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Urban Lifeline

REVIEW

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# Recent advances and applications towards intelligent operation and maintenance of urban pipeline networks

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**Abstract**

As typical lifeline engineering systems, urban pipeline networks (UPNs) play an important role in transmission and distribution of materials or energies in modern society. Over the past years, many efforts have been devoted to the research, development and application towards intelligent operation and maintenance of UPNs in Tongji University, incorporating with the emerging artificial intelligence (AI)-based and internet of things (IoT)-based technologies. This paper presents a review on the recent advances and the important achievements pertaining to this field in Tongji University. Using multi-source data, a data-driven model for the comprehensive risk evaluation of the whole pipeline network is briefly introduced to address the limitation of the insufficiency of reliable data and demonstrated by a case study. Aiming at three major safety problems such as structural failure, leak and third-party intrusion, the advances in techniques and systems for health monitoring of urban pipelines are summarized and the various application scenarios are illustrated as well.

**Keywords** Urban pipeline network, Operation and maintenance, Artificial intelligence, Internet of things, Risk evaluation, Pipeline monitoring

## 1 Introduction

As major infrastructures in cities, urban pipeline networks(UPNs) play an important role in the transmission of gas, water and energy media. According to the statistics [1], the total length of urban pipelines in China is over 3300,000 km by 2021 and keeps a high annual growth. Accompanied by so enormous scale and amount, pipeline accidents occur more frequently. Figure 1 presents the statistical data on the amount of urban pipelines and the causes of pipeline accidents in the recent years in China. It indicates that third-party intrusion and structural damage are the main factors causing pipeline failures. The safe and reliable operation and maintenance of UPN is of great significance for sustainable urban development and public security.

In recent years, with the rapid development and promotion of artificial intelligence (AI), the Internet of Things (IoT), big data, cloud computing and so on, the empowerment of advanced information technologies for traditional infrastructure-related industries has made great progress. In the field of municipal engineering specially for UPN management, some technologies have demonstrated enormous potential. For example, building information modeling (BIM) technology for design, construction and maintenance of pipelines and facilities, advanced sensing and the IoT techniques for health monitoring of pipeline systems, virtual reality technology for inspection, repair and replacement of pipelines, big data and cloud techniques for collection, storage, processing and management of large amount of data associated with UPN, AI-based pipeline survey, detection, diagnosis and decision making. Despite a promising future, it is faced

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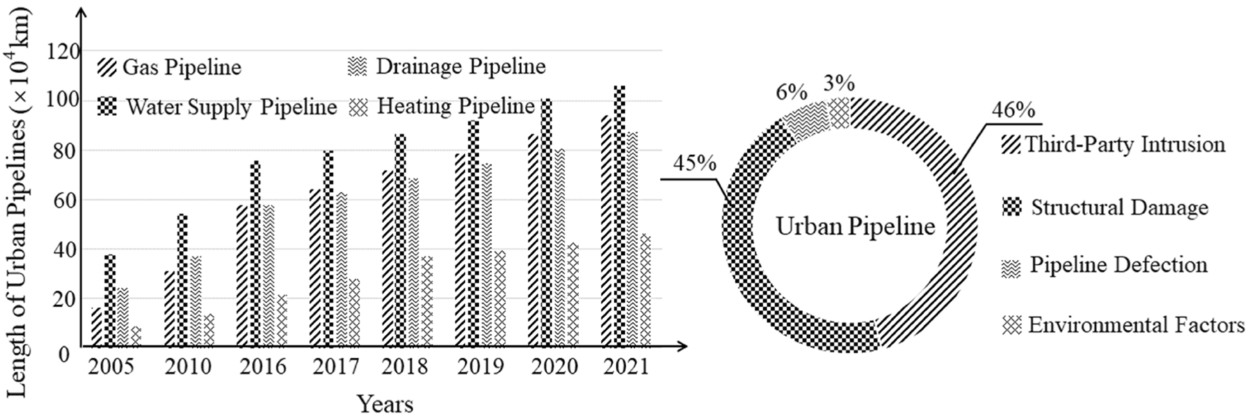



**Fig. 1** Statistical data of urban pipelines in China. **a** Total length of constructed urban pipelines [1]. **b** Cause of pipeline accidents (2018.07~2023.05) [2]

with many problems and challenges for deal with, which attracts more and more attention in industry.

From the perspective of academic research on lifeline engineering, it is originated from the mid-1970s mainly focused on disaster prevention and mitigation. After nearly 50 years, the knowledge on lifeline engineering has been formulated based on a broader background. Some new topics, such as health monitoring of lifeline infrastructures, the resilience of lifeline system and so on, have appeared associated with the progress of science and technology. Now, the research on lifeline engineering is becoming an important driving force for modern civil engineering [3].

Over the past years, many efforts have been devoted to the development and application towards intelligent operation and maintenance of UPNs in Tongji University, incorporating with the emerging AI-based and IoT-based technologies. A brief review of some important achievements pertaining to this field is presented in this paper, mainly including the data-driven risk evaluation models of UPNs as well as the health monitoring techniques of urban pipelines aiming at the major safety problems.

## 2 Overall framework

In the process of construction, operation and maintenance of UPNs, large amount of data have been generated, collected, stored and archived. In general, most cities or districts have established the following data system for UPN management: (1) geographic information system (GIS) for the basic attribute data of UPN including topology structure, pipeline properties, joints, etc.); (2) supervisory control and data acquisition (SCADA) system for on-line measurement of pressure, flow, temperature; (3) inspection and maintenance system for inspection record, failure/damage record, and maintenance record. In addition, (4) environmental monitoring system is sometimes available to acquire the measurements of temperature, humidity, water quality, soil conditions, traffic data, etc. It is worth noting that with the recent extensive promotion of big data, cloud storage and computing and internet of things (IoT) technology, the diversity, quality and efficiency of data collection has made great progress. How to take full advantages of the massive amounts of data, exploit valuable information and provide decision supports is of great significance for UPN management.

On the basis of the multi-source data, an overall framework towards intelligent operation and maintenance of UPN is put forward, as shown in Fig. 2. In the framework, two core physical models are generally involved, including the hydraulic model to simulate transmission and distribution of internal fluid in pipeline network as well as the structural model to simulate mechanical behavior of pipeline structure. The key parts of the framework consist of two aspects. The comprehensive risk evaluation of the whole pipeline network is first conducted, followed by a more elaborate three-level disease diagnosis to identify the disease type, quantify the severity and trace the cause. After determining the hot areas with high-risk pipelines, an integrated pipeline monitoring system can be established aiming at the major safety problems such as structural failure, leak and third-party intrusion. It should be pointed out that the construction of an intelligent operation and maintenance system of UPN in engineering practice may cover a wide variety of technologies, strategies and policies.

## 3 Risk evaluation of UPN

The existing models for risk evaluation of UPN are generally classified into three kinds: index model, data-driven model and physical model. The index model is most popular due to its convenience and simplicity. It usually

