its flat passband and fast response characteristics. To improve the data quality, we use a Butterworth low-pass filter for noise reduction of the leakage acoustic signal. The frequency response equation of the Butterworth filter is as follows.

$$|H(jw)|^2 = \frac{1}{1 + \left({}^{w}/_{w_c}\right)^{2N}} \tag{11}$$

where $H(jw)^2$ represents the square of the filter frequency response, N represents the filter order, w represents the corner frequency, w_c represents the cutoff frequency. N and w_c are hyperparameters.

3.2. Proposed FAE-1D-CNN leak detection model

In this study, data modeling and fault identification of natural gas pipeline leakage signals are based on real industrial environments. Since there are more potential factors affecting the acquisition of leak signals, it is prone to the lack of valid features due to insufficient data sample size. Such a data set is prone to feature extraction difficulties and overfitting during the training process of the network model, which ultimately results in low accuracy and poor generalization of fault identification. In this paper, we propose an “end-to-end” local spatial feature reconstruction network (FAE-1D-CNN). Unlike other data reconstruction methods, this network reconstructs the effective features in the local space instead of reconstructing the original data as a whole.

FAE-1D-CNN consists of two basic frameworks: 1D-CNN and FAE. The network structure and computational principles of the 1D-CNN have been introduced in detail in Section 2.1. The encoder (Encoder) and decoder (Decoder) shown in Fig. 4 are employed to construct the feature encoder (FAE). The following points should be noted. (1) The network structure of FAE is opposite to that of the traditional autoencoder. The encoder part of FAE has an extended structure, i.e., neuron nodes are added layer by layer. The decoder part has a compressed structure, i.e., the neuron nodes are reduced layer by layer. (2) FAE works by using the encoder to extract representative features of the input signal (x) and maps them to the potential space, while the decoder decodes the representative features of the potential space and finally reconstructs the output signal ($\hat{x}$) that is similar to the input signal. (3) The output signal is of the same dimension as the input signal, which means that the decoder only reconstructs the input signal and does not generate new features.

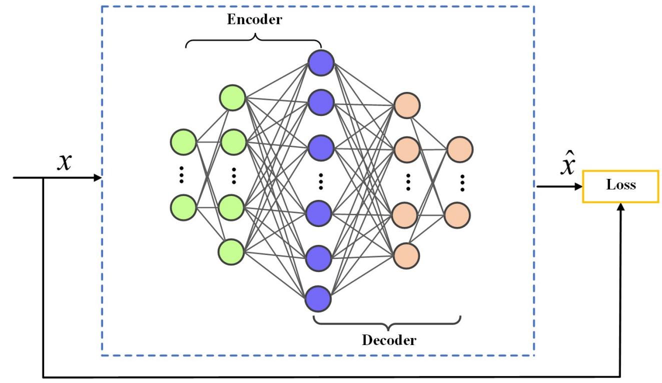

Fig. 4. FAE network structure diagram.

This study expects that the feature encoder can extract extended features for fault detection. The feature encoder (FAE) developed in this paper can perform the previously mentioned task. Its encoder part can not only better capture the features in the local space but also generate more coded vectors. Therefore, the encoder part of the FAE introduced in 1D-CNN can learn extended features, i.e., data enhancement. In contrast, traditional autoencoder networks have a compression structure, which mainly performs dimensionality reduction on the data. Thus, important fault features might be lost during the stage of dimensionality reduction. Therefore, the features extracted by FAE's encoder were used for feature reconstruction in this study. The FAE structural parameters are shown in Table 1.

The network structure of the FAE-1D-CNN leak detection model is shown in Fig. 5. The FAE-1D-CNN designed in this paper first uses the convolution kernel to extract features from the original features in the region space by local convolution, and passes the extracted feature map into the convolution layer after completing the convolution operation (Eq. (1)). Then, the activation function maps the feature into the pooling layer. Finally, different pooling kernels select representative features to form the spatial feature map by Eq. (2). FAE is introduced at this point and a fully connected structure is used to maximize the learning of the input spatial information. In the training process, the encoder of the expanded structure uses the Tanh activation function to nonlinearly transform the input features and perform matrix product operations of the layered network parameters (weights, bias coefficients) to obtain the generated features as much as possible. The decoder of the compressed structure reconstructs the original input by the matrix product operation of network parameters (weights and bias coefficients). It removes redundant features during the training process so that the generated features have a strong correlation with the original features. Finally, the reconstructed feature maps are passed to the classification layer to optimize the model parameters by class label information.

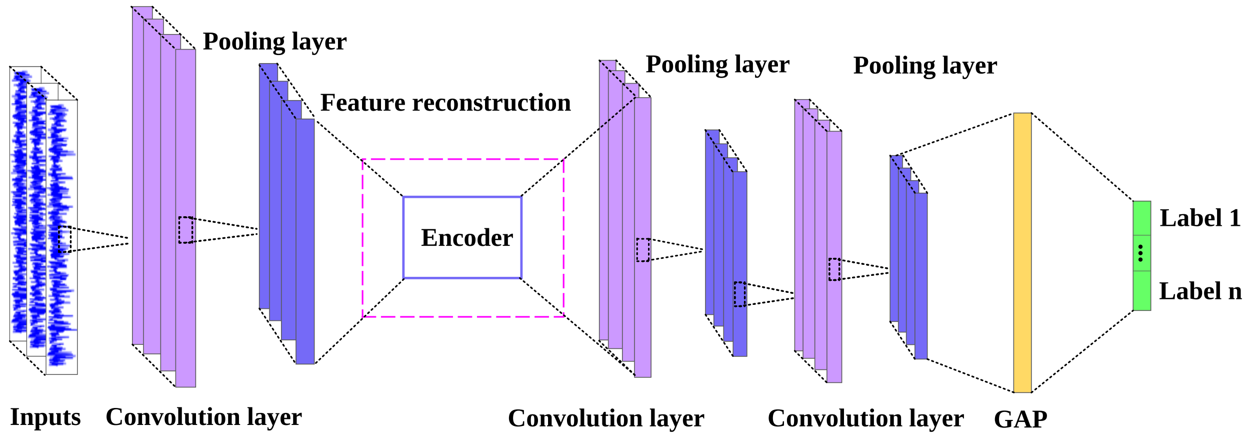

Fig. 5. FAE-1D-CNN network structure diagram.

Table 1
FAE structure parameter settings.

Layer type	Number of neurons
Encoder_layer 1	32
Encoder_layer 2	64
Encoder_layer 3	96
Decoder_layer 1	64
Decoder_layer 2	32

Table 2
Parameter settings of FAE-1D-CNN model.

Layer type	Kernel size	Stride	Kernel number
Convolution 1	1*17	1	32
Max Pooling 1	1*9	9	32
Convolution 2	1*11	1	64
Max Pooling 2	1*7	7	64
Convolution 3	1*9	1	64
Max Pooling 3	1*3	3	64
Global Average Pooling			
Softmax			

Table 3
FAE-1D-CNN training process parameters.

