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Digital Twins and Condition Monitoring for Pressure Pipeline based on Intelligent Acoustic Sensor Framework

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Abstract: During long-term operation in high-temperature and high-pressure environments, the pressure pipelines of boiler heating systems are prone to damage, which directly affects the safe and stable operation of pressure pipelines and boiler heating systems. Generally, the acoustic sensor is employed to detect the abnormal sound of pressure pipelines for condition monitoring. However, the signals obtained from the acoustic sensor are easily drowned out in background noise generated by fans and exhaust equipment, resulting in unsatisfactory performance for condition monitoring. Therefore, the intelligent acoustic sensor framework is proposed to establish a physics-informed digital twin for pressure pipelines, integrating condition monitoring as a core function. By implementing the digital twin, real-time synchronization between physical and virtual systems enables predictive maintenance, early fault diagnosis, and optimized operational strategies, thereby reducing unplanned downtime and enhancing industrial safety. Specifically, the traditional acoustic sensor system is improved based on the noise reduction model, which can obtain the de-noised acoustic signals for all conditions. Furthermore, the real-time decision-making model for abnormal sound detection is embedded in the proposed intelligent acoustic sensor framework based on the long short-term memory network, and the result is employed as the digital twin for pressures pipeline by monitoring their condition. In addition, the experimental platform is built to test the effectiveness and reliability of the proposed intelligent acoustic sensor framework. The results indicate that the quality of acoustic signals is improved by over 3 dB, and the accuracy of condition monitoring can reach 91.67% for different conditions. By comparing and analyzing with other methods, the superiority and effectiveness of the proposed intelligent acoustic sensor framework are further verified. This approach not only improves monitoring precision but also offers broader social benefits, including reduced energy waste in heating systems and minimized risks of industrial accidents.

Keywords: Intelligent Acoustic Sensor; Condition Monitoring; Pressure Pipelines; Acoustic Signal; Abnormal Sound Detection; Digital Twins

1. Introduction

Pressure pipelines are widely used in industrial water and gas supply fields under harsh environments, such as high temperature, high pressure, and strong impact [1]. It easily leads to fatigue and damage of pressure pipeline and its fixing devices, resulting in abnormal vibration and sound without timely condition monitoring. Due to the complex working environment and background noise emitted by different devices such as fan, cooling tower, valve and so on, the abnormal sound is difficult to detect and the accuracy of condition monitoring is unsatisfactory based on traditional acoustic sensor [2]. For the digital twin system, it includes physical experiments and coding. As the core assumption of this research, the construction of digital twin system fundamentally relies on the physical experimental environment, which are employed to establish the mapping relationship between acoustic characteristics and pipeline conditions. Therefore, it is urgent to effectively monitor the operating condition and realize physics-informed digital twin for pressure pipelines through abnormal sound detection, which is crucial for safe and stable operation of pressure pipeline and transmission system based on the condition monitoring results. This technology integration demonstrates its generic necessity not only in pipeline monitoring scenarios, but also shows potential applicability for other industrial equipment requiring physical-digital interaction.

Currently, pipeline condition monitoring method mainly focuses on faults such as blockage and leakage, and it lacks research on abnormal detection for vibrations and sounds [3]. Generally, the pressure pipelines of boiler systems operate in high-temperature environments, and it is wrapped with thick protective materials on the surface [4]. It limits the direct application of contact monitoring sensor, such as strain gauge and vibration sensor [5]. Conversely, the acoustic sensor, as non-contact and non-destructive testing, is widely employed to monitor the pressure pipelines based on high-quality acoustic signals. However, the monitoring signals obtained from acoustic sensor are contaminated by background noise, which leads to the unsatisfactory application for acoustic sensor-based condition monitoring method [6]. On the other hand, the occurrence of abnormal sound in pressure pipelines has strong randomness and suddenness with short duration, resulting in insufficient abnormal sound data for pressure pipelines. It further limits the application of condition monitoring and abnormal sound detection of pressure pipeline [7]. Therefore, it is necessary to study intelligent acoustic sensor framework for effective noise reduction and abnormal sound detection methods based on the noisy and limit acoustic signals, which is significant for pressure pipeline condition monitoring.

At present, noise reduction methods are applied through two aspects, including signal processing, and different denoising models [8]. For the signal processing denoising method, it includes several signal decomposition and reconstruction algorithm and its improvement methods, such as empirical mode decomposition (EMD) [9], variational mode decomposition (VMD) [10], wavelet packet decomposition (WPD) [11], etc. It decomposes the noisy signal by manually selecting the parameter and reconstruction way based on expert experience, resulting in insufficient stability and generalization of the noise reduction. On the other hand, with the development of artificial intelligence and deep learning model, Europe [12], the United States [13], Russia [14], and other countries [15] are actively researching the application of AI. Specially, several denoising models have emerged by establishing different deep learning network, including autoencoders (DAEs) [16], generative adversarial networks (GANs) [17], transfer learning (TL) [18] and so on. Those methods can achieve satisfactory denoising performance through training and testing with a large amount of data. However, this type method requires a large amount of data to improve its denoising effectiveness, which has a long training period, insufficient stability, and poor adaptability [19]. In addition, low-quality signals and insufficient samples limit the application and performance of abnormal sound detection for pressure pipelines.