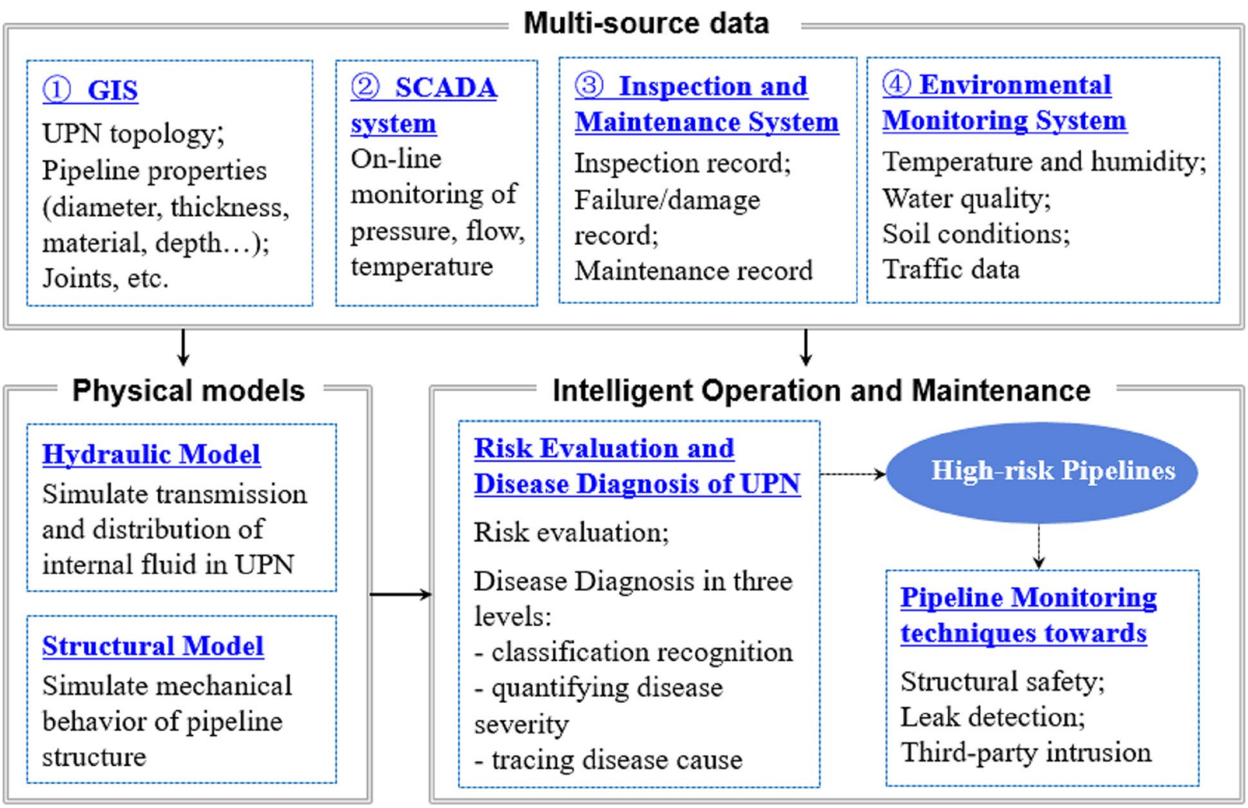



**Fig. 2** Schematic of intelligent operation and maintenance of UPNs

selects a number of criteria, assigns different weights based on domain knowledge, and then sums them up to obtain the risk scores. However, the distinct disadvantage of the index model is the high subjectivity involved in the scoring and weighting process. The data-driven model can provide more objective evaluation since it is entirely based on data statistical analysis with no artificial judging involved. With the flourishing development of machine learning algorithms, the data-driven model has attracted a great deal of attention recently. The main problems lie in the insufficiency of reliable data and the lack of physical significance of a typical black-box model. The physical model can reveal the degradation and failure mechanism of pipelines, but the sophisticated structural analysis relies on high quality data and thorough insights into the mechanism. In the past years, we have worked on the development and application of all the three kinds of models. Considering the length limitation of the paper, only data-driven risk evaluation model is introduced here briefly.

### 3.1 Data-driven risk evaluation model

As mentioned above, the multi-source data collected by various means may play an important role in intelligent evaluation and decision support for operation and maintenance of UPN. However, in most engineering practice for risk evaluation, such data is far from satisfactory in many aspects. This is because that the absence of attributes and the presence of noise in the feature data are common, which causes aleatory or statistical uncertainty. Besides, the dataset suffers from severe class imbalance as the number of damaged pipelines is much less than that of the undamaged pipelines, which raises the difficulty for binary classification. Furthermore, in many areas worldwide, only short-term (usually within 10 years) historical failure records are available, which leads to label noise in the form of the positive and unlabeled dataset (PU dataset), and hence weakens the correlation between features and labels.

To address the limitation of the insufficiency of reliable data, a data-driven model is proposed for risk evaluation of UPN. As shown in Fig. 3, the model consists of two critical parts: the development of a classification model to determine the failure probability of all pipelines and thereby yield risk ranking; the utilization of a Gaussian mixture model to cluster the failure probabilities and assign the risk levels. To examine the evaluation results, four indicators as defined in Fig. 3 are adopted including the area under the curve (AUC) and benefit coefficient $\alpha^{1\%}$ for risk ranking, and the coefficient of determination

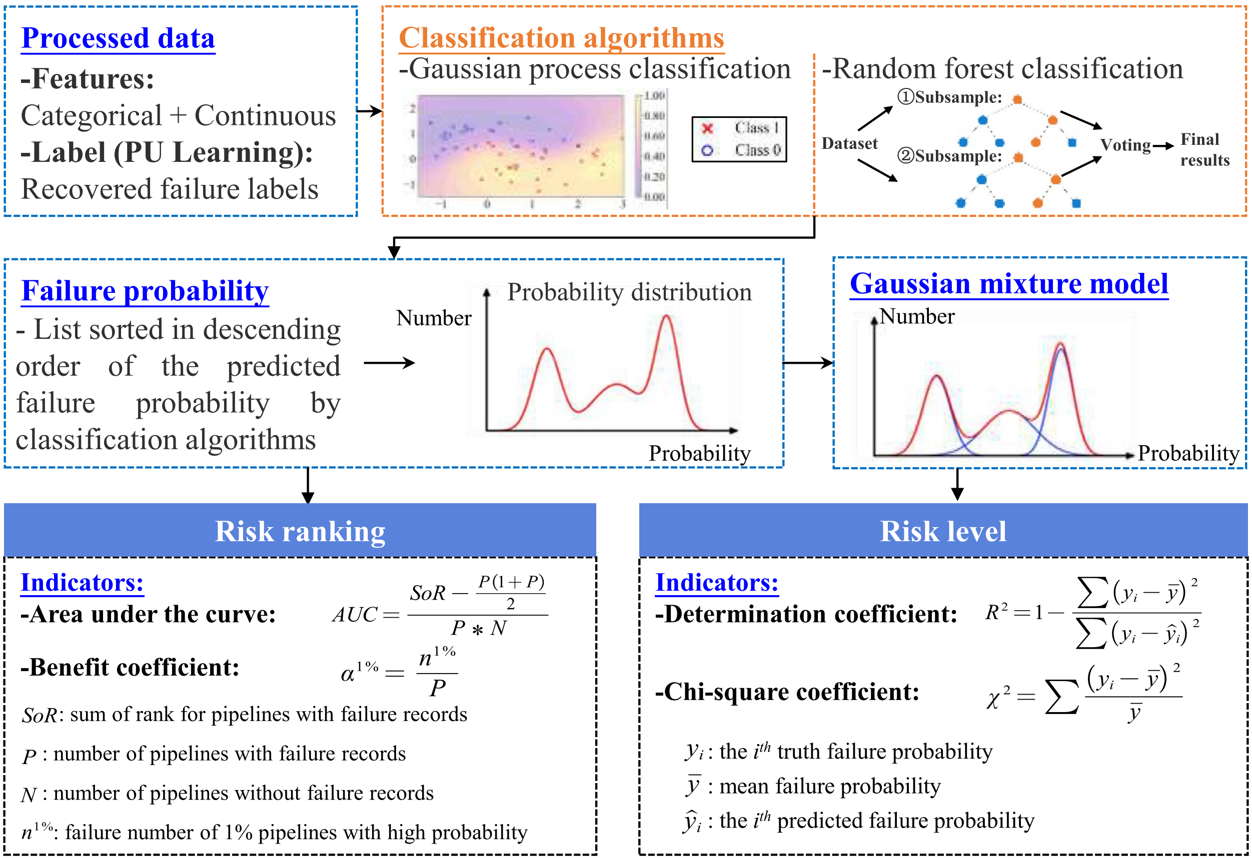



**Fig. 3** Data-driven risk evaluation model of UPN

$R^2$ and the Chi-square coefficient $\chi^2$ for risk level assignment.

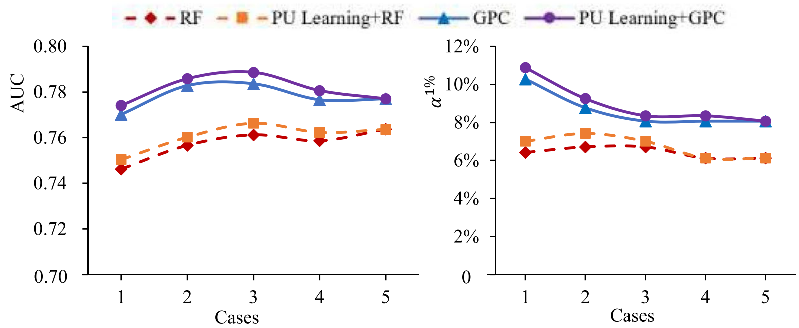
The data-driven risk evaluation model proposed in Fig. 3 is elaborately devised to solve the aforementioned problem in data deficiency. In our research, the PU learning algorithm is chosen for data preprocessing, which aims to recover the labels for the unlabeled data by using the positive samples in the dataset [4], which effectively deals with the typical PU dataset and the problem of data imbalance. Under the assumption of being selected completely at random (SCAR) that the pipeline failure pattern remains largely unchanged in a relatively short period of time, a binary classification model can be trained by using the short-term historical failure records to predict the relative failure probability of each pipeline in the near future. In this case, the probabilistic model Gaussian process classification (GPC) may perform better in the presence of incomplete data with aleatory uncertainty than the traditional supervised models such as random forest (RF) classification. In addition, the utilization of Gaussian mixture model (GMM) helps to cluster the probabilities and assign risk levels avoiding subjectivity, fitting any failure probability distribution.