Optimizer	Adam
Learning rate	0.001
Epochs	150
Batch size	32
Loss function	Cross entropy

To speed up the convergence of the leak detection model and prevent the overfitting phenomenon, FAE-1D-CNN changes the underlying structure of 1D-CNN and adopts the global average pooling layer (GAP) instead of the fully connected layer. In the FAE-1D-CNN network, its leak detection process is as follows: (1) The convolution layer extracts high-level features from the original signal, and the pooling layer reduces the dimensionality; (2) The FAE with expanded structure reconstructs the effective fault features; (3) The cross-entropy loss function is used to optimize the training process parameters; and (4) The model is tested and classified. Convolutional and pooling layers directly affect the training accuracy and convergence speed of the leak detection model. If the number of layers is small, it is difficult for FAE-1D-CNN to learn advanced features. However, too many layer settings can easily lead to overfitting of the model. Especially, the size selection of the first layer convolution kernel and pooling kernel directly affects the spatial feature reconstruction of FAE. According to the experimental study, three groups of "convolutional layers + pooling layers" are selected in this paper, and their structural parameters are shown in Table 2. The suitable training process parameters are closely related to the quality of FAE-1D-CNN and the accuracy of leak detection recognition. The parameters of the FAE-1D-CNN model training process are shown in Table 3, including the optimizer, optimizer learning rate, batch size, and the number of iterations.

4. Experimental results and analysis

4.1. Experimental data description

A brand-new leakage detection platform for natural gas pipelines (as shown in Fig. 6) has been established in Chongqing's key laboratory of online analysis and control. Significantly different experimental settings compared to previous studies have been adopted, such as using a fixed leak orifice and unchanged valve states, variable pipeline pressures and environmental noise. One of the purposes of doing so is to take into account the fact that the setting in our experimental environment is a typical process state for monitoring leaks after the commissioning of a natural gas pipeline, which is also a key research aspect of this study to diagnose the natural gas pipeline leaks. Extensively exploring and studying this typical operational state can provide insights and guidance for leak monitoring and prevention in similar scenarios. The second purpose is to explore the possibility of the refined classification of natural gas pipeline fault types,

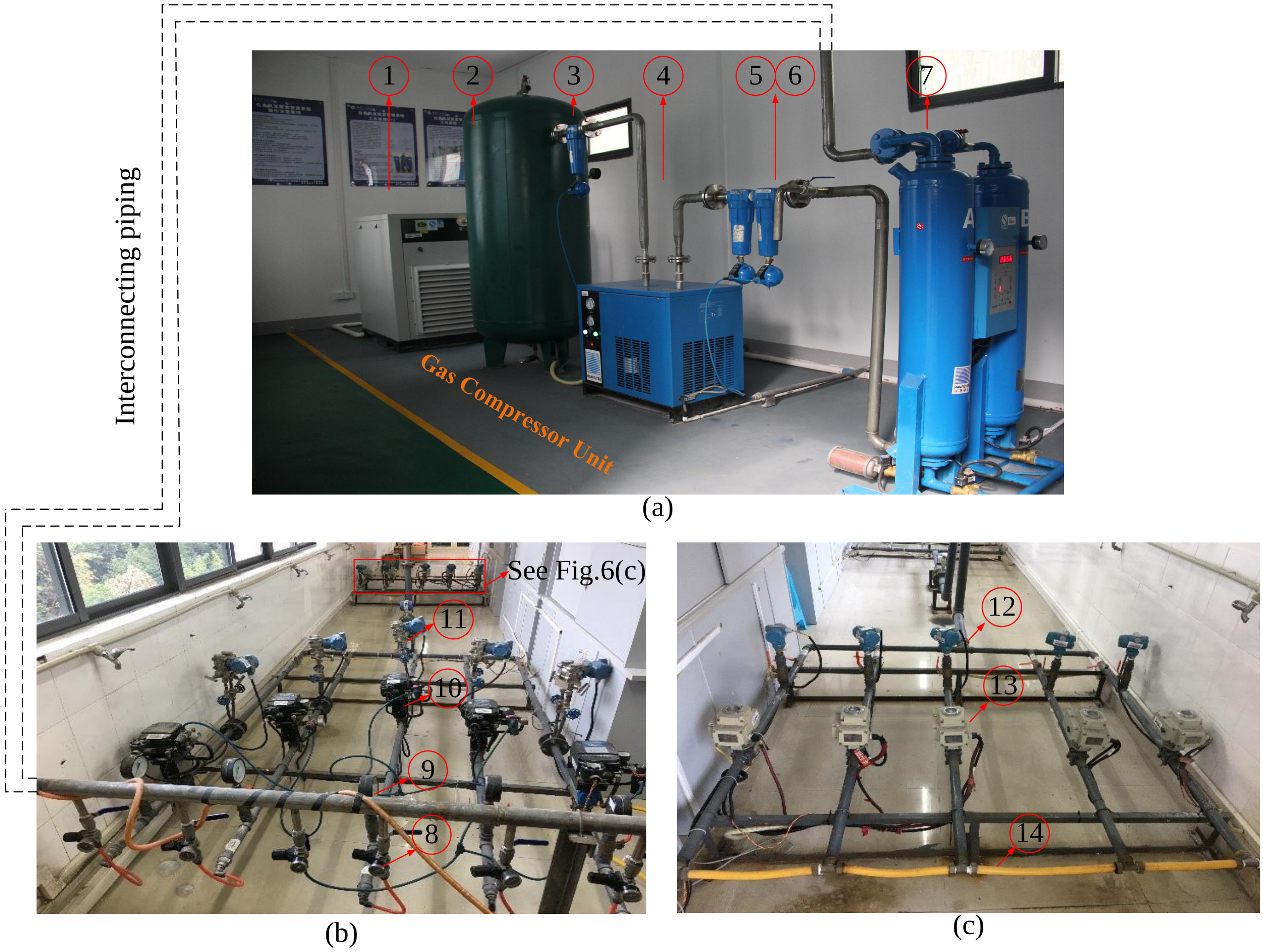

Fig. 6. Images of the gas pipeline system. (a) Gas compressor units, (b) The front end of the gas pipeline system, and (c) The back end of the gas pipeline system. Note that key components in the system are denoted with corresponding numbers (i.e., 1. screw compressor, 2. gas tank, 3. water elimination filter, 4. refrigeration dryer, 5. dust removal filter, 6. oil removal filter, 7. heatless regenerative adsorption dryer (HRAD), 8. pressure regulating valve, 9. pressure gauge, 10. pneumatic control valve, 11. different pressure orifice flowmeter, 12. pressure transmitter, 13. electric control valve, and 14. gas discharge tube) [51].

which existing approaches have not covered. Besides, other experimental factors and different operating conditions of natural gas pipelines can be gradually considered to develop more systematic diagnostic methods.

