

An Accurate Leakage Localization Method for Water Supply Network Based on Deep Learning Network

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An accurate leakage localization method for water supply network based on deep learning network

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Abstract

In the water supply network, leakage of pipes will cause water loss and increase the risk of environmental pollution. For water supply systems, identifying the leak point can improve the efficiency of pipeline leak repair. Most existing leak location methods can only locate the leak point approximately to the node or pipe section of the pipe network, but cannot locate the specific location of the pipe section. This paper presents a framework for accurate location of water supply network leakage based on ResNet. The framework is to pinpoint leaks to specific locations along the pipeline. The leakage of two kinds of pipe networks is simulated. For a pipe network containing 40 pipes, the positioning accuracy of the pipe section is 0.94, and the MSE of the specific location of the leakage point is 0.000435. For the pipe network containing 117 pipes, the positioning accuracy of the pipe section is 0.91, and the MSE of the specific location of the leakage point is 0.0009177, and the leak location ability under different sensor arrangements is analyzed. Experiments verify the robustness and applicability of the framework.

Keywords Leakage localization · Water distribution network · Deep learning · Water loss management

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1 Introduction

Water loss is a key issue in the management of water distribution systems, because in addition to water consumption, it leads to the use of additional energy and chemicals for water treatment and supply, and carries the risk of bacterial and pollutant contamination (Fontanazza et al. 2015). In addition to these hydraulic and water quality impacts, pipeline rupture can also cause damage to surrounding infrastructure (such as ground collapse), posing a serious threat to public safety (Guo et al. 2013). The impact of water loss in urban water supply systems on water and energy resources and the quality of public services has become a continuing global challenge (Duan 2018; Del Teso et al. 2019). For example, in 2016, more than 100 pipe breaks were recorded in Guangzhou, China, which significantly affected the service quality of urban WDSs (Zhang et al. 2016). In addition, they often lead to social impacts such as water supply disruptions and traffic delays (Berardi et al. 2008). Therefore, the precise location of the leak is critical to effectively restore the water supply.

In the past century, the fluid transportation through pipelines and pipeline networks has made great progress, and the leakage detection technology (WDN) of water supply network has been developed for more than twenty years. Commercial departments now have a variety of hardware-based leak detection equipment (Aghda et al. 2018). Similarly, software-based leak detection algorithms have been proposed in recent studies, including steady-state and transient-state (Zhou et al. 2019, Xing et al 2019). Hardware-based leak detection technology equipment can be roughly divided into " out of tube " or external equipment and " in tube " or robot equipment. Most software-based leak detection methods run under steady-state conditions (Perez et al. 2014). These technologies are based on the analysis of flow rate, pressure, consumer demand or acoustic data collected from a large number of sensors to collect enough information from the pipeline system. Two different machine learning classifiers based on linear discriminant analysis (LDA) and neural network (NNET) were developed to determine the probability of leakage of each node in WDN (Irofti et al. 2020). Three transient signal decomposition methods are presented and evaluated, which are used to train artificial neural network to identify burst location and calculate leakage flow (Manzi et al. 2019). (Xu et al. 2020) proposed

and verified a real-time leak detection method of water distribution network based on data drive. A unique integration of interference extraction and isolation forest technology is used to enable the detection of subtle burst signals from pressure data. Many attempts have been made in recent studies to locate which pipeline leaks. Some of the methods are to classify the pipeline to form several areas, and then locate it in this area. For example, a leakage detection model (DBSCAN-MFCN) based on density-based spatial clustering application with noise (DBSCAN) and multi-scale Full convolutional network (MFCN) is proposed to manage water loss. To reduce the number of categories, DBSCAN divides a large water network into several partitions to detect leaking areas (Hu.et.al 2021). (Grueiro et al. 2021) proposed a leak detection, estimation and location method combining data-driven and model-based methods. Deep neural network is used in leak detection task. Then, gaussian process regression is used to estimate the leakage size range. Some methods are positioned directly on the pipeline. A paper proposes a burst position recognition framework based on fully linear dense network (BLIFF). The framework can effectively narrow down the potential burst area to one or more pipelines (Zhou et al. 2019). A new leak detection method based on pipeline flow sensitivity matrix is proposed. The sensitivity matrix of pipeline flow to node pressure and pipeline flow is derived. Then, the least square method based on pipeline flow sensitivity is used to fit the actual state of the pipeline network (Geng et al. 2019).