To address the above issues and overcome its shortcoming, the intelligent acoustic sensor framework is proposed for physics-informed digital twin for pressure pipelines based on improved noise reduction model and real-time decision-making model. It can reveal the working condition of the pressure pipeline through digital twins with the core function of condition monitoring. The generative adversarial network (GAN) and denoising autoencoder (DAE) is used to consist the improved noise reduction model, and the GAN is embedded in the DAE model to improve the performance of noise reduction. It is trained to obtain high-quality acoustic signals. In addition, the long short-term memory (LSTM) network is employed to build the real-time decision-making model for abnormal sound detection for pressure pipelines. The performance of noise reduction and accuracy of condition monitoring is evaluated through the pressure pipeline experimental platform. Besides, the superiority of the proposed method is test by comparing with the existing methods on noise reduction and condition monitoring for pressure pipelines. The main contributions of the research lie in introducing an intelligent acoustic sensor framework for pressure pipelines and a real-time decision-making model, including:

1. The intelligent acoustic sensor framework is proposed to monitor the condition, which is employed to establish physics-informed digital twin for pressure pipeline based on improved noise reduction model and real-time decision-making model;
2. The improved noise reduction model is constructed by means of noise reduction autoencoders and generative adversarial networks, which can generate high-quality acoustic signals for different conditions;

3. The pressure pipeline experimental platform is established to evaluate the performance of the proposed framework. The experimental data further verified the superiority of the proposed framework.

The remainder of this research is organized as follows. Section 2 introduces theoretical background. The proposed intelligent acoustic sensor framework is detailed in Section 3. Section 4 displays the pressure pipeline experimental platform and performance of the proposed intelligent acoustic sensor framework. Finally, Section 5 concludes this research.

2. Theoretical Background

2.1. Denoising Autoencoder

As an unsupervised learning model, auto-encoder directly encodes and decodes signals through encoder and decoder. The encoder maps the original signal X to the hidden layer for the mapped data Y, which is decoded to obtain reconstructed signal GY based on the decoder. By comparing the original signal X and the reconstructed signal GY, the error is calculated and the model is modified [20]. The loss function calculation during the process of encoding and decoding is expressed as

$$\begin{aligned} Y &= f(X) = f(\omega_1 X + b_1) \\ GY &= g(Y) = g(\omega_2 Y + b_2) \end{aligned} \tag{1}$$

where the ω_1 and b_1 are the weight coefficients and biases of the encoder, the ω_2 and b_2 are the weight coefficients and biases of the decoder, X, Y and GY are the original signal, mapped data, and reconstructed signal, respectively.

$$L_H(X, GY) = \frac{1}{n}\sum_{i=1}^{n}(x_i - gy_i)^2 \tag{2}$$

where L_H is the loss function, n is the signal length. DAE is an improved version of the auto-encoder, which constructs the new input signal X' by randomly destroying the original signal X. It also employs the encoder and decoder for mapping and decoding to obtain the reconstructed signal GY. Besides, the model is modified based on the difference between input and output signal [21]. By utilizing the randomness of noise and the stability of real data, the robustness of DAE is improved through multiple random destruction and iterations, which is suitable for noise reduction. The structure and process of DAE is shown in **Figure 1**.

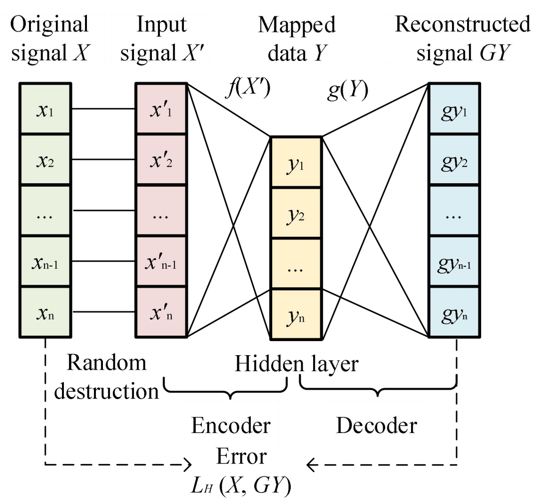


Figure 1. The structure and process of DAE.

2.2. Generative Adversarial Network

GAN is an adversarial neural network model proposed by the Goodfellow in 2014, including two networks: Generator and Discriminator [22]. The generator can generate deceptive fake data by inputting noise, while the discriminator is used to determine the difference between real and fake data to determine authenticity. Through continuous adversarial iterative training of the generator and discriminator, the performance of the generator continues to improve, and the quality of the fake data increases subsequently [23]. However, the discriminative performance of the discriminator gradually weakens until it is unable to distinguish between real and fake data. At this point, adversarial iterative training ends [24]. Finally, the trained generator is employed to generate high-quality fake data. The structure of GAN is shown in **Figure 2**.

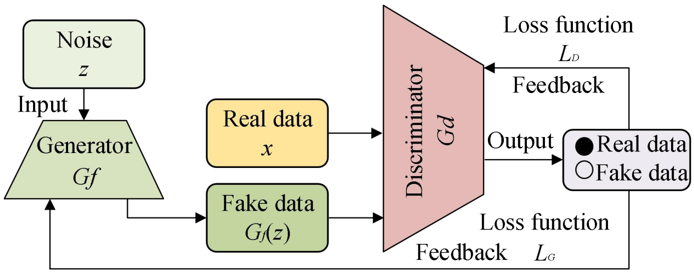


Figure 2. The structure of the GAN.

For the GAN, the adversarial process and loss function of Generator and Discriminator can be expressed as

$$\min_G \max_D V(G,D) = E_{x\sim p_x}[\log D(x)] + E_{z\sim p_z}\left[\log\left(1 - D\big(G(z)\big)\right)\right] \tag{3}$$

where x and $G(z)$ are the real and fake data, $E_{x\sim Px}$ and $E_{z\sim Pz}$ are the expectation of x and $G(z)$, $x\sim P_x$ and $z\sim P_z$ are the generate distribution of x and $G(z)$, G and D are the Generator and Discriminator, respectively.

$$\begin{gathered} L_G = \log\left(1 - D\big(G(z)\big)\right) \\ L_D = -\log\big(D(x)\big) + \log\left(1 - D\big(G(z)\big)\right) \end{gathered} \tag{4}$$

where L_G and L_D are loss function for the Generator and Discriminator.