In addition, considering the limited availability of training data from real natural gas pipeline sites, this study also follows the scenario that simulates the on-site conditions as closely as possible. In other words, we take a small number of data samples used to train the model and test its effectiveness. The small number of data samples we used in our experiments constitute the GPLA-12 dataset [51], which is the first publicly available dataset for natural gas pipeline leakage based on acoustic signals. This dataset released by our team fills in the gap in this field. Moreover, GPLA-12 facilitates the training of lightweight models, saving more time for timely fault detection.

The related experiments and effectiveness validation of this study were conducted in an environment that closely simulates a real industrial site of natural gas pipelines. This environment objectively represents most common leakage states that occur during the transportation process of natural gas pipelines. The specific description of the environment is as follows: (1) The length of the natural gas pipeline is 150 meters. (2) The pipeline material is 304 stainless steel pipes. (3) The pipeline has undergone anti-seismic treatment. (4) Two types of acoustic sensors, MAX4466 and LM386, are used. The MAX4466 sensor captures a frequency range of 0Hz-600kHz, while the LM386 sensor captures a frequency range of 100Hz-10kHz. Using two sensors with overlapping frequency bands allows for different sensitivity ranges, highlighting the characteristics of the leakage signals. (5) The distance from the leakage point to the sensor is 1 meter. (6) The temperature of the pipeline is 26.5 degrees Celsius. (7) The gas flow rate is 60 m^3/h. (8) The sensor sampling frequency is 3000Hz. (9) The leakage signals are classified into 12 fault types, as shown in Table 4, based on different pressures (0.2MPa, 0.4MPa, 0.5MPa) and the presence or absence of environmental noise. (10) The PC console is used to store and process the acoustic signals from the natural gas pipeline leaks. (11) A total of 684 sets of small sample

Table 4
GPLA-12 dataset.

Label	Data attribute	Number
1	No environmental noise, acoustic sensor 1, pipeline pressure 0.2MPa	57
2	Environmental noise, acoustic sensor 1, pipeline pressure 0.2MPa	57
3	No environmental noise, acoustic sensor 1, pipeline pressure 0.4MPa	57
4	Environmental noise, acoustic sensor 1, pipeline pressure 0.4MPa	57
5	No environmental noise, acoustic sensor 1, pipeline pressure 0.5MPa	57
6	Environmental noise, acoustic sensor 1, pipeline pressure 0.5MPa	57
7	No environmental noise, acoustic sensor 2, pipeline pressure 0.2MPa	57
8	Environmental noise, acoustic sensor 2, pipeline pressure 0.2MPa	57
9	No environmental noise, acoustic sensor 2, pipeline pressure 0.4MPa	57
10	Environmental noise, acoustic sensor 2, pipeline pressure 0.4MPa	57
11	No environmental noise, acoustic sensor 2, pipeline pressure 0.5MPa	57
12	Environmental noise, acoustic sensor 2, pipeline pressure 0.5MPa	57

data are involved in the leakage diagnosis, with each data set having a length of 1460. (12) There are 57 data sets for each fault type, and one-hot encoding is used for fault labels.

As the test dataset used in our work covers more complex scenarios or fault types of natural gas pipeline leakage than previous works, we propose a novel method for detecting leakage in natural gas pipelines based on acoustic signal analysis and feature reconstruction. More capable than previous approaches, the proposed method can realize the fine division of natural gas pipeline leakage status, i.e., it can identify which type of natural gas pipeline leakage belongs to, such as the 12 types described in the paper.

4.2. Experimental results and analysis of acoustic signal processing techniques

4.2.1. Energy modal clustering analysis

For the original signals with large distribution differences, the method in this paper used the sample mean as a representative feature of the samples, and the matrix mean as the discriminative basis for energy modal clustering. The energy modal clustering method is validated on the GPLA-12 dataset, where the energy modal parameters $c = 0.5$. The experimental results are shown in Fig. 7, which verified that the energy modal clustering method can better form the high-energy modal features and low-energy modal features.

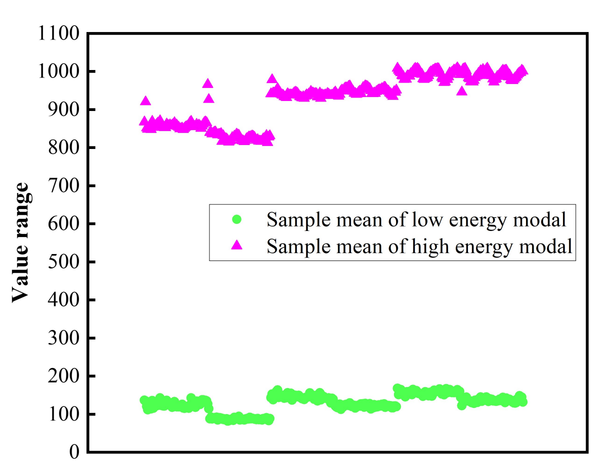

Fig. 7. Energy modal cluster diagram.

4.2.2. Experimental analysis of association function

In this study, the original leakage signals can be divided into high/low energy modal features after performing energy modal clustering (Eqs. (7-9)). As stated in Section 3.1.2, the low energy modal features represent a collection of acoustic signals with important feature deficiencies or attenuations. After performing energy modal clustering in the experiment, the leakage signals represented by fault types 1-6 in Table 4 are classified into the low energy modal features, while the leakage signals represented by fault types 7-12 are classified into the high energy modal features. Therefore, the above results indicate that the leakage signals represented by fault types 1-6 suffer from missing important features or weakened effective features. Such leakage signals usually have a small numerical distribution range, which is not conducive to accurately identifying leakage fault types in subsequent network models.

Therefore, the association function method is introduced into low-energy modal features to improve the effectiveness of their fault features by adding association factors (i.e.,$\gamma = 450$) to each type of fault feature. The experimental results are shown in Fig. 8. Among them, each subfigure from Fig. 8(a) to Fig. 8(f) represents a class of fault types. Based on the blue signal in Fig. 8, it can be observed that most of the values of the original 6 types of fault features are lower than 400, and more fault features have a value of 0. After adding associative factors to each type of fault feature, it is found that the values of each type of fault feature are enhanced, as shown by the orange signal in Fig. 8.

4.2.3. Butterworth low-pass filter denoising

To address the problem of background noise in high-energy modal features, this paper uses an 8th-order Butterworth filter for noise reduction of high-energy modal features and sets the cutoff frequency to 180 Hz. The experimental results are shown in Fig. 9. It can be clearly found that the Butterworth filter can eliminate the background noise covered in each class of fault features (Fig. 9(a)-Fig. 9(f)) very well.