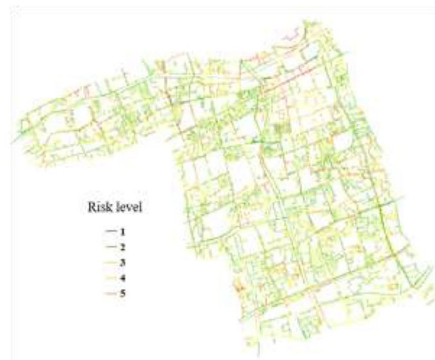
### 3.2 Case study on a water supply UPN

A case study has been carried out on a UPN in the central district of a city in China [5]. Within the area of about 11 km$^2$, there are over 467 km long water supply pipelines. The original data is provided by a local water company. After selecting and preprocessing the raw data, a set of features are adopted, among which the continuous features include pipe age, diameter, length, wall thickness and buried depth, and the categorical attributes include pipe material, and the area where the pipe is located.

The pipeline failure records exported from the database in the maintenance division are also employed. Since the historical accident data before 2015 is severely lacking, the failure records during 2016–2021 are finally adopted. The number of pipelines with no failure records to those with failure records is around 88:1, which indicates the data is quite unevenly distributed. Four cases are designed by separating the records into different training and testing sets. As shown in Fig. 4c, the failure records in 2021 are taken as the testing set, and those in one or a few years before 2020 serve as the training set.

The risk evaluation results are presented in brief in Fig. 4. The performance of the proposed data-driven




| Cases | Training set | Testing set | $R^2$ | $\chi^2$ |
|---|---|---|---|---|
| Case1 | 2020 (1 year) | 2021(1 year) | 0.892 | 1.842 |
| Case2 | 2019-2020 (2 years) | | 0.941 | 2.301 |
| Case3 | 2018-2020 (3 years) | | 0.950 | 2.015 |
| Case4 | 2017-2020 (4 years) | | 0.985 | 2.455 |
| Case5 | 2016-2020 (5 years) | | 0.991 | 2.724 |

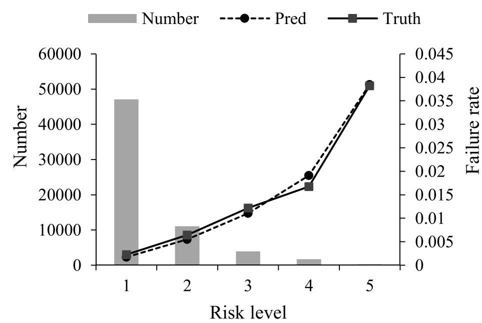



**Fig. 4** Risk evaluation results of the case study

model for risk ranking in terms of AUC and $\alpha^{1\%}$ is shown in Fig. 4a, b, which indicates that the GPC performs better than the RF in the task of predicting pipeline failure probability. Using the GPC as the classification algorithm, the effectiveness of the model for risk level assignment in terms of $R^2$ and $\chi^2$ are listed in Fig. 4c. It can be found that the prediction accuracy of risk level improves as the number of historical accident records grows. With more than 1 year of failure records, $R^2$ can reach more than 0.94. The indicator $\widehat{\chi}^2$ are larger than 1.8 in each case, passing the chi-square test. Figure 4d also confirms that the predicted failure rate of the pipelines with different risk levels using the accident records in the past 5 years agree well with the true failure rate in the year 2021. As an outcome of this work, the evaluation results of the risk level for all the pipelines can be graphically represented and loaded as a function module in GIS as Fig. 4e for enterprise service and decision support.

## 4 Pipeline monitoring techniques

According to the results of risk evaluation of UPNs as mentioned above, the pipelines with high-risk level can be determined. Then more attention should be putted on the aspect of daily inspection and monitoring in the area with high-risk level. Aiming at three major safety problems in urban pipelines such as structural failure, leak and third-party intrusion, several pipeline-monitoring techniques have been developed and put into applications.

### 4.1 Pipeline structural health monitoring based on NB-IoT

#### *4.1.1 System design*

Compared with other urban infrastructures, UPNs are generally distributed in a large area with the topology structures of the networks, which calls for the monitoring techniques capable of wide spatial coverage, massive device access, and low cost and power consumption. As one of the leading low power wide area (LPWA) technologies, narrowband (NB)-IoT [6] provides an excellent solution to deal with the massive number of devices constantly evolving with underlying requirements such as coverage, reliability, latency and cost effectiveness, which in nature perfectly fits the requirement of pipeline monitoring. Moreover, the variation of structural behavior or the degradation of structural performance of pipelines is generally a slow process, which allows for the data acquisition with relatively large interval of time. In view of this, NB-IoT provides the standby sleep mode for saving battery power and thereby enables low power low cost in the applications of pipeline structural health monitoring (PSHM).

In view of the above considerations, an integrated PSHM system based on NB-IoT has been developed, as shown in Fig. 5, which is in accordance with the basic architecture of a typical SHM system consisting of sensors, data acquisition, data transmission and data application in structural analysis, safety evaluation and early warning. From the view of practical engineering

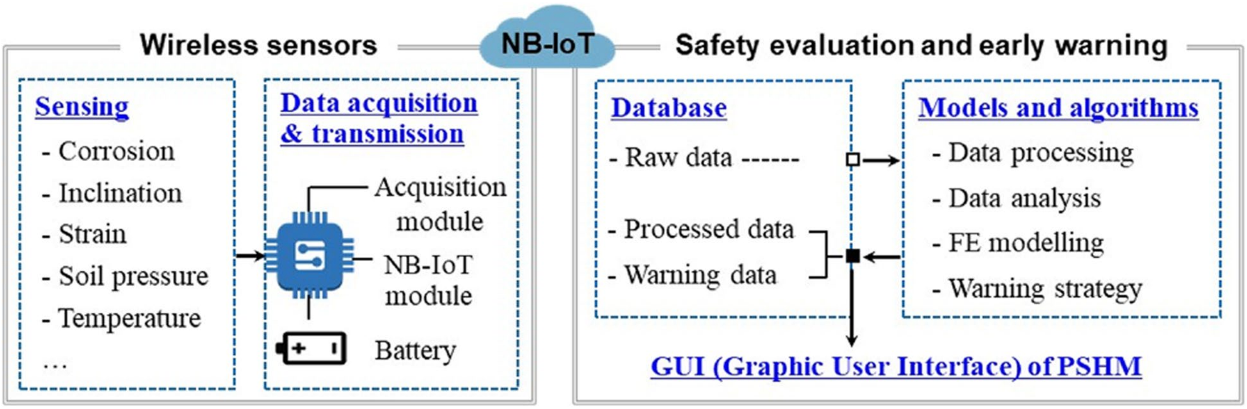


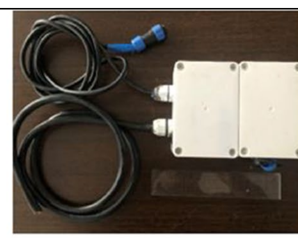
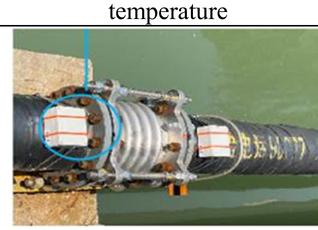

**Fig. 5** PSHM system based on NB-IoT

application, the unique aspect of the system lies in the development and utilization of the NB-IoT based wireless sensors characterized by a compact structure, a generic interface to most loads and responses measurements of pipeline structures, and low power consumption, which contributes to high cost and labor efficiency in sensor installation, maintenance and replacement.