3. Intelligent Acoustic Sensor Framework for Pressure Pipeline

3.1. Noise Reduction Model

With the disadvantages of poor stability and insufficient adaptability, the DAE model is modified through the GAN, which constitutes the proposed noise reduction model, as shown in the **Figure 3**.

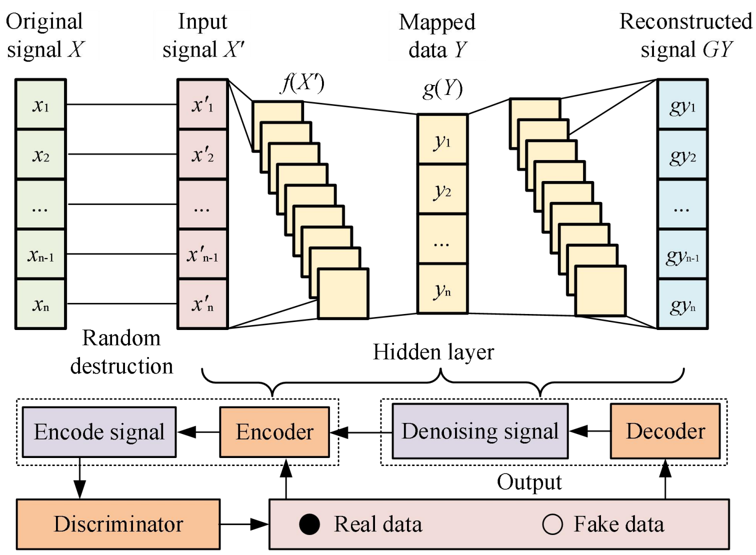


Figure 3. The structure of the proposed noise reduction model.

For this model, the generator of GAN is employed as the encoder of the DAE to generate encode signal, and the denoising signals is obtained from the decoder. To supervise the denoising process of DAE, the discriminator of the GAN is employed by distinguishing the encode and denoising signals. Through continuous adversarial training, the noise reduction model is trained and modified, which is implemented to generate denoising signal through the trained decoder.

The denoising process of the proposed noise reduction model include three parts: encode-decode-discriminator processing, training and feedback, and noise reduction.

1. Encode-decode-discriminator processing: According to characteristic of DAE, the input signal is random destroyed, and it is normalized for the same amplitude range of [0,1]. Besides, the normalized signals are inputted into the Encoder to generate encode signals, which are decoded by the Decoder to obtain the denoising signals. To evaluate the performance of noise reduction, the denoising signals are encoded by the Encoder, different types of encode signals are analyzed by the Discriminator, and it is employed to determine whether it is real or fake data;
2. Training and feedback: To evaluate the authenticity of the encode signal and improve the quality of noise reduction, the loss function is calculated based on the judgment result of the Discriminator. It conforms to the loss function of the GAN and Generator, which is expressed as

$$L_{X'} = log\left(1 - D\left(G(X')\right)\right) \tag{5}$$

where $L_{X'}$ is the loss function for the input signal X'. For the proposed noise reduction model, the loss function of Discriminator is the result of signal judgment, and it is expressed as

$$L_D =- log\left(D(X_R)\right) + \sum log\left(1 - D\left(G(X_i')\right)\right) \tag{6}$$

where L_D is the loss function for the Discriminator, X_R is the real data (noiseless signal), X_i' is the i-th input signal, M is the number of input data types (including noisy and denoising signals). In addition, the root mean square error (RMSE) is employed to evaluate the effectiveness of proposed noise reduction model. The result is used as the loss function for Decoder, and it is expressed as

$$L_{DE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(X_{Ri} - X_{Di})^2} \tag{7}$$

where L_{DE} is the loss function for the Decoder, X_{Ri} and X_{Di} are the i-th value of real data (noiseless signal) and denoising signal, n is the signal length. Due to the Generator is embed in the DAE, the loss function of Encoder includes two aspects: DAE and GAN. It is calculated as

$$L_{EN} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(X_{Ri} - X_{Di})^2} + \sum_{i=1}^{M} log\left(1 - D\left(G(X_i')\right)\right) \tag{8}$$

where L_{EN} is the loss function for the Encoder. After calculating different loss functions, the results are fed back to the Encoder, Decoder, and Discriminator, respectively. According to the process of adversarial training, the loss function of the proposed noise reduction model is calculated and fed back during continuous iterations. Finally, adversarial training is completed when the Encoder and Discriminator reach Nash equilibrium, where the trained noise reduction model is obtained. The process of the adversarial training is expressed as

$$\min_G \max_D V(G,D) = E_{x\sim p_x}[log\, D(X_R)] + E_{z\sim p_z}\left[\sum_{i=1}^{M} log\left(1 - D\left(G(X_i')\right)\right)\right] \tag{9}$$

3. Noise reduction: Based on the trained noise reduction model, the noisy acoustic signals are inputted into the trained Encoder, and the denoising signals are obtained from the trained Decoder, which are the output of the proposed model.

3.2. Real-time Decision-making Model

Based on the noise reduction model, the high-quality acoustic signals are obtained as denoising monitoring signals. To realize condition monitoring for pressure pipelines, the real-time decision-making model is proposed based the LSTM. By inputting the denoising monitoring signals, the LSTM is trained for forget gate and the input gate (memory gate). Finally, the trained LSTM is employed to obtain real-time decision for condition monitoring of for pressure pipeline, as shown in **Figure 4**.