We combined two acoustic signal techniques, associative function and Butterworth filter, which can better solve the problems of few effective features, poor representability, and noise pollution. The above strategies help to bring out the best performance of the data-driven model. The characteristic

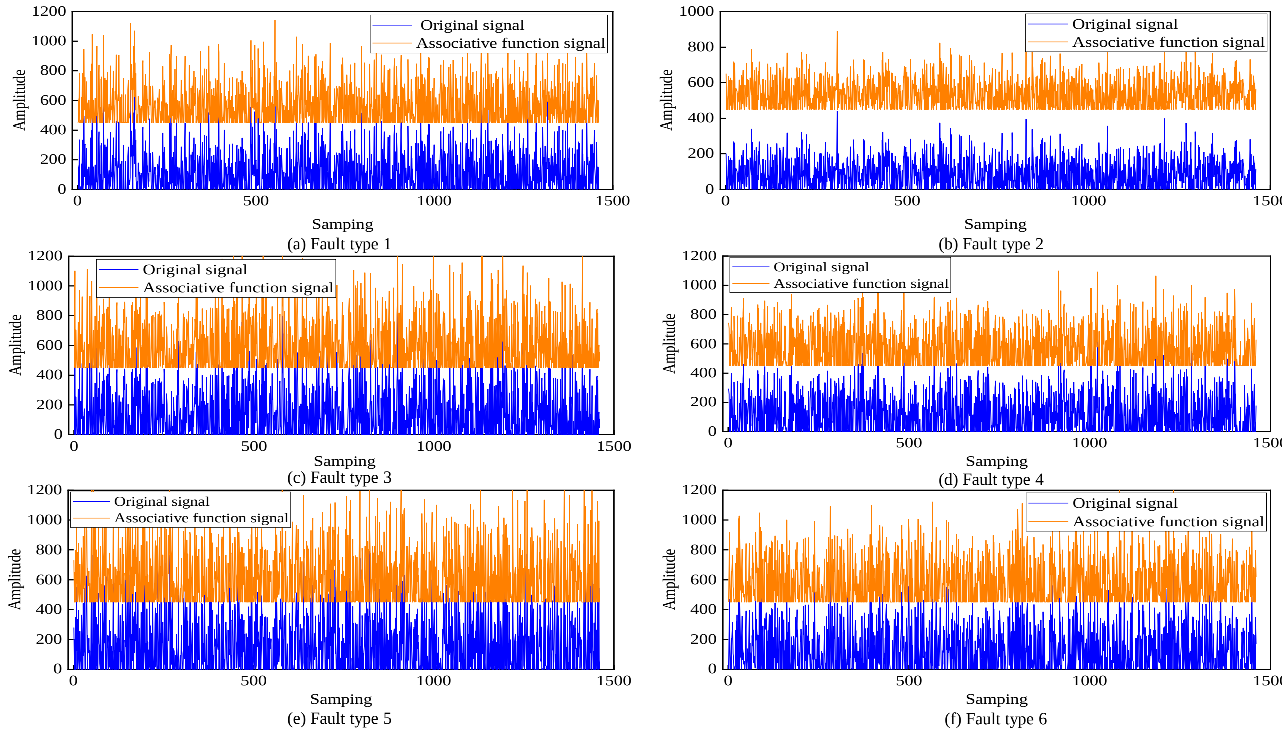

Fig. 8. Association function feature processing diagram.

changes during the experiment are shown in Fig. 10. Taking Fig. 10(a) as an example, the discretized leakage acoustic signal is projected in 3-dimensional space in this paper. So, the distribution of acoustic features can be clearly observed.

4.3. Leak detection model experimental platform and model evaluation index

The software environment for performing the performance evaluation in this study is as follows: Python3.8, Tensorflow2.8.0, Win 11 Pro, and Win 64 OS. The hardware environment is i5-12500H CPU, NVIDIA GeForce RTX3060 GPU, RAM 16.0GB, and SSD 512GB. It should be noted that the experiments in this paper are all based on the test set results. Considering that leakage detection accuracy is the main focus in practical engineering, the effectiveness of FAE-1D-CNN model performance is verified by fault identification accuracy in this paper. The evaluation method is as follows.

$$Accuracy = \frac{TP + TN}{TP + FN + TN + FP} \tag{12}$$

where TP represents the number of positive instances that are classified correctly, FP represents the number of negative instances that are misclassified, TN represents the number of negative instances that are classified correctly, and FN represents the number of positive instances that are misclassified.

Table 5
Algorithm performance test.

Case number	Method
Case1	1D-CNN
Case2	1D-CNN+EAB
Case3	FAE-1D-CNN
Case4	FAE-1D-CNN+EAB

4.4. Evaluating designed EAB and FAE-1D-CNN properties

In order to compare the feature extraction ability of 1D-CNN and FAE-1D-CNN, as well as to further check the ability of EAB to improve the convergence speed of the model, we designed an experimental scheme as shown in Table 5. Case1 and Case3 indicate that the original signal is input into 1D-CNN and FAE-1D-CNN network models respectively. Case2 and Case4 indicate that the original signal is input into 1D-CNN and FAE-1D-CNN network models by EAB signal processing respectively. The training strategies of these four experimental schemes are the same. We first normalize all the input data, set the learning rate to 0.001, the batch size to 32, and initialize all the weight parameters. The experimental results are shown in Fig. 11. It can be seen that both models converge better for the acoustic signals after EAB signal processing. FAE-1D-CNN converges faster than 1D-CNN and has better generalization.