#### *4.1.2 Sensors and applications*

The NB-IoT based wireless sensors developed in our team as well as the typical application scenarios in UPN are briefly presented in Table 1. Three devices have been designed and manufactured to implement the on-line monitoring on the cathodic protection (CP) system, inclinations, and multi-parameters including strain, pressure and temperature. Despite the limited

**Table 1** Wireless sensors and application scenarios

| Sensors | 1 | 2 | 3 |
|---|---|---|---|
| Photos |  |  |  |
| Monitoring | Cathodic protection (CP) | Inclination | Multi-parameters: strain, pressure, temperature |
| Application scenarios in UPN |  |  |  |
| | CP well | Well cover | Crossover pipeline |
| |  |  |  |
| | CP station | Tank/device | Buried pipeline |

number of devices, they cover the measurements of main loads and responses of pipeline structures under most normal operational conditions, capable of tracing the structural behavior of pipelines subjected to corrosion, ground deformation, temperature variation and so on. Table 1 demonstrates some practical applications in CP wells/stations, tanks, crossover pipelines and buried pipelines. It is worth pointing out that this work presents a successful case by promoting the practical applications of advanced IoT technologies in UPN-concerned industries.

### 4.2 Leak detection in pressurized pipelines

Leak detection is a critical task in the process of maintenance and management of urban pipelines. As one of the most popular techniques, acoustic-based methods [7] have attracted wide interests for their capability of capturing the acoustic signals propagated in the filled fluid, the pipe wall and the surrounding soil or air. Figure 6 presents the schematic diagram of acoustic-based methods for leak detection and localization. In general, the acoustic signals in the fluid are acquired by pressure sensors or hydrophones, while the acoustic signals in the pipe or soil are collected by accelerometers. Aiming to the main challenges of such techniques in the practical implementation of efficient leak detection, accurate localization, and long-term monitoring of real networks, our recent efforts are devoted to mechanism investigations on generation and propagation of leak-induced acoustic waves as well as the improvement of device and algorithm for practical applications in real pipelines in service.

When a pressurized pipeline leaks, it disturbs the normal flow of the fluid inside the pipe and creates turbulent jets near the leak orifice, resulting in leak noise. The recent progress in fluid acoustic methods for leak detection and localization is summarized as follows.

#### *4.2.1 Theoretical models of the leak noise in gas pipelines*

*(1) Model-based health indicator* During the leakage of a gas pipeline, there is continuous mass exchange between the pipeline and the surrounding environment, resulting in the formation of a monopole source with a certain intensity. The intensity of this acoustic source is correlated with the leakage velocity and the area of the leakage orifice, leading to the generation of corresponding leakage noise. Research suggests that the generation mechanism of leakage noise is mainly attributed to the pulsating mass flux at the leak orifice, which forms a monopole acoustic source. Based on this concept, a theoretical model for leak noise spectrum [8] is established as:

$$S_{pp}(\omega) = \frac{8\rho_0^2 c_0^2 \overline{u^2}}{\pi^4}\left(\frac{a}{R}\right)^4 \frac{\Lambda}{U} \frac{1}{1+(\omega\Lambda/U)^2} \tag{1}$$

where $S_{pp}$ is the leak noise spectrum, $\rho_0$ is the density of the gas, $c$ is the sound speed in gas, $\overline{u^2}$ is mean square velocity, $a$ is the radius of leak orifice size, $R$ is the radius of the pipe, $\Lambda$ is the integral length-scale, $U$ is the exit speed of gas, and $\omega$ is the angular frequency.

This theoretical model distinctly differs from the statistical power spectrum model obtained through general leakage noise observations. According to Eq. (1), the power spectral density of leakage noise exhibits a power-law distribution approaching $\omega^{-2}$ in the slightly higher frequency range. On the log-log scale, the power spectral density of leakage noise has a linear relation with frequency. The operational conditions of gas pipelines can be hence characterized by the gradient of the power spectral density of a signal with frequency on a log-log scale, referred to as the characteristic power-law $\beta$ [9].

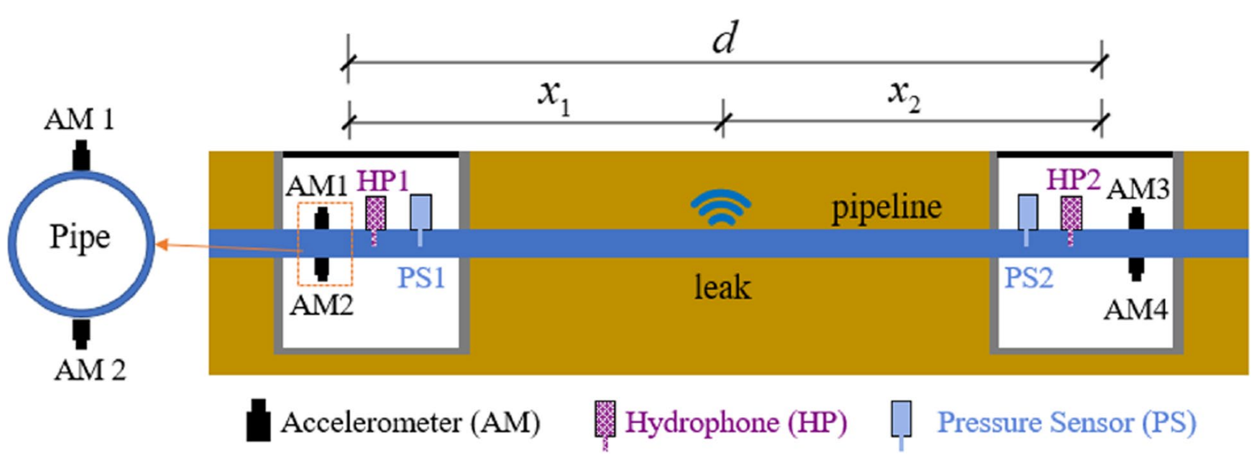



**Fig. 6** Schematic of acoustic-based leak detection and localization

Different from most previous studies which require a baseline case to determine a threshold discriminating the leak and leak-free states, $\beta$ can be directly applied for leak detection in gas pipelines. Besides, as a physical-model based health indicator, $\beta$ has better robustness under varying working conditions than the traditional features extracted from the acoustic signals in time or frequency domain.

*(2) Model-based correlation function* For leak localization, the current mainstream methods are still based on cross-correlation analysis, which estimate the time delay between two signals either side of a suspected leak and the sound speed in fluid. Combining the wave propagation characteristics in gas pipelines with the leakage noise spectrum and considering the influence of physical parameters such as turbulence parameters, pipe parameters, and flow parameters, a theoretical model of correlation function for leakage noise [10] is proposed as:

$$R_{x_1x_2}(\tau) = \frac{16\rho_0^2 c_0^2 \overline{u^2}}{\pi^4}\left(\frac{a}{R}\right)^4 \frac{\Lambda}{U}\int_0^{\infty}\frac{e^{-\alpha\sqrt{\omega}(x_1+x_2)}e^{i\omega\tau}e^{i\omega T_0}}{1+(\omega\Lambda/U)^2}\mathrm{d}\omega \tag{2}$$

where $T_0$ is the time delay, $\tau$ is the time lag, $x_1$ or $x_2$ is the distance between the sensor and the leak source (see Fig. 1).

The physical model is capable of describing the main features of the correlation function in gas pipelines. Moreover, this model gives an estimation on the detection limits of the fluid acoustic methods, which is crucial to the deployment of sensors in real gas pipelines. The findings of this study provide theoretical insight and experimental evidence in optimizing the cross-correlation methods for leak localization.

#### 4.2.2 Methodology

Figure 7 presents a general framework of the acoustic-based methods for leak detection and localization. Compared with the conventional signal processing methods, data-driven approaches are strong self-adaptive for the training process, which helps to make better decisions in the task of leak detection. In this work, the traditional machine learning (TML) algorithms including artificial neural network (ANN), support vector machine (SVM) and random forest (RF) are employed to develop a binary classifier for leak detection. Particularly, the proposed health indicator $\beta$ can be included as an important feature to identify the leak in gas pipelines.