Machine learning algorithms, such as traditional support vector machines, artificial neural networks (ANN), and clustering have been used to detect and or locate leaks (Romano et al., 2014; Wu et al. 2016), the feature extractors of these methods need to be manually set, and it is difficult to learn for complex features. In recent years, as a new branch of artificial neural networks, deep learning technology (Le Cun et al. 2015), has become a tool for pattern recognition and feature recognition. Compared with machine learning algorithms, deep learning methods can learn relatively complex functions through data and can automatically extract features. Convolutional neural network (CNN) is a type of deep learning, often used for feature extraction and classification (Han et al. 2020) Since AlexNet, the most advanced CNN architecture has become deeper and

deeper. AlexNet has only 5 convolutional layers, and the subsequent VGG network (Simonyan and Zisserman 2014) and GoogleNet (Szegedy et al. 2015) have 19 and 22 layers respectively. Due to the vanishing gradient problem, deep networks are difficult to train. Therefore, (He et al. 2016) proposed a new densely connected convolutional network (ResNet) architecture. The residual network is characterized by easy optimization and can increase the accuracy by adding considerable depth. The internal residual block uses jump connections, which alleviates the problem of gradient disappearance caused by increasing depth in the deep neural network, strengthens the propagation of features, and has better accuracy. Therefore, this paper proposes a leak detection and location model based on ResNet to improve the accuracy of detection.

In the current research work, most of the leakage location of the water supply network is located at the node of the pipe network. Some studies have also tried to locate the pipe section where the leak is located. Some methods use the clustering method to divide the pipe network, and the cluster number of the pipelines was used as the category label. Some methods directly locate the leaking pipeline, but the research on the location of the specific location of the leak on the pipeline is very lacking. Therefore, this paper proposes a ResNet-based precise identification framework for the location of the leak. It can effectively identify the precise location of the leak.

2 Method

Based on the hydraulic model of WDN, the ResNet-based leakage precise positioning framework of water supply pipe network is proposed in this paper to extract the characteristics of pressure mode when each pipe burst occurs. For any emergency, the pressure drop response caused by the emergency outlet is different at different nodes of the WDN and in different pipelines. The leaking pipeline is identified through the classification process, and the leak is located through the regression process. Section 2.1 introduces the framework structure of precise leakage localization, 2.2 introduces the backbone network of framework based on ResNet. 2.3 introduces the Multi-supervision module structure, Section 2.4 introduces the preparation process of dataset.