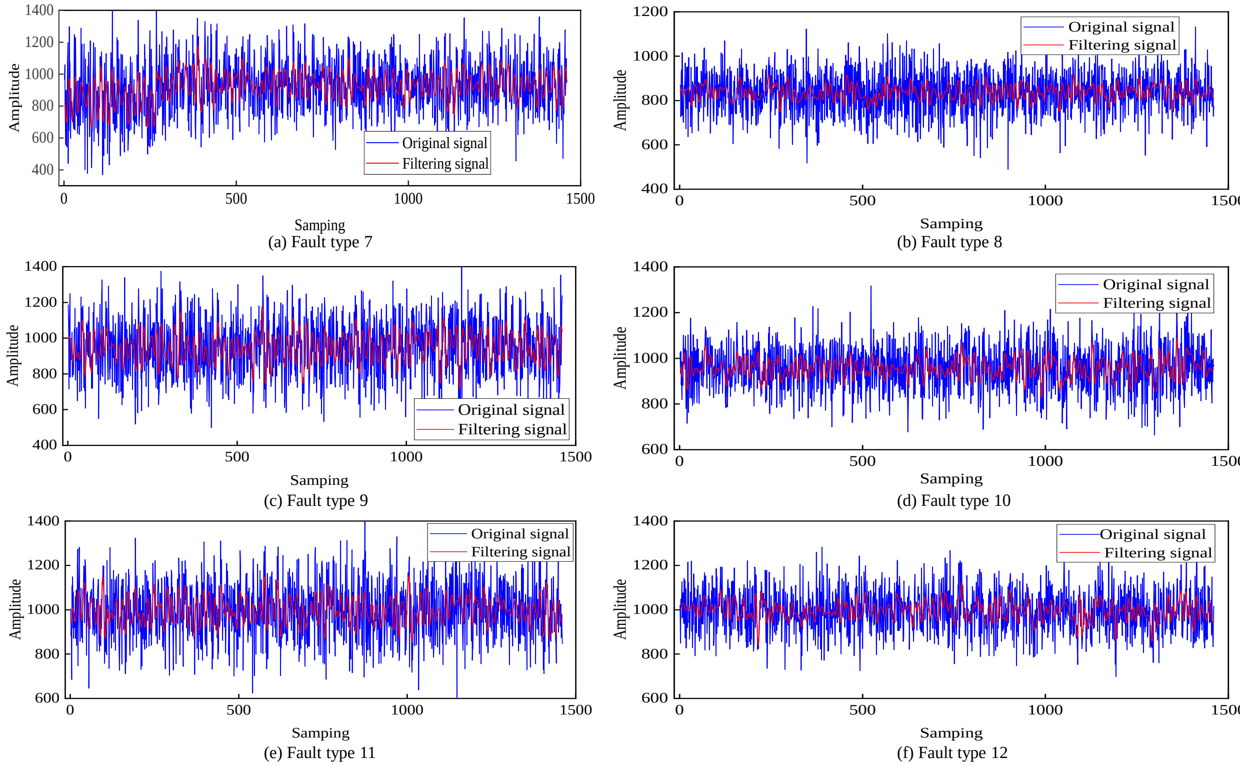

Fig. 9. High energy modal feature noise reduction diagram.

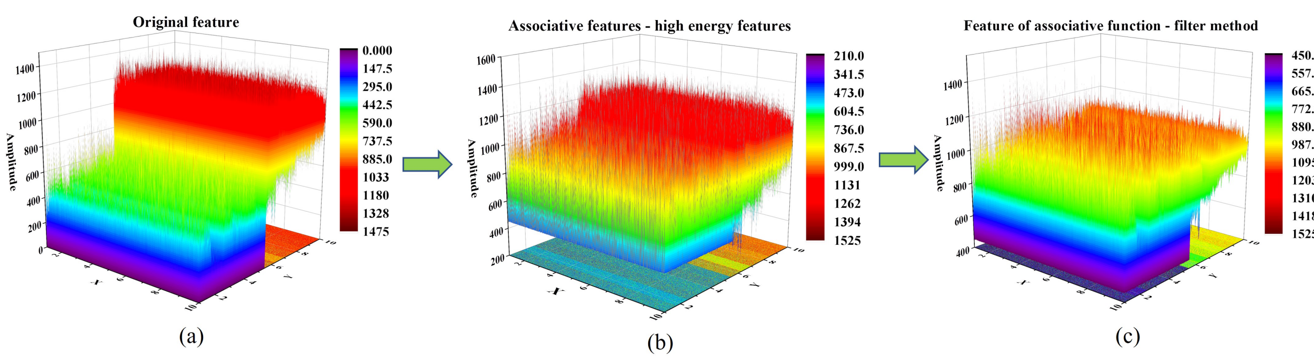

Fig. 10. Acoustic signal distribution in 3D space.

4.5. Ablation study

To further examine the robust performance of EAB and FAE-1D-CNN, we update the dataset with the association factor and the cutoff frequency of the Butterworth low-pass filter as single control variables, respectively, in EAB. In addition, in the FAE-1D-CNN network, the FAE network parameters are used as control variables to detect the help of the FAE spatial feature reconstruction ability to the recognition performance of the FAE-1D-CNN. In this section, the 10-fold cross-validation method is used, and the average value of the experimental results is taken. Table 6 and Table 7 show the detailed results of model testing under different association factors and cutoff frequency. It can be found that $\gamma = 600$ and $w_c = 180$Hz are the optimal parameters of the EAB algorithm.

To further find the optimal parameters for FAE, we set the network parameter configuration as shown in Table 8 based on the experimental study. In this paper, we choose the best

Table 6
FAE-1D-CNN test results under different association factors.

Association factor	400	450	500	550	600	650	700
Denoising frequency(Hz)	180	180	180	180	180	180	180
Accuracy(FAE-1D-CNN)	85.81%	90.17%	92.39%	92.96%	95.17%	93.99%	92.09%

Table 7
FAE-1D-CNN test results under different cut-off frequencies.

Association factor	600	600	600	600	600	600	600
Denoising frequency(Hz)	120	140	160	180	200	220	240
Accuracy(FAE-1D-CNN)	88.00%	87.96%	94.87%	95.17%	93.11%	94.87%	93.40%