The common used cross-correlation method is adopted for leak localization by estimating the time difference of arrivals (TDOAs) between two signals collected by the sensors placed on either side of a suspected leak and the acoustic wave velocity in fluid. By calculating the coherence function between signals, the

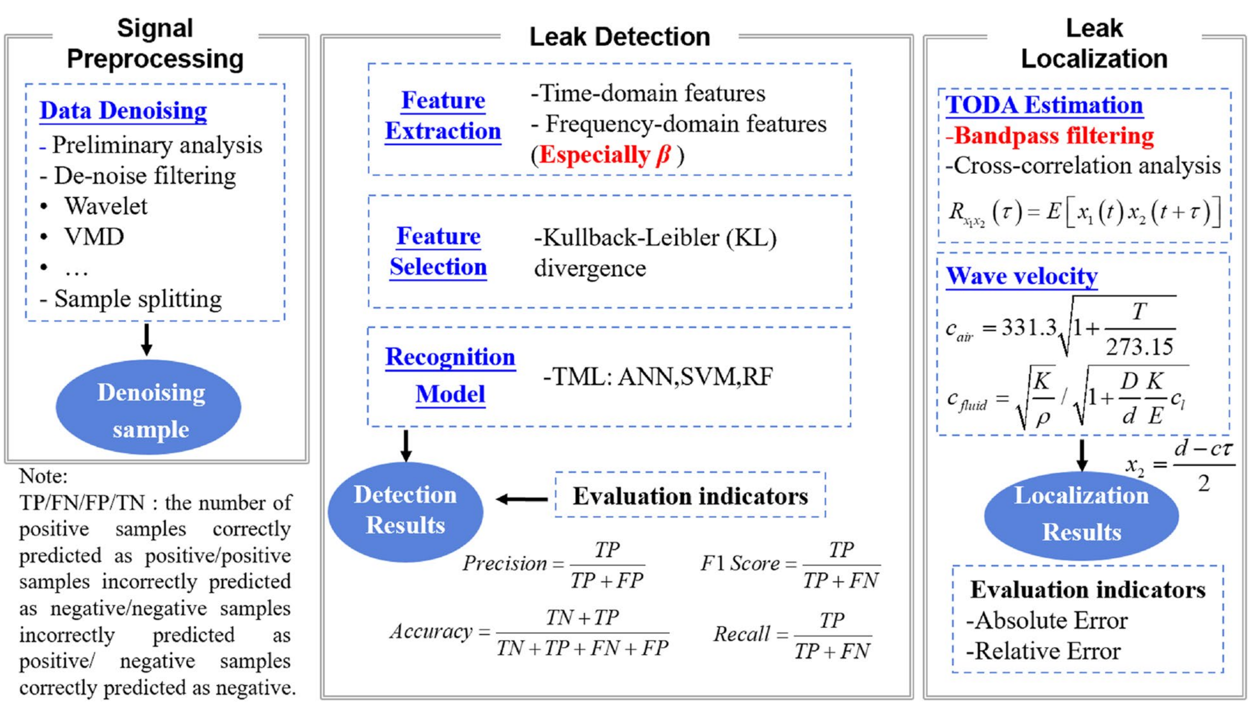



**Fig. 7** Framework of the fluid acoustic method

frequency ranges with coherence values greater than a threshold can be first selected to filter the leak signals, which are then adopted for TDOAs estimation. Particularly for gas pipelines, the physical model of correlation function shown in Eq. (2) can be used to determine the maximum monitoring distance of the acoustic sensors, providing guidance for sensor installation in gas pipelines.

#### *4.2.3 Test and application*

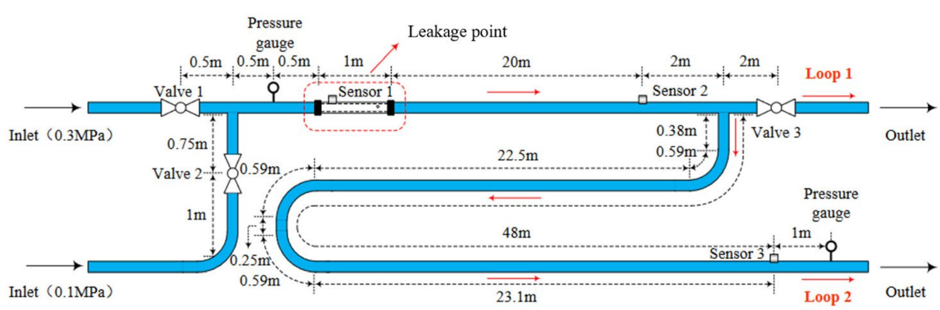
*(1) Gas pipeline at test site* A field test has been conducted on an 80 m long outdoor gas pipeline [9]. As shown in Fig. 8, a 1 m replacement pipe with the same diameter and material as the main pipeline is installed by directly introducing punctures to simulate an actual leak. By replacing this replacement pipe, it is easy to modify the leak characteristics. The experiment discussed the impact of pipeline pressure, leakage shape, and leakage size on the results.

The acoustic leak signals as well as environmental noise are collected. For leak detection, totally 13 features are extracted, including the health indicator $\beta$ and the traditional signal characteristics in time or frequency domains. Based on the Kullback-Leibler (KL) divergence, the features can be sorted by order of importance. The normalized KL divergence values of all the features are sorted and plotted in Fig. 9. It can be observed that the feature $\beta$ is of greatest importance, which validates that this feature is a better indicator for leak detection than the other traditional features. Finally, the top four features including $\beta$, maximum value, median frequency, and RMS are selected and used as inputs to train the leak detection model.

The results of leak detection using the three TML models are presented and compared in Table 2. Four indicators including accuracy, precision, recall and F1 score as defined in Fig. 7 are employed to evaluate the model performance on the near-field and far-field datasets. It can be observed that compared to the near-field signals, the recognition results of the three models on the far-field signals are slightly lower, but they still demonstrate satisfactory prediction accuracy.

Figure 10 presents the results of leak localization in the different cases. It is indicated that except for the minimum leak size and minimum pipeline pressure conditions, accurate localization results can be obtained for all the other leak sizes regardless leakage shape at different pipeline pressures. The absolute error is within a range of 1 m, and the maximum relative error is 0.83%.

*(2) Water supply pipeline in service* A leak monitoring system has been installed on a real water supply pipeline in-service [11]. As shown in Fig. 11, the total length of the pipeline is about 1822 m, along which there is 19




(a) Schematic diagram of the experimental pipeline system

| Leakage shape | Circle | | | | | | Rectangle | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Leakage size(mm) | Φ=1 | | Φ=3 | | Φ=5 | | 2×1 | | 2×3 | | 2×10 | |
| pressure(MPa) | 0.1 | 0.3 | 0.1 | 0.3 | 0.1 | 0.3 | 0.1 | 0.3 | 0.1 | 0.3 | 0.1 | 0.3 |
| Case No. | 1-2 | 3-4 | 5-6 | 7-8 | 9-10 | 11-12 | 13-14 | 15-16 | 17-18 | 19-20 | 21-22 | 23-24 |

(b) Leak Cases

**Fig. 8** Field test on an outdoor gas pipeline. **a.** Schematic diagram of the experimental pipeline system. **b.** Leak cases

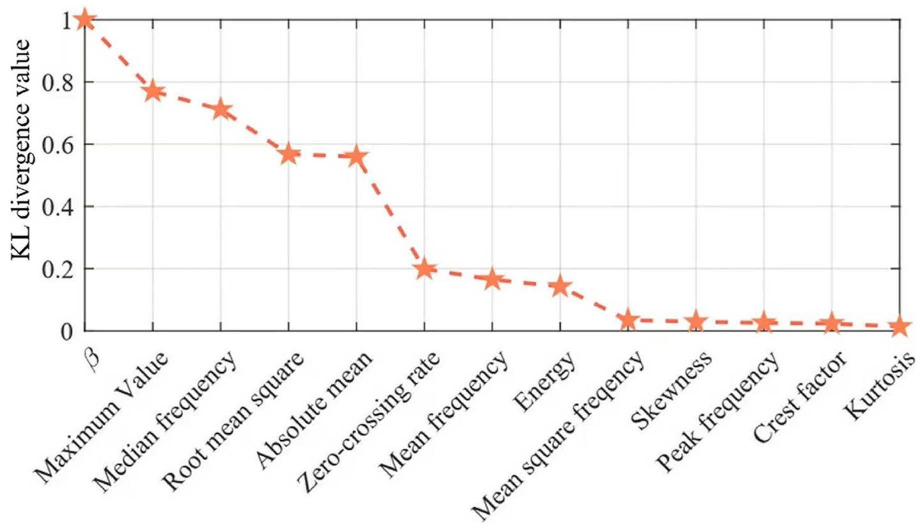



**Fig. 9** Normalized KL divergence values of the 13 features

**Table 2** Performance of the TML models for leak detection on the near-field/ far-field datasets

| TML Models | Accuracy (%) | Precision (%) | Recall (%) | F1 Score (%) |
|---|---|---|---|---|
| ANN | 99.13/95.53 | 99.70/98.97 | 99.02/94.22 | 99.36/96.54 |
| SVM | 99.00/95.13 | 99.70/98.87 | 98.83/93.93 | 99.26/96.34 |
| RF | 99.33/97.80 | 99.71/99.40 | 99.32/97.36 | 99.51/98.37 |

observation points. The sensor devices are installed at both ends of the pipeline and the leakage is simulated by opening valves of the hydrants in between. The innovation of this work lies in: (a) the development and utilization of a wireless synchronous high-speed data acquisition system for long-distance leak localization; (b) performance comparison of pressure sensors and hydrophones in practical application of pipeline leak monitoring; (c) in-situ tests on a water pipeline under real operational condition.