2.1 Water supply network leakage precise Location Identification framework based on ResNet

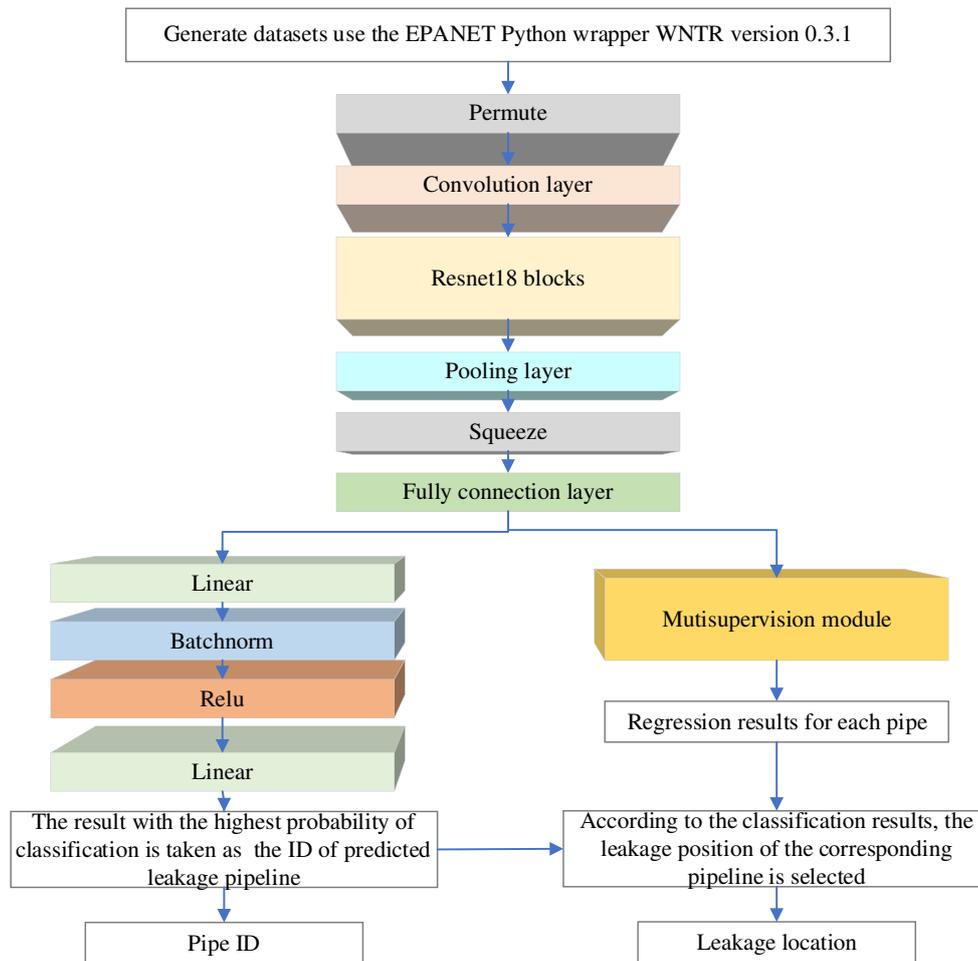


Fig. 1. Frame structure

Fig. 1. shows the flowchart of the proposed precise positioning framework. The framework can be roughly divided into four parts, which are dataset generation; ResNet training; classification process and regression process. The first step of the framework is to set different leakage sizes and locations according to the hydraulic model. First, through simulation obtain pressure data at each node of the pipe network. Then, depending on the nodes that the sensors place, data at corresponding nodes are selected and input into ResNet network. The output of the network is classified and regression respectively. the output of the classification is the probability value P_n of leakage of each pipeline, and the corresponding pipeline ID with the maximum probability value is selected as the classification result, that is, the judged leakage pipeline. For the regression process, regression is performed for each pipeline sample to output its corresponding leakage position L_{on} .

According to the classification results, the regression result of the corresponding pipeline is selected, which is the specific location of leakage on the pipe section. The process is shown in Fig. 2.

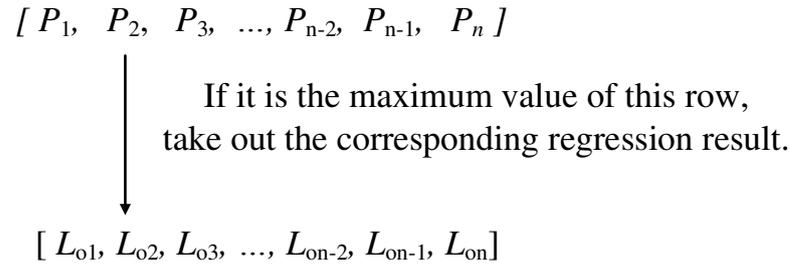


Fig. 2. The extraction process of leakage localization results.

In Figure. 2, the value of n is N_{pipe} , P_n is the probability value of leakage of each pipeline, L_{0n} is the output of corresponding leakage position. The shape of the output prediction of classification process is $B \times N_{pipe}$, In which B is the batch size, that is the amount of input data per training. N_{pipe} is the number of pipes in a water supply network.

2.2 The backbone network of framework based on ResNet

This paper constructs a ResNet based network architecture with a convolution layer to reduce the size required for storage. Residual block which is shown in Fig. 3 is used to extract information and a global average pooling is used for the feature pooling. The network connects a fully connected layer as output. Regression and classification tasks are performed for the output of the network respectively.

The ResNet was first proposed by (He et al. 2016), explicitly reformulate the layers as learning residual functions with reference to the layer inputs, instead of learning unreferenced functions.

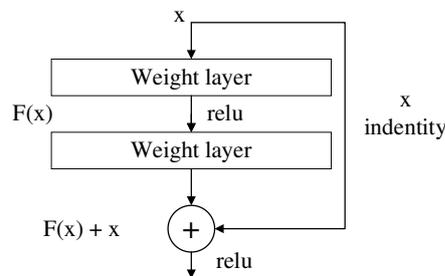


Fig. 3. Residual block in a ResNet

Experience shows that deeper neural networks can extract more complex information, and better results

can be obtained by making neural networks deeper. As the gradient disappears, with the increase of network depth, the accuracy of the network becomes saturated or decreased. Residual learning framework is used to solve this problem. If the input is x , the feature that the architecture should learn is $H(x)$, but in the residual learning framework, it is expected that the residual $F(x) = H(x) - x$ can be learned, and the original feature that should be learned is $F(x) + x$, so that the network performance will not decrease. When the residual error is 0, the stacking layer is only mapped identically, at least the network performance will not decrease, and in fact, the residual error will not be 0, which will enable the stacking layer to learn new features based on the input features, thus having better performance. The residual learning framework also reduces the learning challenge, because the residual is usually small, which means that ResNet needs to learn less information than the traditional framework. Compared with most computer vision tasks, the datasets input in this paper is simpler, so ResNet18 is chosen as the backbone network.