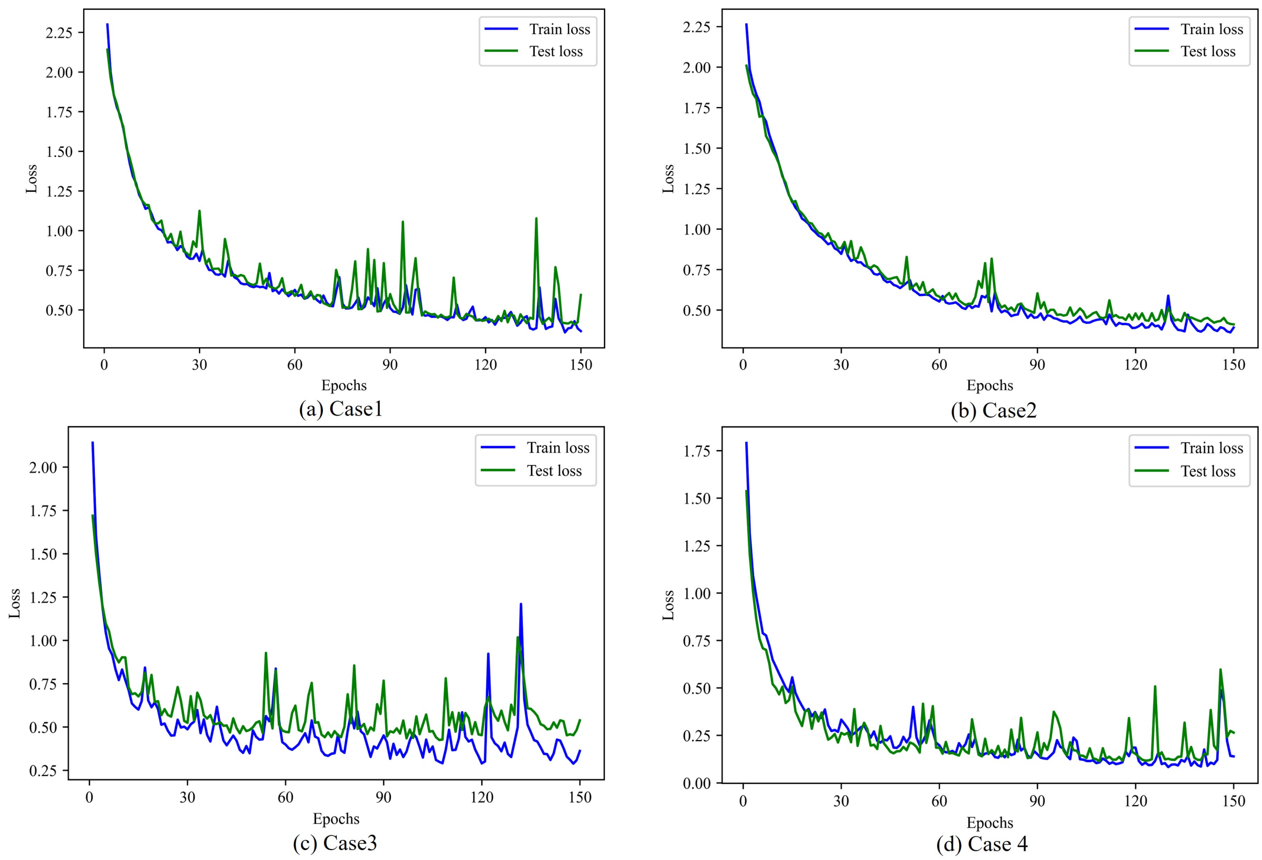

Fig. 11. Model performance tests.

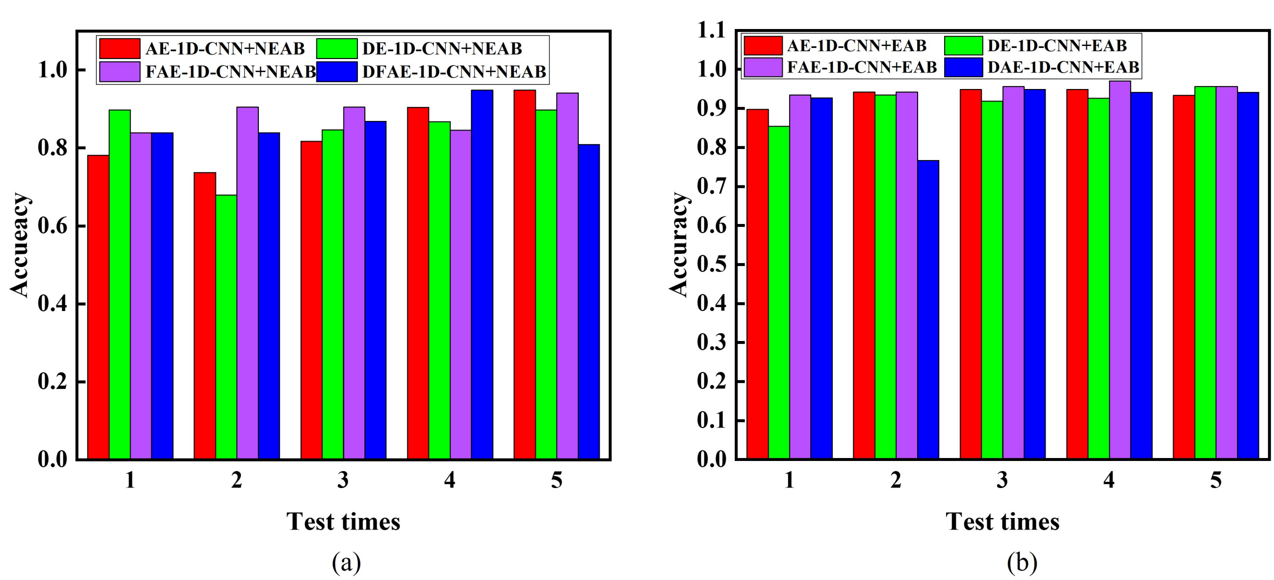

Fig. 12. FAE-1D-CNN performance test under NEAB-EAB.

Table 8
FAE parameter scheme.

Case number	Encoder - decoder parameters
Case1	(16,32,64,32,16)
Case2	(32,64,96,64,32)
Case3	(64,96,128,96,64)

Table 9
Model recognition accuracy under different parameters of FAE.

Method	Accuracy
FAE-1D-CNN+NEAB(Case1)	82.88%
FAE-1D-CNN+NEAB(Case2)	88.73%
FAE-1D-CNN+NEAB(Case3)	80.24%
FAE-1D-CNN+EAB(Case1)	93.41%
FAE-1D-CNN+EAB(Case2)	95.17%
FAE-1D-CNN+EAB(Case3)	87.40%

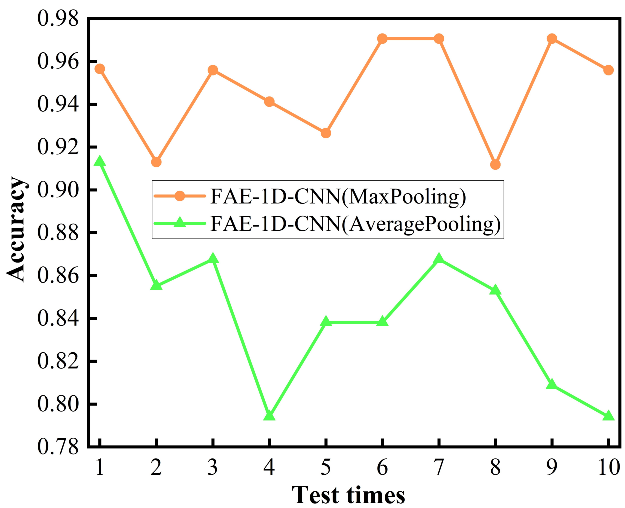

Fig. 13. FAE-1D-CNN fault identification under different pooling layers.

association factor and Butterworth filter cutoff frequency from the previous experiment step. The experimental results are shown in Table 9 (NEAB indicates the original signal as the model input). It can be found that the optimal parameter configuration of FAE is Case2.

To explore whether the FAE network structure is expanded or compressed, and to further explore the connection mode of API in 1D-CNN, we designed the experimental scheme as shown in Table 10. The results in Fig. 12 show that plugging the encoder of the FAE into the 1D-CNN can lead to higher fault identification accuracy. Moreover, in this paper, we introduce autoencoder (AE) and feature encoder (FAE) into 1D-CNN, respectively, which gives us two models (i.e., AE-1D-CNN and FAE-1D-CNN). Then, the above models were trained with data without signal processing (NEAB) and data with signal processing (EAB) to compare their performances in fault recognition. It can be found from the experimental results in Fig. 12(a) and Fig. 12(b) that FAE-1D-CNN has higher fault recognition accuracy. This indicates that FAE can effectively perform data enhancement and help 1D-CNN extract representative fault features.