The absolute and relative errors of leak localization are given in Fig. 12. It can be found that the leak monitoring system can locate the leak with satisfactory accuracy in most cases. For pressure sensors, the absolute error is less than 40 m and the maximum relative error is 2.6%; for hydrophones, the absolute error is less than 30 m and the maximum relative error is 2.3%. Meanwhile, considering the cases in which the results are absent as the distances between the leak source and one sensor ($x_1$ or $x_2$ in Fig. 2) are too far to acquire the meaningful acoustic signals, it can be observed that the effective monitoring distance of pressure sensors is approximately 1060 m, whereas the distance of hydrophones is approximately 1360 m under the exactly same test condition, which confirms that hydrophones have better performance in longer monitoring distance besides less errors of leak localization than pressure sensors.

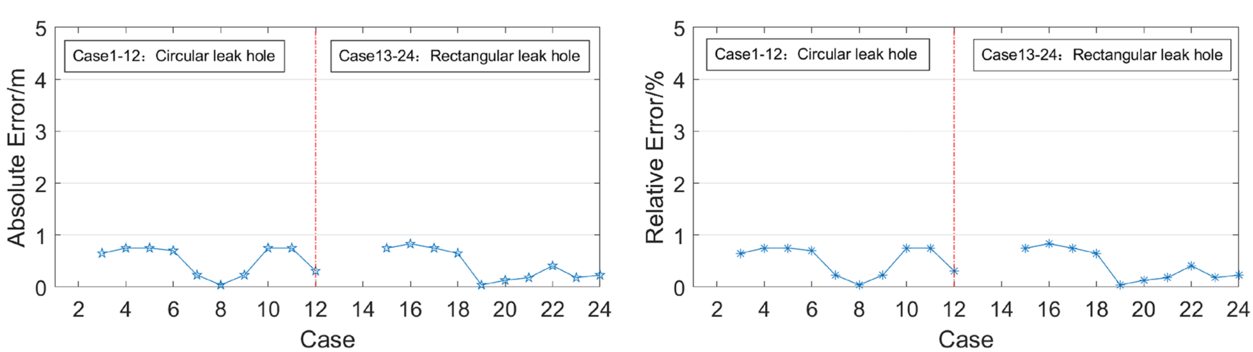



**Fig. 10** Leak localization results. (Note: The absence of error results in the leakage cases means that it cannot be localized)


(a) Experimental setup of the pipeline system

| $d$ (m) | 1822 (HP1/HD1 placed at No.1; HP2/HD2 placed at No.19) | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $x_1$ (m) | 1474 | 1381 | 1279 | 1185 | 1071 | 973 | 851 | 758 | 694 | 587 | 469 | 260 | 182 |
| Case No. | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 |
| $d$ (m) | 1279 (HP1/HD1 placed at No.1; HP2/HD2 placed at No.14) | | | | | | | | | | | | |
| $x_1$ (m) | 101 | 182 | 260 | 358 | 469 | 587 | 694 | 758 | 851 | 973 | 1071 | 1185 | |
| Case No. | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 | 25 | |

(b) Leak Cases

**Fig. 11** In-situ test on a water supply pipeline in service. **a.** Experimental setup of the pipeline system. **b.** Leak cases

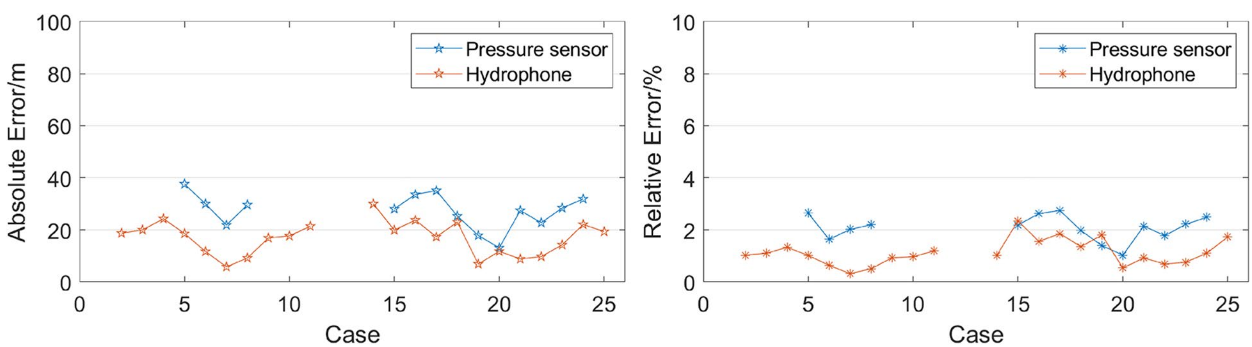



**Fig. 12** Leak localization results. (Note: The absence of error results in the leakage cases means that it cannot be localized)

### 4.3 Perimeter monitoring of third-party intrusion

Third-party threats, such as construction activities and man-made sabotage, have become the main cause of pipeline accidents. For the convenience of installation and maintenance, most urban pipelines are directly buried under roads or greenbelts. The pattern of the third-party activities is usually clear and characterized as excavation of roads and soils by excavator or by hand. Aiming at perimeter monitoring and early warning of urban pipelines subject to third-party intrusion, two kinds of techniques have been developed and applied in engineering practice: fiber optic sensor (FOS) based surveillance for long-distance buried pipelines and video/audio surveillance for pipelines enclosed at construction site.

#### *4.3.1 Fiber optic sensor (FOS) based surveillance for long-distance pipeline*

Distributed fiber optic sensors have great ascendancy in pipeline monitoring since they can acquire the long-distance measurements using a single optical fiber. in long-distance perimeter monitoring. As a popular Distributed acoustic sensor (DAS), the phase-sensitive optical time-domain reflectometry (ϕ-OTDR) [12] is capable of detecting very small perturbation and suitable for the development of a perimeter monitoring system. The associated recent efforts are summarized in the following sections.

*(1) Technical framework* Using the distributed vibration measurements acquired by ϕ-OTDR, an integrated framework is proposed for perimeter monitoring and early warning of third-party activities alongside a buried urban pipeline. As shown in Fig. 13, it is mainly composed of a two-stage recognition process and a warning strategy. After data preprocessing, the coarse recognition can determine whether the input time-space sample is a third-party or not. If the recognition result is positive, then the fine recognition can further identify the location and specific type of the third-party activities. To enhance the recognition rate and reduce the false alarm rate, a time-space matrix is finally introduced to put forward an early-warning strategy.

Three data-driven recognition models have been developed for the two-stage recognition process, including the traditional machine learning models (TML models) [13], the convolutional neural network models (CNN models) [14] and the objective detection models (OD models) (Li S, Liu Z, Kuang Z: Perimeter monitoring of urban buried pipeline threated by construction activities based on distributed fiber optic sensing and Faster R-CNN, forthcoming). From a comparison perspective, the OD models in general has much larger receptive field for time-space samples and hence may achieve highest recognition rate and computational efficiency among the three models; the CNN models have higher recognition accuracy since they