2.3 Multi-supervision module structure

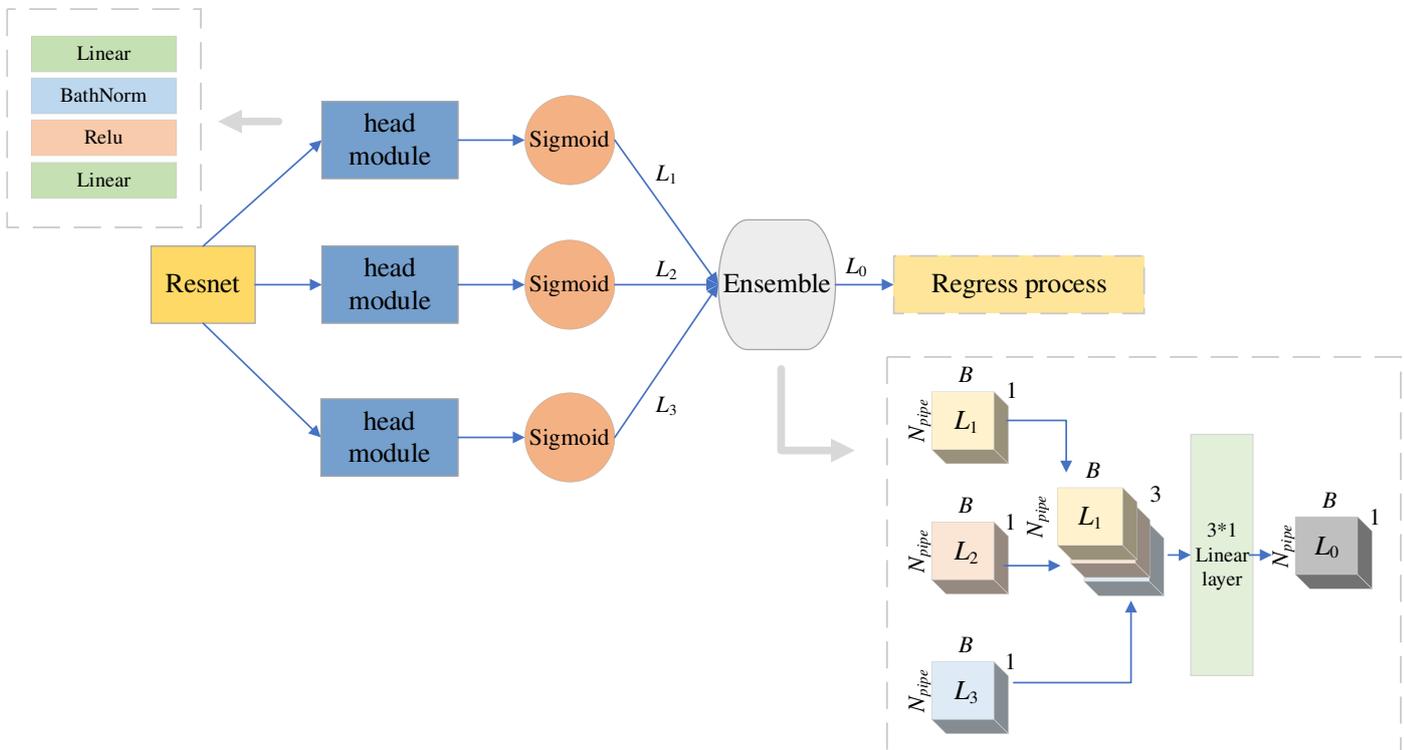


Fig. 4. Multi-supervision module structure

In the regression process, this paper proposes a multi-supervision module to speed up the regression convergence of the model, which can improve the convergence ability of the network for the poorly fitting

network. The structure of the module is shown in Fig. 4. The output of ResNet flowing through the head structure three times, which consists of a full connection layer, Normalization process, Rectified Linear Unit, and a full connection layer. Each output is activated by sigmoid function. The output of the three times is ensembled and the regression is performed together.