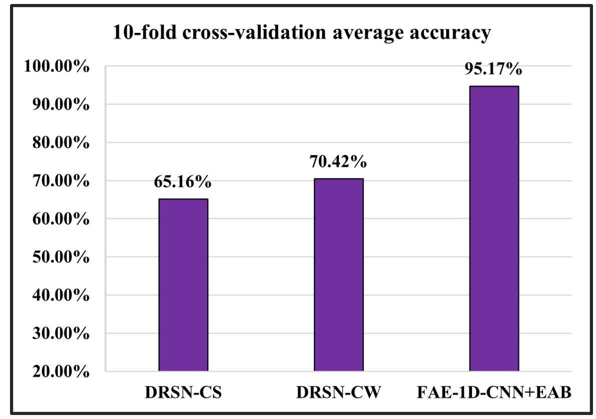

Fig. 14. Experimental results comparison of FAE-1D-CNN+EAB, DRSN-CS, and DRSN-CW.

FAE is a secondary reconstruction based on the feature map of the pooling layer. Therefore, the selection of the pooling layer directly affects the reconstruction ability of FAE local space features and the fault recognition accuracy of FAE-1D-CNN. In this experiment, we use the signal processed by EAB as the input and evaluate the model by 10-fold cross-validation. The results in Fig. 13 show that MaxPooling-based local spatial feature reconstruction shows better performance in FAE-1D-CNN networks and less fluctuation in fault recognition accuracy, which can be better applied to natural gas pipeline leak detection in real industrial environments.

4.6. Comparison experiment between the proposed method and other methods

We compare the methods in this paper with the detection methods commonly used in industrial inspection. In this paper, five methods are selected for comparison with FAE-1D-CNN, namely, Support Vector Machine (SVM), KNN, BPNN, Autoencoder (AE), and 1D-CNN.

The results in Table 11 show that the EAB method does not help much in the shallow network leak detection performance, while the deep network performance is substantially improved. Compared with 1D-CNN+NEAB, it can be seen from Table 11 that the fault identification accuracy of FAE-1D-CNN+NEAB and FAE-1D-CNN+EAB is improved by 7.61% and 15.81%, respectively. This indicates that FAE-1D-CNN and FAE-1D-CNN+EAB can capture more effective fault features. To demonstrate the effectiveness and superiority of the proposed method, this study compares and analyzes the proposed method with other adaptive deep learning neural networks. The adaptive deep learning neural network chosen for this study is an extremely popular deep residual shrinkage network framework with channel-shared thresholds (DRSN-CS) and channel-wise thresholds (DRSN-CW) [41].

The proposed approach and the deep residual shrinkage networks (i.e., DRSN-CS and DRSN-CW) both employed a 10-fold cross-validation method, taking the average as the fault detection accuracy. The training hyperparameters of the

Table 10
FAE test scheme under NEAB-EAB.

Method	Expanded or compressed structure	API relationship in 1D-CNN	Parameter Settings
AE-1D-CNN+NEAB	Compressed structure	Connection of encoder	(96,64,32,64,96)
DE-1D-CNN+NEAB	Compressed structure	Connection of decoder	(96,64,32,64,96)
FAE-1D-CNN+NEAB	Expanded structure	Connection of encoder	(32,64,96,64,32)
DFAE-1D-CNN+NEAB	Expanded structure	Connection of decoder	(32,64,96,64,32)
AE-1D-CNN+EAB	Compressed structure	Connection of encoder	(96,64,32,64,96)
DE-1D-CNN+EAB	Compressed structure	Connection of decoder	(96,64,32,64,96)
FAE-1D-CNN+EAB	Expanded structure	Connection of encoder	(32,64,96,64,32)
DFAE-1D-CNN+EAB	Expanded structure	Connection of decoder	(32,64,96,64,32)

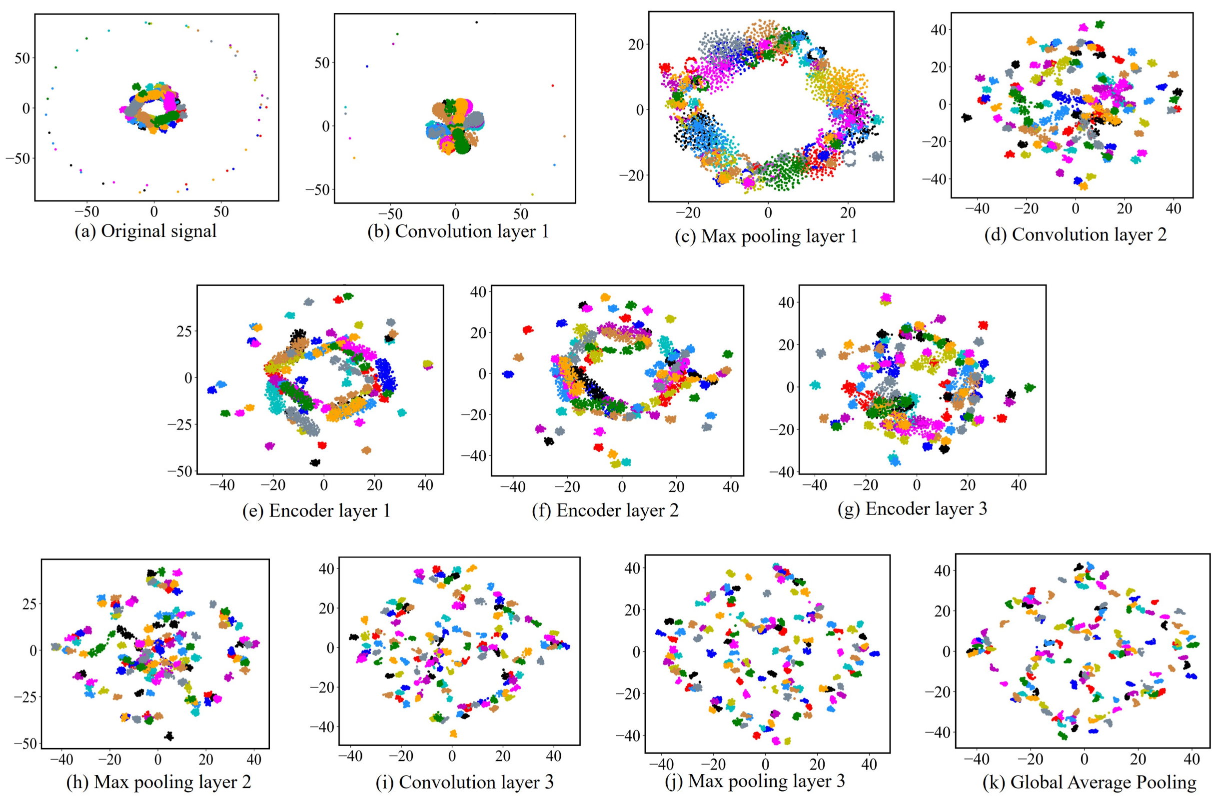

Fig. 15. Visualization of the FAE-1D-CNN network.