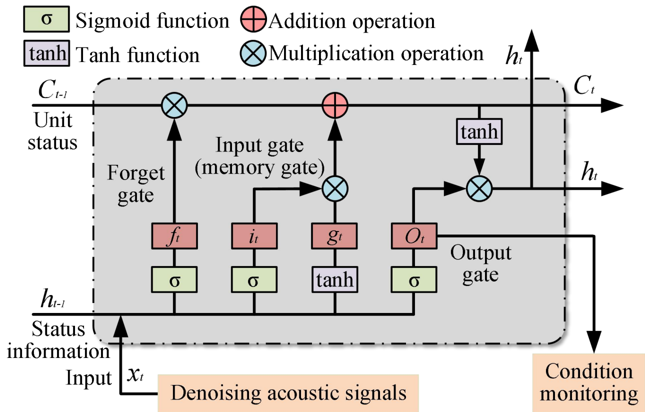


Figure 4. The structure of the real-time decision-making model.

The denoising monitoring signals generated from the trained noise reduction model are inputted into the forget gate with different labels, and it determine which information to discard based on state information h_{t-1} at time t-1 and the current input denoising acoustic signals x_t at time t. It is expressed as

$$f_t = \sigma\left(W_f[h_{t-1}, x_t] + b_f\right) \tag{10}$$

where W_f and b_f are the weight and bias of forget gate, σ is the Sigmoid function, f_t is the output at time t for the forget gate. In addition, the input gate is used to process current information and update long-term states using the Tanh function. It is expressed as

$$\begin{gathered} i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \\ g_t = tan\,h\left(W_g[h_{t-1}, x_t] + b_g\right) \end{gathered} \tag{11}$$

where W_i and b_i are the weight and bias of Sigmoid function, W_g and b_g are the weight and bias of Tanh function, i_t and g_t are the output at time t for the Sigmoid and Tanh function. Besides, the i_t and g_t are multiplied as the output information for the input gate. The current unit status C_t is updated based on the historical unit status C_{t-1}, and it is expressed as

$$C_t = f_t C_{t-1} + i_t g_t \tag{12}$$

After being processed by the Sigmoid function, the output O_t is obtained for the condition monitoring of pressure pipeline, while the status information h_t changes with the Tanh function at the output gate. It is expressed as

$$\begin{gathered} O_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \\ h_t = O_t\,tan\,h(C_t) \end{gathered} \tag{13}$$

where W_o and b_o are the weight and bias of output gate, O_t is the output at time t for the output gate.

3.3. Intelligent Acoustic Sensor Framework for Pressure Pipeline

Based on the noise reduction model and real-time decision-making model, the Intelligent acoustic sensor framework is proposed for pressure pipelines. The process of the proposed framework is shown in **Figure 5**. It includes the following steps:

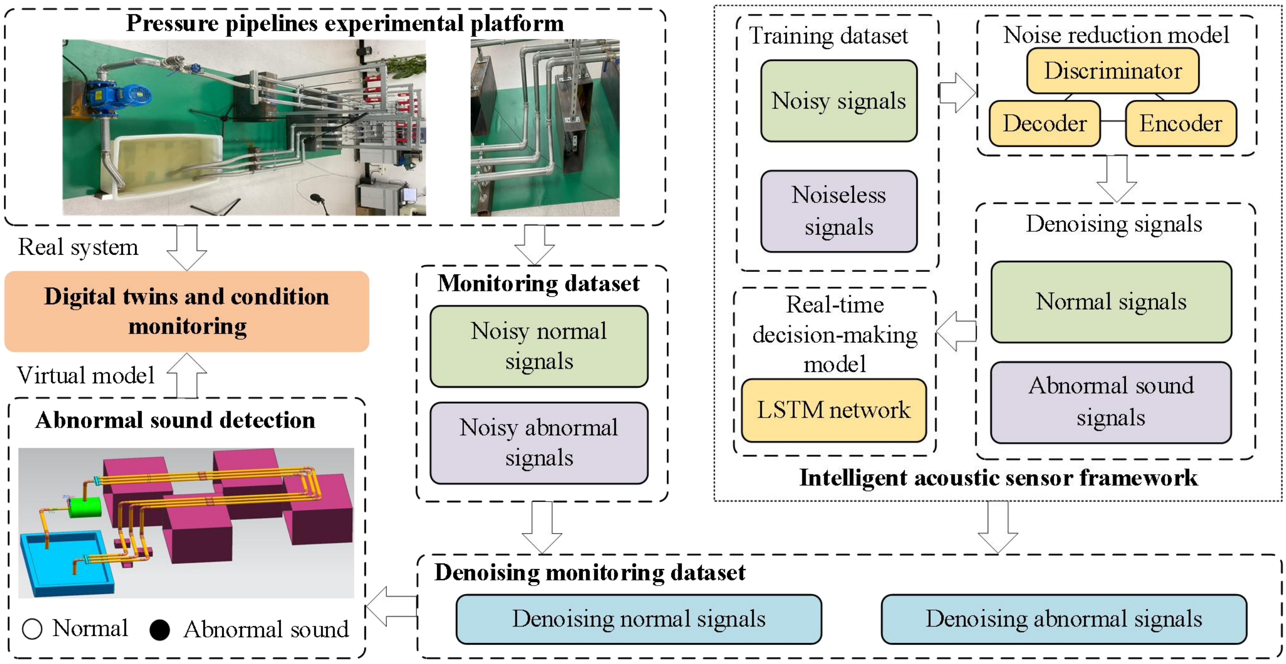


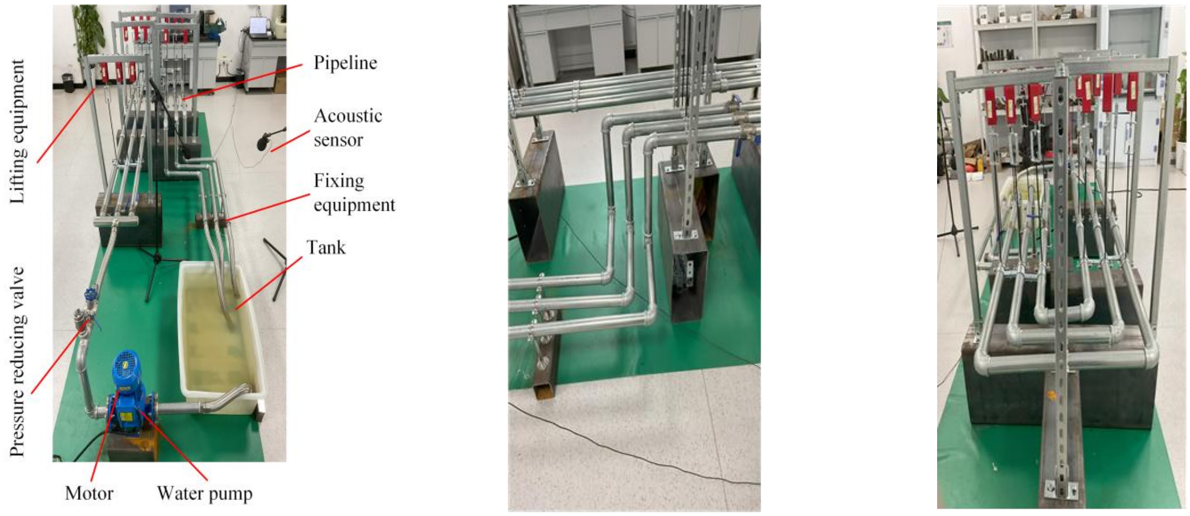
Figure 5. The process of the proposed intelligent acoustic sensor framework.

1. Signal acquisition: Based on the pressure pipeline experimental platform, different types of acoustic signals are collected to establish the training and monitoring dataset. Specially, the training dataset includes noisy and noiseless signals under one working condition, and the monitoring dataset is consisted of several noisy normal condition and abnormal condition signals under different working conditions;
2. Noise reduction model training and applying: The signals obtained from the training dataset are inputted into the noise reduction model for training and testing. After adversarial training, the trained noise reduction model is applied to generate denoising acoustic signals with normal and abnormal condition label;
3. Real-time decision-making model training: The denoising acoustic signals obtained are inputted into the real-time decision-making model. Based on the LSTM network, the real-time decision-making model is training for abnormal sound detection;
4. Digital twins and condition monitoring for pressure pipeline: Based on the trained noise reduction model, the noisy normal condition and abnormal condition signals are processed to generate denoising monitoring dataset. Besides, the denoising signals are inputted into the trained real-time decision-making model, and the abnormal sound is detected under different working conditions, which can realize digital twins for the pressure pipelines with the core function of and condition monitoring. The digital twin framework achieves dynamic synchronization between physical pipelines and virtual models through continuous assimilation of de-noised monitoring data, enabling multi-physical field coupling analysis that integrates acoustic patterns, pressure fluctuations, and mechanical vibration characteristics.

4. Experiment Platform and Condition Monitoring Results

4.1. Experiment Platform

To evaluate the effectiveness and reliability of the proposed intelligent acoustic sensor framework, the pressure pipeline experimental platform is established with several devices, as shown in **Figure 6**. It includes motor, water pump, pressure reducing valve, pipelines, tank, lifting and fixing equipment, and acoustic sensor. The water in tank is pumped out by a water pump, and it is regulated by a pressure reducing valve to move along the pipeline. After passing through the experimental pipeline section, it flows back to the tank, which forms a closed loop. As shown in the **Figure 6b**, the experimental pipeline section is a typical pipeline system, consisting of four pipelines with three degrees of freedom. To simulate the installation way of the actual pipeline in boiler system, the experimental pipelines are suspended in the air through the lifting equipment, which are fixed at the outlet of pressure pipeline, as shown in **Figure 6c**. Besides, the fixed device is loosened to simulate abnormal vibration of the pressure pipeline, thereby generating abnormal sound signal.



(**a**) (**b**) (**c**)

Figure 6. The equipment of pressure pipeline experimental platform: (**a**) Experimental platform; (**b**) Typical pipeline system; (**c**) Lifting equipment.

Besides, the acoustic sensor (INV9206) is employed to collect two types acoustic signals at noisy and noiseless environments under three pressures: 5 PSI, 10 PSI and 15 PSI. To simulate the actual noise environment of pressure pipelines, the sound recorded on boiler site is played during signal acquisition. The sampling frequency is 2560 Hz with 1 s, and each condition has 100 samples. Finally, there are 2 × 2 × 3 × 100 (2 conditions: normal and abnormal sound, 2 environments: noisy and noiseless, 3 pressures: 5, 10 and 15 PSI) monitoring acoustic signals with 2560 data in each sample. The parameters of the experimental platform are shown in **Table 1**.

Table 1. The parameter of the experimental platform.

Type	Value
Pressure/PSI	5, 10 and 15
Sampling frequency/Hz	2560
Environments	Noisy and noiseless
Number of samples	100
Conditions	Normal and abnormal sound

4.2. Results

Based on the length and characteristics of the acoustic samples, the parameters of the noise reduction model are selected for the Encoder, Decoder and Discriminator. The structural and parameters of the proposed model are shown in the **Figure 7**. The CONV, DECONV and FCN are the convolutional layer, deconvolution layer, and fully connected layer, respectively.

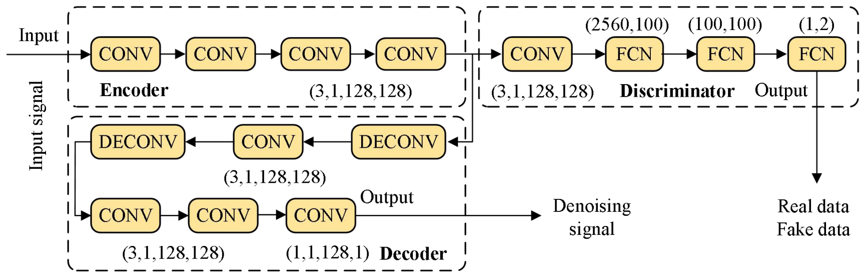


Figure 7. The structural and parameters of the proposed model.