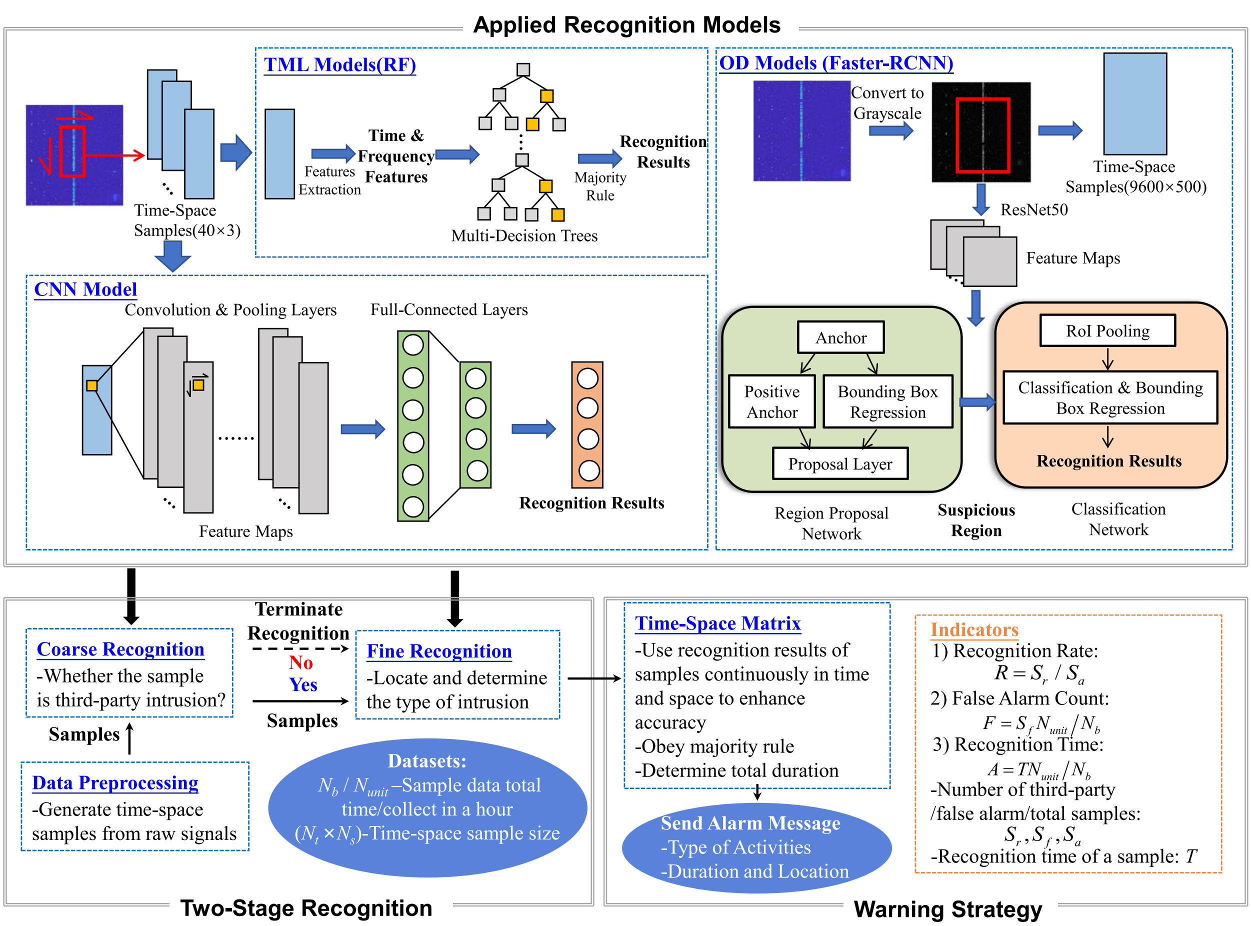



**Fig. 13** Framework of FOS-based surveillance for long-distance pipeline

can extract features automatically, whereas the TML models can run faster due to their lightweight frameworks.

*(2) Test and application* Field tests have been conducted on a long-distance urban gas pipeline in service. As shown in Fig. 14, a 5.25 km-long single-mode optical fibre cable is laid along the pipeline with the buried depth of 1 m. The cable covers the most common scenarios in cities. The sampling rate of the data acquisition system is 250 MHz, and the spatial resolution is set as 10 m. Four common third-party activities including pickaxe, shovel, hammer and electric hammer are carried out on the ground near the pipeline at seven locations.

Totally 27.5GB data has been collected involving the measurements in the case of various third-party activities as well as the environmental noise. Using the exactly same datasets and computing hardware, the recognition results based on the proposed framework by employing the random forest (RF) model, the CNN model and the fast-RCNN (Region-based CNN) model are presented in Table 3. Three indicators including the recognition rate $R$, the false alarm count $F$ and the recognition time $A$ as defined in Fig. 13 are employed to evaluate and compare the model performance. It indicates that the fast-RCNN model has superior overall performance in good recognition accuracy, low false alarm rate and high computation efficiency. Compared with the RF model, the CNN model displays the features as higher recognition accuracy and lower false alarm rate but much more time-consuming.

**Table 3** Recognition results of different models

| Models | $R$(%) | $F$ | $A$(s) |
|---|---|---|---|
| RF | 82.27 | 10.76 | 10.17 |
| CNN | 97.12 | 0.0286 | 122.08 |
| Fast-RCNN | 98.85 | 0.0032 | 0.5 |

#### 4.3.2 *Video/audio surveillance for pipelines enclosed at construction site [14]*

In addition to main pipelines across a long distance, another type of pipelines in urgent need of a surveillance system for third-party intrusion are those enclosed at a construction site where a routine inspector is usually not allowed to enter. In this situation, it is easy to set up an apparatus equipped with camera and microphone around the pipelines to collect the video/audio signals, based on which recognition models and early warning strategies can be developed for surveillance on third-party intrusion.

*(1) Technical framework* The framework of the video/audio surveillance system for pipelines enclosed at construction site is given in Fig. 15. The monitoring device in situ is mainly composed of a camera, a microphone, and a module incorporating the functions of data acquisition, analysis and transmission. When the alarm is triggered, the data containing the alarm information as well as the video/audio signals with a certain length before and after the alarm moment is sent to data management