Table 11
Comparison of experimental results of different algorithms.

Method	Accuracy
SVM [52]+NEAB	<30%
KNN [53]+NEAB	32.64%
BPNN [54]+NEAB	44.36%
AE [49]+NEAB	74.77%
1D-CNN [52]+NEAB	79.36%
FAE-1D-CNN+NEAB	86.97%
SVM+EAB	<30%
KNN+ EAB	46.17%
BPNN+ EAB	41.20%
AE+ EAB	79.60%
1D-CNN+ EAB	88.42%
FAE-1D-CNN+ EAB	95.17%

proposed method and the deep residual shrinkage networks are set as follows. The Adam optimizer was used in the training process. The learning rate was set to 0.001. The batch size was 32. The training epoch was set to 150. The loss function used is the cross-entropy loss function. In the presented method, the original signals are first subjected to energy modal clustering, which yields high/low energy modal features. Secondly, a Butterworth low-pass filter is used to eliminate the strong background noise in the high-energy modal features. Using the association function adds association factors to low-energy modal features, enhancing the validity of fault features. Thirdly, the signal-processed dataset is fed into FAE-1D-CNN for feature extraction and local spatial feature reconstruction. Finally, the classifier is utilized to discriminate the type of faults. However, deep residual shrinkage networks are trained by feeding the original signals into DRSN-CS and DRSN-CW for feature extraction. DRSN-CS and DRSN-CW utilized soft thresholding to adaptively eliminate the noise and redundant features, which in turn enable fault identification.

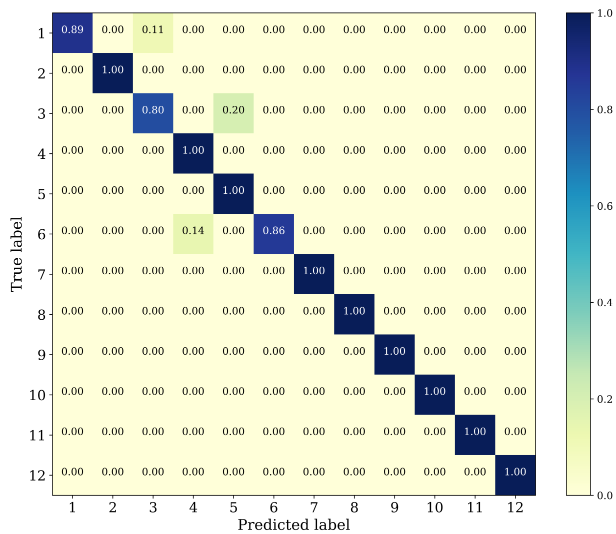

Fig. 16. Confusion matrix of fault diagnosis from FAE-1D-CNN.

The experimental results in Fig. 14 show that the fault identification accuracy of the proposed method is improved by 30.01% and 24.75% compared to DRSN-CS and DRSN-CW, respectively. The reason for such good performance is that the method in this paper integrates the double advantages of signal processing and the leak detection model. Specifically, the signal processing technique eliminates the background noise and enhances fault characteristics, while the following leak detection model can fully extract the representative features in the signal. So, it can finally obtain high fault detection accuracy. Although DRSN-CS and DRSN-CW can eliminate noise hidden in signals, they ignore the problem of important fault features missing and are weaker than the presented method in terms of fault identification performance.

4.7. Visual Analysis

To investigate the internal mechanism of the FAE-1D-CNN network, we use the EAB-processed signal as the input to the FAE-1D-CNN. The feature distribution of fault features in each network layer was visualized by t-SNE dimensionality reduction. Fig. 15(a)-Fig. 15(k) are visualizations of each network layer in the leak detection model (FAE-1D-CNN). In this paper, all sub-plots are divided into 3 layers. Among them, the first and third layers mainly visualize the convolution and pooling layer data. The intermediate layer mainly visualizes the coding layer data of the feature encoder (FAE), which represents the implication that the feature encoder is introduced in the 1D-CNN network structure. The results in Fig. 15 show that the various types of fault acoustic signal features are mixed together in Fig. 15(a), and after Fig. 15(b), Fig. 15(c) there is a trend of separation. Then, after Fig. 15(e), Fig. 15(f), and Fig. 15(g), the fault characteristics are gradually separated. After feature extraction in the convolutional layer and feature dimensionality reduction in the maximum pooling layer, the fault features are further separated, as shown in Fig. 15(d), Fig. 15(h), Fig. 15(i), and Fig. 15(j). Finally, Fig. 15(k) is transferred to the Softmax classifier for fault classification.

In addition, to clarify the identification of each class of faults, the confusion matrix experiment as in Fig. 16 is conducted in this paper, and it can be seen that the model has a good generalization ability for each class of faults.

5. Conclusions

The bottleneck problems of natural gas pipeline leak detection with small-sample acoustic signals are the scarcity of effective features and background noise coverage. This paper proposes a natural gas pipeline leak detection method based on acoustic signal analysis and feature reconstruction. The main findings are as follows. (1) In the signal analysis stage, the proposed EAB technique, which involves initial clustering (energy mode clustering) followed by modular processing, can be used to enhance the effectiveness of low-energy modal features and eliminate strong background noise from high-energy modal features. (2) In the fault recognition stage, the constructed FAE-1D-CNN detection model utilizes FAE to reconstruct fault features and obtain more comprehensive representative features, which helps improve the fault recognition accuracy of the leak detection model. (3) The series of experimental results demonstrate that the proposed method performs better in eliminating background noise and enhancing feature validity with more significant fault identification performance compared with traditional machine learning models and deep learning models.

The detection model framework presented in this study provides a new approach for fault diagnosis of natural gas pipeline leaks. Furthermore, fault recognition tasks based on acoustic signals, vibration signals, and current signals have strong correlations. Therefore, the method proposed in this paper can be effectively applied to fault recognition in the fields of vibration signals and current signals, further expanding the application scope of this study. In the future, we will collaborate with the local government and the oil and gas energy companies to establish the detection tasks on real gas pipelines. We will build and release a more comprehensive acoustic dataset for natural gas pipeline leakages, providing new impetus for technological innovation in this field. We will also explore the fusion strategy of locating unknown leak points and fault type identification, and strive to establish a comprehensive theory for pipeline leak diagnostics, in order to facilitate new developments in pipeline leak detection technology.

CRediT authorship contribution statement

Yu Zhang: Conceptualization, Writing – original draft, Methodology, Investigation, Validation, Software. **Lizhong Yao:** Writing – review & editing, Funding acquisition, Supervision. **Tiantian He:** Investigation,Writing – review & editing, Validation. **Haijun Luo:** Investigation, Software.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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