The noisy and noiseless signals under one condition are employed to trained the proposed noise reduction model. According to the 7:3 ratio for training and testing, there are 70 and 30 training and testing samples under one condition. Specially, the training epoch is 100, and the maximum batch is 32 with the adaptive gradient optimizer. After adversarial training, the noise reduction model is trained, and it is applied for noisy signals to generate denoising signals under other two working conditions. To evaluate the performance of noise reduction and verify the proposed model, the root mean square error (RMSE) [25] and signal-to-noise ratio (SNR) [26] are used as the evaluation index to calculate the differences between noisy and denoising signals. It is expressed as

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(X_{Ri} - X_{Di})^2} \tag{14}$$

$$SNR = 101g\frac{\sum_{i=1}^{n} X_{Di_S}^2}{\sum_{i=1}^{n}(X_{Ri} - X_{Di})^2} \tag{15}$$

where *RMSE* is the value of mean square error, *SNR* is the value of signal-to-noise ratio. Based on the RMSE and SNR, the performance of noise reduction is quantitatively analyzed. Taking normal samples as an example, the noise reduction effect of training and transfer under different working conditions is shown in **Table 2**. Clearly, the RMSE and SNR of noisy samples are higher and lower, indicating the presence of noise in the original samples, which has significant effect on signal quality. After denoising by the proposed model, the RMSE effectively decreased to below 0.02, while the SNR can reach over 3.5 dB for the samples at 15 PSI. It can increase by about 5 dB for three conditions. It further verifies the effectiveness and reliability of the proposed noise reduction model.

Table 2. Noise reduction effect of training and transfer under different working conditions.

Evaluation Index	Sample Type	Training at 5 PSI		Training at 10 PSI		Training at 15 PSI	
		10 PSI	15 PSI	5 PSI	15 PSI	5 PSI	10 PSI
RMSE	Noisy	0.039	0.037	0.058	0.037	0.058	0.039
	Denoising	0.017	0.008	0.019	0.007	0.020	0.016
SNR	Noisy	−2.55	−2.18	−3.02	−2.18	−3.02	−2.55
	Denoising	3.21	3.56	2.58	3.47	2.51	3.15

Based on the denoising acoustic signals, the real-time decision-making model is trained for abnormal sound detection and condition monitoring for pressure pipeline. For the real-time decision-making model, the LSTM network is employed with the hidden units of 200, the epoch of 100, the solver of the adaptive moment estimation with the gradient threshold of 1 and dropping learning rate of 0.2, respectively. Specially, the parameters of the LSTM network are selected based on the actual experience and testing results [27]. By training and testing the real-time decision-making model through denoising signals, the abnormal sound is detected for condition monitoring of pressure pipelines. By comparing the monitoring result, the noisy and noiseless samples are trained and tested directly by the real-time decision-making model with the ratio of 7:3. To avoid randomness, the result is the average value by repeating 5 times, and it is shown in the **Table 3** for three working conditions. Specially, the Mixture represents the trained denoising model is applied for all samples under three working conditions, which are trained and tested by the real-time decision-making model to evaluate the proposed method.

Clearly, the accuracy of condition monitoring with noisy samples is only 68.33% for 10 PSI, and it illustrates negative impact of noise. Based on the proposed intelligent acoustic sensor framework, the accuracy is effectively improved for three conditions. Specially, by training the noise reduction model and real-time decision -making model with the signals collected at 5 PSI, it can reach the highest detection accuracy of 91.67% and 87.00% by applying it into the signals collected at 5 and 10 PSI. The reason is that the noise is strong for low pressure, and the anti-noise ability of the trained model is improved to be applicable to other conditions. When applied the trained model to high pressure with low noisy, the accuracy is further improved for condition monitoring. Besides, the accuracy of proposed intelligent acoustic sensor framework is close to the noiseless samples, and it is about 15% higher than the noisy samples. This result further demonstrates the effectiveness and reliability of the proposed intelligent acoustic sensor framework.

Table 3. The condition monitoring results for pressure pipeline.

Conditions		Denoising Samples	Noisy Samples	Noiseless Samples
Denoising Training	Application			
5 PSI	5	91.67%	71.67%	93.33%
	10	86.33%	68.33%	90.67%
	15	87.00%	73.33%	90.33%
	Mixture	85.67%	69.33%	91.67%
10 PSI	5	84.67%	71.67%	93.33%
	10	89.33%	68.33%	90.67%
	15	86.33%	73.33%	90.33%
	Mixture	84.67%	69.33%	91.67%
15 PSI	5	85.33%	71.67%	93.33%
	10	84.33%	68.33%	90.67%
	15	88.67%	73.33%	90.33%
	Mixture	85.67%	69.33%	91.67%

4.3. Discussions

To test the performance of the proposed noise reduction model, the original, denoising and noiseless acoustic signals are compared based on the proposed and original method in time frequency. Taking acoustic sample at 5 PSI as an example, the three types signals are shown in **Figure 8.** The amplitude of the noisy signal is higher and more chaotic. After being processed by the proposed noise reduction model, the amplitude of the acoustic signal decreased by losing the noise, and the result is closer to the noiseless signal.