The structure of the Multi-supervision is described as follows:

1. Output results from ResNet pass through header structure and activation function, and then output L_1 .
2. Step 1 is executed three times, and three outputs L_1, L_2, L_3 are obtained. This moment the shape of the output L_n is $B \times N_{pipe}$, in which B is the batch size, that is the amount of input data per training, N_{pipe} is the number of pipes.
3. Upgrade the dimension of L_n , the shape of L_n is $B \times N_{pipe} \times 1$. L_n is spliced together and form L_0 . The shape of L_0 is $B \times N_{pipe} \times 3$.
4. L_0 through a 3×1 linear layer, dimension is transformed into $B \times N_{pipe} \times 1$. Perform dimension reduction on L_0 to obtain an output with a $B \times N_{pipe}$ shape.

2.4 Datasets preparation

The framework proposed in this paper is data-driven, so the amount of information contained in the datasets has an important impact on the accuracy of deep learning tasks. In this paper, the generated datasets consist of differential pressure data, these data contain information on different leak locations and leak sizes. The first step, the network without leakage was simulated to access pressure data under normal conditions of each node. And then, define a new node and simulate leakage by setting the water requirement and flow rate of this node. In order to get the characteristics of pressure fluctuation caused by the leakage, subtract the pressure value at each point with leakage from the pressure value without leakage, take the differential pressure as the value of the datasets.

2.4.1 Datasets generation

For a water supply network, the length of each pipe varies, so when determining the leak location of the pipe, use the EPANET Python wrapper to get the start and end nodes of the pipe. The location of leak point is confirmed by declaring its location between the start node and end node. For example, when the leakage position is 0.5, indicates that the leak point is in the middle of the pipe. In the actual water supply network. In the actual water supply network, leaks can occur at any point in the network. To simulate the real situation, using uniform random number to define the leakage position. The random sample ranges from 0 to 1, excluding 1.

For leak size Settings, leaks are modeled with a general form of the equation proposed by Crowl and Louvar (Crowl et al.,2019) where the mass flow rate of fluid through the hole is expressed as:

$$Q_l = C_d A p^\alpha \sqrt{\frac{2}{\rho}} \quad (1)$$

where Q_l is the leak demand, C_d is the discharge coefficient, and for turbulent flow taken as $C_d = 0.75$, A is the area of the hole, α is an exponent related to characteristics of the leak, where $\alpha = 0.5$ assuming a steel pipe with a large hole, p is the gauge pressure, and ρ is the density of the fluid.

To obtain the leakage diameter information, the formula is expanded as:

$$Q_l = \frac{C_d \pi D_{leak}^2}{4} p^\alpha \sqrt{\frac{2}{\rho}} \quad (2)$$

Among them, D_{leak} is the leak diameter. In this paper, by introducing the leakage factor to adjust the diameter of the leakage, control the size of the leakage:

$$D_{leak} = D_{pipe} f_{leak} \quad (3)$$

Where, D_{pipe} is pipe diameter, f_{leak} is the introduced leakage factor. For a pipe network, each pipe has a different diameter. Therefore, f_{leak} is introduced to simulate the randomness of the leakage size under the actual operation of the pipe network, and f_{leak} is a random sample value of 0.2-0.5 subject to uniform distribution.

Because leaks in the water supply network are random, every pipe has the potential to leak. So, when the datasets are generated, each pipe is set as a potential leak pipe. In the simulation, each pipe is traversed, the leak location of each pipe and the size of leakages are random. When building the datasets, each run simulated a leaking pipe, its location along the pipe, and the leak diameter. The model traverses every location and diameter combination to generate the full network state simulations. After each simulation, the differential pressure from all of the nodes were saved to the datasets. The flowchart of data generation is shown in the Fig.

5.