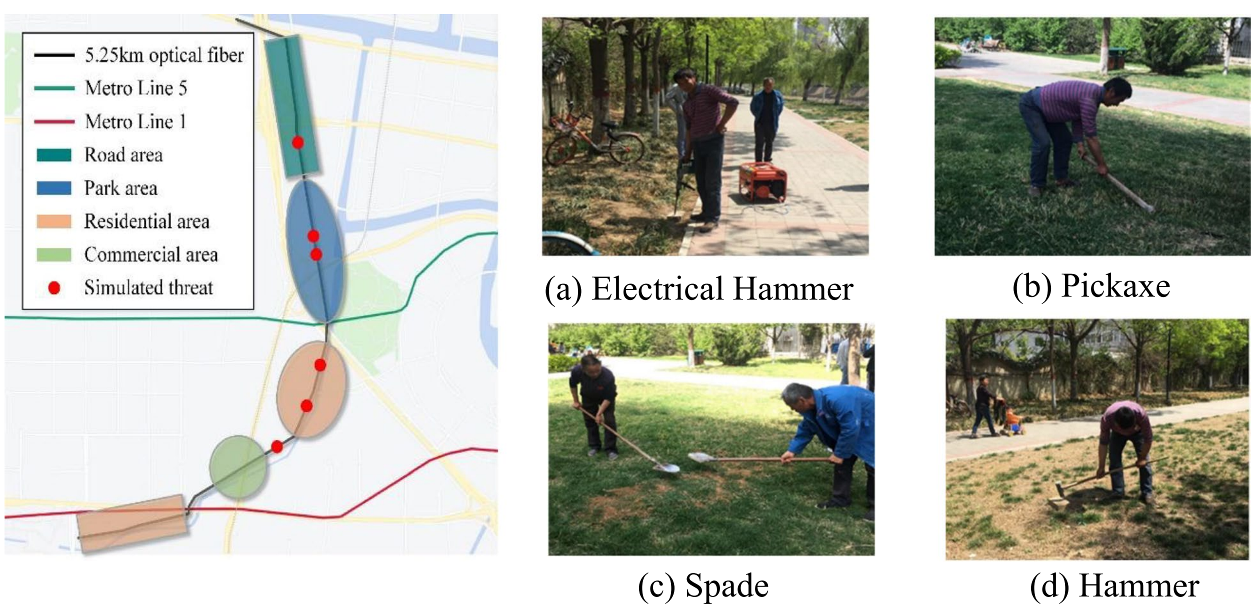



**Fig. 14** Field tests on a buried urban gas pipeline

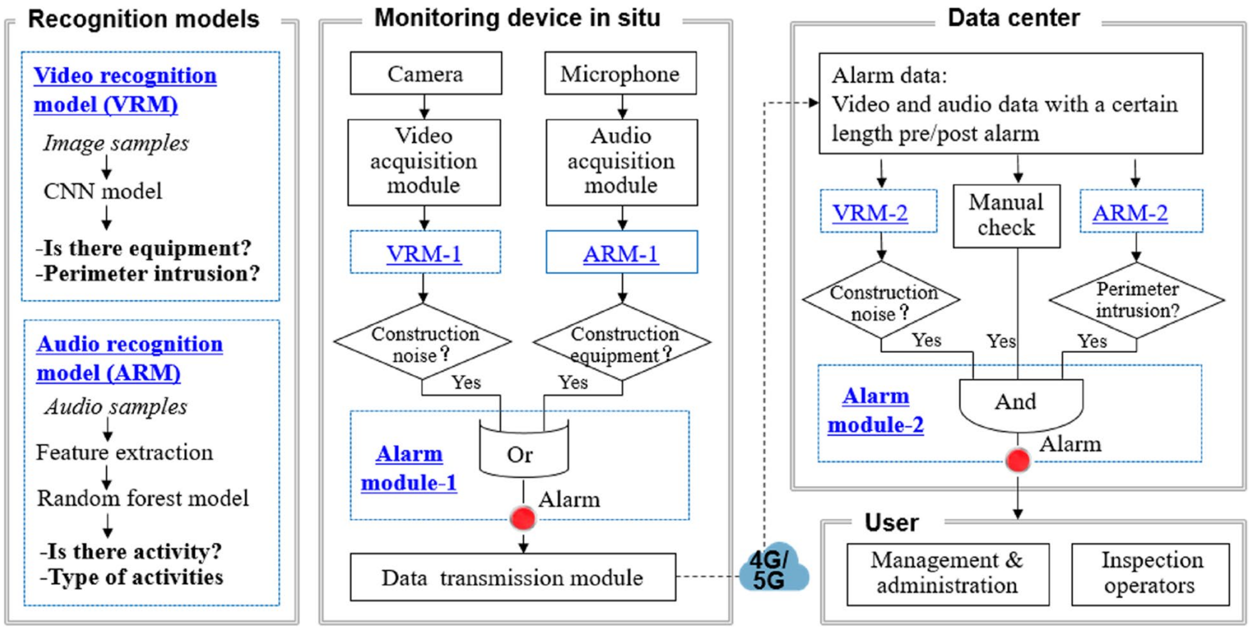



**Fig. 15** Framework of video/audio surveillance for pipelines enclosed at construction site

center, where a more sophisticated recognition are conducted in combination with manual re-check and a final alarm message is issued to the divisions and inspectors responsible for routine patrol.

Two recognition models by using the video and audio signals respectively are developed to detect the occurrence and types of the third-party activities. The recognition results obtained by the two independent technical routes can be comparatively verified and their combination can provide a more reliable alarm information. Furthermore, the two-stage strategy consisting the coarse recognition in situ and the fine recognition in data center facilitates the design of monitoring device, the efficient data transmission and the reliable alarm function.

*(2) Case study* A case study shown in Fig. 16 has been conducted by installing a monitoring device on the

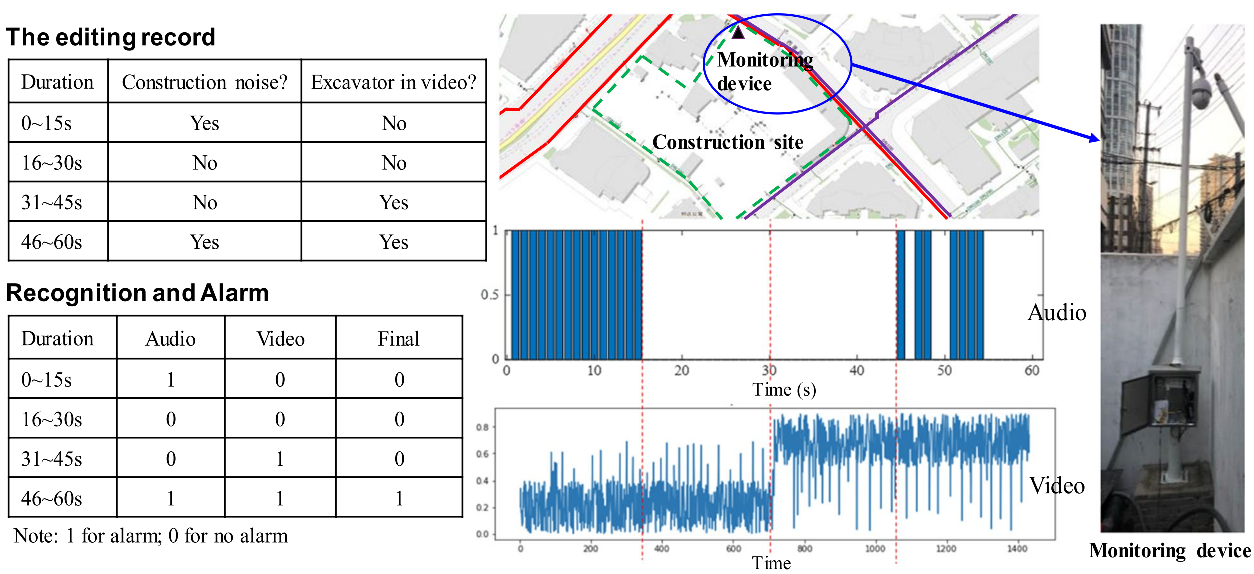



**Fig. 16** A Case study of video/audio surveillance system

corner of a construction site for surveillance of the third-party treats on the nearby pipelines. To demonstrate the effectiveness of the system, a 1-min record monitored on site is artificially edited composed of four equivalent segments with each quarter for the case with different combination of the presence of construction noise and construction equipment. The probability of the detection on the third-party threat using audio and video signals is displayed. It can be found from the alarm message that the cross validation of audio and video recognition improve the accuracy of alarm.

## 5 Conclusions

This paper presents a review on our recent efforts in development and application pertaining to intelligent operation and maintenance of UPNs, incorporating with the emerging AI-based and IoT-based technologies. The major achievements are summarized as follows.

(1) An overall framework is proposed on basis of multi-source data and physical models, which consists of two essential parts including the risk evaluation and disease diagnosis methods for the entire network as well as the health monitoring techniques for the important pipelines.

(2) To deal with the problem of data inadequacy in quantity and quality commonly encountered in practice, a data-driven model for risk evaluation of UPNs has been developed based on PU learning and supervised machine learning. The effectiveness of the model has been demonstrated by a case study on a real-world water supply UPN with over 467 km long pipelines within the area of about 11 $km^2$.

(3) Aiming at three major safety problems in urban pipelines, a number of pipeline monitoring techniques have been developed including the NB-IoT based PSHM, acoustic-based leak detection in pressurized pipelines, and perimeter monitoring of third party intrusion. The focuses are particularly placed on the theoretical investigation on the methods and principles of pipeline monitoring, the practical implementation of advanced sensing, AI-based recognition models, and efficient warning strategies, as well as the capability of long-term monitoring for real pipeline networks. The corresponding tests or applications are provided to demonstrate the feasibility of various monitoring techniques and systems.

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**Author contributions**
JL: Conceptualization, Funding acquisition, Project administration, Supervision, Writing-review & editing. SL: Investigation, Methodology, Validation, Writing-original draft.

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**Competing interests**
The authors declare they have no competing interests.

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**References**

1. The Ministry of Housing and Urban-Rural Development of China (2022) Statistical yearbook of urban and rural construction in 2021. (in Chinese)
2. Beijing Underground Pipeline Comprehensive Management Research Center (2023) Pipeline accidents report from 2018-2023 (in Chinese)
3. Li J, Liu W (2020) Lifeline engineering systems. Springer Nature Singapore, Singapore
4. Bekker J, Davis J (2020) Learning from positive and unlabeled data: a survey. Mach Learn 109:719–760
5. Li S, Li Z (2022) Risk assessment of water supply pipeline network: a case study. Technical report, LSHM -2022-01. Tongji University, Shanghai
6. Rastogi E, Saxena N, Roy A, Shin DR (2020) Narrowband internet of things: a comprehensive study. Comput Netw 173:107209
7. Hu Z, Tariq S, Zayed T (2021) A comprehensive review of acoustic based leak localization method in pressurized pipelines. Mech Syst Signal Process 161(2):107994
8. Xiao R, Joseph P, Li J (2020) The leak noise spectrum in gas pipeline systems: theoretical and experimental investigation. J Sound Vib 488:115646
9. Xiao R, Hu Q, Li J (2021) A model-based health indicator for leak detection in gas pipeline systems. Measurement 171:108843
10. Xiao R, Joseph P, Muggleton J, Li J (2022) Limits for leak noise detection in gas pipes using cross correlation. J Sound Vib 520:116639
11. Li S, Zhang Y (2023) Leak detection and localization in water supply pipelines: field tests on a pipeline in service. Technical report, LSHM -2023-01. Tongji University, Shanghai
12. Lu P, Lalam N, Badar M, Liu B, Chorpening BT, Buric MP, Ohodnicki PR (2019) Distributed optical fiber sensing: review and perspective. Appl Phys Rev 6(4):041302
13. Li S, Peng R, Liu Z (2021) A surveillance system for urban buried pipeline subject to third-party threats based on fiber optic sensing and convolutional neural network. Struct Health Monit 20(4):1704–1715
14. Li S (2022) A video/audio surveillance system for third-party threats on pipelines under roads. China Patent, 202210922512.8

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