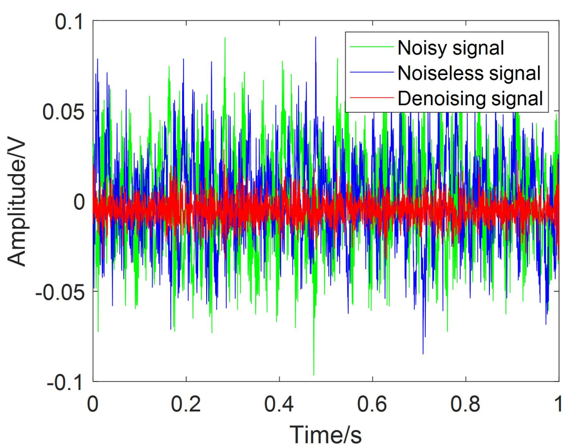


Figure 8. Noise reduction performance for three types signals.

To intuitively reflect the accuracy and bias of the real-time decision-making model for abnormal sound detection and condition monitoring, taking the one result of Mixture condition with 5 PSI training as an example, the confusion matrix for three types signals is shown in **Figure 9**. Due to the interference of noise, the accuracy of noisy samples is the lowest, and there are also more cases of false detection. Based on the denoising samples obtained from the proposed noise reduction model, the accuracy is improved, and some false conditions are modified. The result of the proposed real-time decision-making model is close to noiseless samples, and it illustrates the effectiveness of the proposed intelligent acoustic sensor framework. Besides, the false samples are basically equal for normal and abnormal sound signals, which proves the stability and balance of the proposed intelligent acoustic sensor framework.

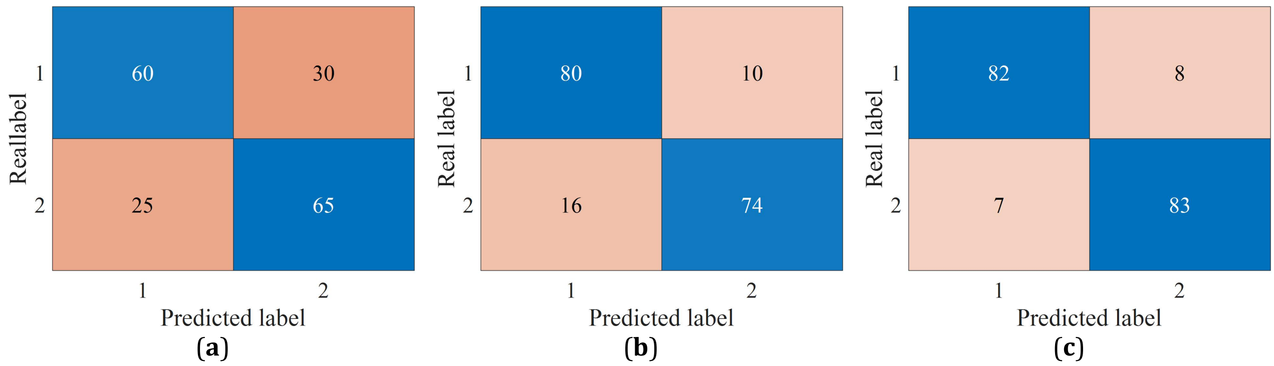


Figure 9. Confusion matrix for different signals: (**a**) Noisy sample; (**b**) Denoising sample; (**c**) Noiseless sample.

Due to the randomness and uncertainty of the noisy signals collected in the experiment, Gaussian white noise is added to the noiseless signal to test the denoising effect of the proposed method. Due to sensor placement variability and transient background noise, the noisy signals inherently exhibit randomness and uncertainty, and the digital twin framework actively mitigates these challenges through bidirectional virtual-physical synchronization. By continuously calibrating the virtual model with real-time de-noised signals and feeding back diagnostic insights to the physical system, the DT reduces operational haphazardness and enhances predictability across both domains.

Specifically, three types of Gaussian white noise are added, including –5 dB, –10 dB and –15 dB, which are processed using the proposed method. This methodology enables quantitative evaluation of the denoising method under progressively challenging pressure conditions. The results are compared with noiseless and noisy data, as shown in **Table 4**.

Table 4. The comparative denoising results for different Gaussian white noise.

Different Types of Experimental Data	Training at 5 PSI		Training at 10 PSI		Training at 15 PSI	
	RMSE	SNR	RMSE	SNR	RMSE	SNR
−5 dB samples	0.185	−3.12 dB	0.198	−3.45 dB	0.214	−3.78 dB
−10 dB samples	0.201	−4.25 dB	0.215	−4.63 dB	0.228	−4.90 dB
−15 dB samples	0.238	−6.37 dB	0.242	−7.81 dB	0.275	−8.67 dB
Noisy samples	0.207	−1.96 dB	0.221	−2.60 dB	0.230	−2.38 dB

Due to the influence of noise, the RMSE value of the signal increases with the intensity of Gaussian white noise. However, the proposed method improved the SNR value after processing and remained relatively stable under different operating conditions. Specially, the pressure-induced error amplification shows strong noise-level dependency, with –15 dB samples exhibiting 18.9% RMSE degradation at 15 PSI versus 5 PSI, compared to 11.1% for complex noisy samples. Besides, the signal preservation capability remains stable across pressure variations, evidenced by <0.5 dB SNR fluctuations in noisy samples despite 11.1% RMSE growth. The result illustrates the denoising performance before and after noise cleansing.

In addition, the experiments and comparative analysis is implemented through different methods, including the signal processing method and denoising model. Specially, the WPD [11] is employed as the signal processing method, while the DAE [16] and CGAN [28] is used as the noise reduction models. The RMSE and SNR are used as the evaluation index to measure the performance of noise reduction, and the results are shown in **Table 5**. Specially, the results are the average value by applying to different pressure.

Table 5. The comparative denoising results for different methods.

Methods	Training at 5 PSI		Training at 10 PSI		Training at 15 PSI	
	RMSE	**SNR**	**RMSE**	**SNR**	**RMSE**	**SNR**
Noisy samples	0.207	–1.96 dB	0.221	–2.60 dB	0.230	–2.38 dB
WPD	0.184	–0.73 dB	0.195	–1.15 dB	0.200	–1.21 dB
DAE	0.152	1.67 dB	0.155	1.93 dB	0.161	1.79 dB
CGAN	0.167	1.45 dB	0.145	1.95 dB	0.176	1.83 dB
The proposed method	0.114	3.39 dB	0.114	3.03 dB	0.134	2.83 dB

Clearly, the original noisy samples have poor RMSE and SNR due to the complex noisy. By processing with the WPD, the signal quality is improved, and the RMSE can decrease about 0.11 for three conditions. Based on different denoising models, the results of DAE and CGAN have effective performance on noise reduction, and it ran reach the better result than the WPD. Besides, the result of the CGAN model is unstable for the complexity and uncertainty of the input noise. Compared with other methods, the denoising signals obtained by the proposed intelligent acoustic sensor framework have the smaller RMSE and higher SNR, and the result is relatively stable in various conditions. This result quantitatively demonstrates the performance of the proposed intelligent acoustic sensor framework for condition monitoring for pressure pipeline.

To analyze the effectiveness of the proposed intelligent acoustic sensor framework, the accuracy of condition monitoring is calculated for different methods, and the average results are shown in **Table 6.**

Table 6. The comparative condition monitoring results for different methods.

Methods	Training at 5 PSI		Training at 10 PSI		Training at 15 PSI	
	10 PSI	**15 PSI**	**5 PSI**	**15 PSI**	**5 PSI**	**10 PSI**
Noisy samples	68.33%	73.33%	71.67%	73.33%	71.67%	68.33%
WPD	90.67%	90.33%	93.33%	90.33%	93.33%	90.67%
DAE	78.33%	82.00%	78.00%	80.33%	78.00%	81.33%
CGAN	82.67%	80.67%	80.33%	82.33%	81.67%	70.33%
The proposed method	84.67%	83.67%	80.67%	81.33%	82.67%	79.33%

The accuracy of abnormal sound detection is the lowest for the noisy sample, and it has been improved by reducing the noise of noisy signals through different methods. The denoising methods based on WPD can improve the accuracy about 10% for some condition, while the accuracy is unstable for some working conditions due to the influence of noise. For the denoising model-based method, it has about 85% detection accuracy, such as the DAE and the CGAN. It indicates the effectiveness of the denoising model. In addition, the proposed method can achieve an accuracy of about 85% for different conditions, which is close to the result of noiseless samples and better than other methods. It indicates that the proposed intelligent acoustic sensor framework can improve the accuracy of abnormal sound detection and condition monitoring by reducing noise in the acoustic signal, further verifying the effectiveness of the proposed intelligent acoustic sensor framework.

Specially, the physical experiments have confirmed the effectiveness of the original model in some cases, but there are significant differences between the experiments and industrial sites. When applied to practical industrial scenarios, a more concise and efficient model is crucial to meet the practical requirements of strong noise and efficient processing. Besides, the programmatic implementation demonstrated that the simplified version maintained equivalent predictive capability while significantly reducing computational demands. Through cross-validation the condition results between experimental data and digital twin outputs, the proposed model can be further simplified to improve processing efficiency and enhance applicability in the future.

5. Conclusions

This paper proposes intelligent acoustic sensor framework for pressure pipelines based on improved noise reduction model and real-time decision-making model. It establishes the noise reduction model based on the DAE and GAN, which is trained by comparing the noisy and noiseless acoustic signals under single working condition. By continuous adversarial training, the denoising ability of noise reduction model is improved, and it is applied for different conditions to obtain high-quality denoising signals. Further, the real-time decision-making model is established for abnormal sound detection based on the LSTM network, and it realizes the condition monitoring for pressure pipeline through complete denoising signals dataset. Based on the experimental platform, the effectiveness and reliability of the proposed intelligent acoustic sensor framework is tested and evaluated for three pressure conditions. The results indicate that the proposed intelligent acoustic sensor framework can effectively reduce the noise of the noisy signals and reach about 92% condition monitoring accuracy for different conditions, which is close to the accuracy of noiseless samples. In addition, the ablation experiments and comparative analysis is implemented to verify the superiority of the proposed intelligent acoustic sensor framework, and the result further demonstrates its effectiveness and performance. Furthermore, the digital twin is established to integrate physical signals, virtual simulations, and operator decisions as a three-dimensional socio-technical perspective, which is essential for balancing industrial safety, environmental constraints, and human intervention in energy systems.

In the future, more abnormal sound conditions can be simulated and tested to generate abnormal acoustic signals, which is the extension for implementing condition monitoring. In addition, there is a certain gap for the noise between experimental and actual signal. By monitoring the abnormal sound obtained from the actual condition, the applicability and stability of the proposed method can be further tested. Besides, the proposed model can be further simplified to improve processing efficiency and enhance applicability, which can be applied to practical industrial scenarios in the future. Additionally, geolocation-aware data integration and cross-disciplinary collaborations with urban planners are significant to enhance the societal relevance for the proposed framework.

Author Contributions

Conceptualization, Y.W. and S.L.; methodology, Y.W. and K.W.; software, C.J. and K.W.; validation, Y.W., Y.G. and Y.Y.; formal analysis, C.J.; investigation, Y.G. and K.W.; resources, Y.Y.; data curation, Y.W.; writing—original draft preparation, Y.W. and K.W.; writing—review and editing, S.L., C.J. and Y.Y.; visualization, Y.G.; supervision, S.L. and K.W.; project administration, Y.W. and K.W.; funding acquisition, Y.W., S.L., and Y.G. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement

The data that support the findings of this study are available on request from the corresponding author.

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Conflicts of Interest

The authors declare no conflict of interest. The funders had no role in the design of the study, in the collection, analyses, or interpretation of data, in the writing of the manuscript, or in the decision to publish the results.

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