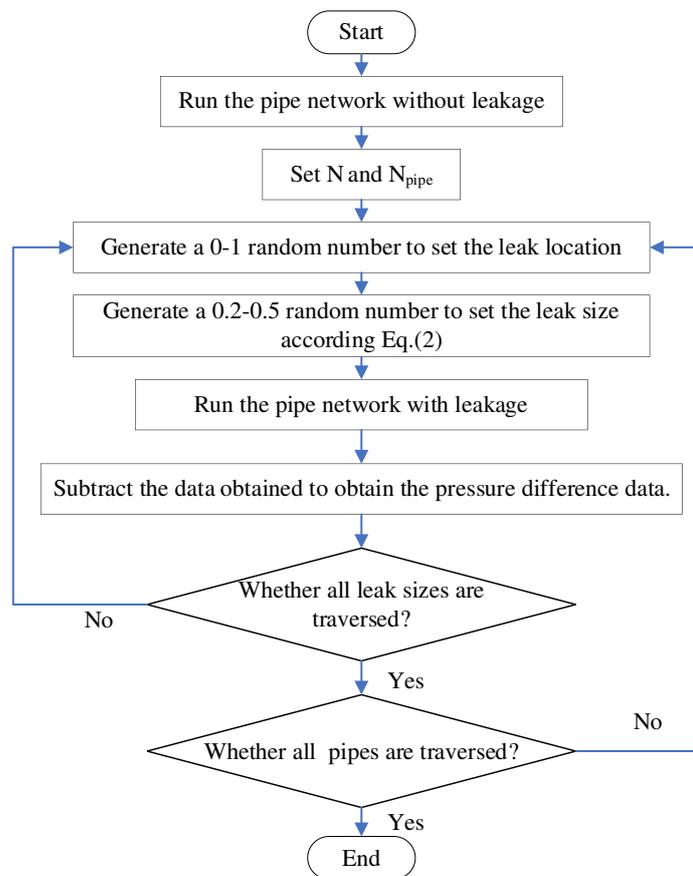


Fig. 5. The flowchart of data generation

The main steps in datasets generation are summarized as follows:

1. Run the pipe network without leakage and obtain the pressure data without leakage of each node.
2. Set the number of simulations for each pipeline N , the leakage size of each simulation is random. Control the size of the dataset by adjusting N . The number of generated data is $N \times N_{pipe}$.

3. Set the location of the leak point. The random sample number of 0-1 following uniform distribution was used to define the leak location.
4. Set the leak size. Introducing leakage factor f_{leak} , The random sample number of 0.2-0.5 following uniform distribution was used to define the leakage factor. The leakage diameter D_{leak} is the product of the leakage factor and the pipe diameter D_{pipe} . The generated leakage flow can be calculated by Eq. (2).
5. Set the label of datasets: leak pipe, leak point location.
6. Run the pipe network with leakage and obtain the pressure data with leakage of each node.
7. Subtract the data obtained in steps (1) and (6) to obtain the pressure difference data.
8. Repeat steps (2) - (7) until the set simulation times for each pipe are reached and each pipe is traversed.

2.4.2 Data preprocessing

Since the pressure range of different instruments may vary depending on the position and height of the instruments, it is necessary to standardize the pressure values of different instruments in order to make the pressures of different instruments more comparable. In addition, standardization helps to improve the accuracy and efficiency of the training network. Before training the algorithm, the data must be standardized to a uniform scale. After normalization, the mean and standard deviation of each feature in the data set are 0 and 1 respectively. The data set is composed of pressure difference data for each node. Therefore, the normalized calculation formula is as follows:

$$\bar{x} = \frac{x - \mu_{data}}{\sigma_{data}} \quad (4)$$

where x and \bar{x} represents the original data and the normalized data, respectively. μ_{data} and σ_{data} represents mean and variance of data, respectively.

3 Case studies and results

Two cases (a benchmark network and a relatively complex network) are studied to demonstrate the reliability and applicability of the proposed framework. For the training process, N is set to 300. And generate $N \times N_{pipe}$ leaking data as the training samples. To test the performance, N is set to 30. After being

trained, predicts the location of the leakage in the test samples. Positioning accuracy for leaking pipeline of a test sample can be assessed by Eq. (5):

$$Accuracy = \frac{n_{correct}}{n_{total}} = \frac{TP + TN}{TP + FN + FP + TN} \quad (5)$$

TN is True Negative, the number of negative classes predicted as positive classes can be called false positive rate. FP is False Positive, the number of negative classes predicted as positive classes can be called false positive rate. FN is False Negative, the number of positive classes predicted as negative classes can be called the false negative rate. TP is True Positive, predict positive classes as the number of positive classes.

The effect of accurate location of leaks can be evaluated by Eq. (6):

$$MSE = \frac{1}{m} \sum_{i=1}^m (y - \hat{y})^2 \quad (6)$$

Where y is the true values on the test set, which is expressed by Eq. (7). \hat{y} is the predicted value on test set, m is the number of test set samples.

$$y = \frac{L_{leak} - L_{start}}{Length_{pipe}} \quad (7)$$

Where L_{leak} is the leak point location, L_{start} is the pipeline starting point position, $Length_{pipe}$ is Is the length of the corresponding pipe.

4.1 Case1

Anytown (Walski et al.,1987) network, which is a small WDN with high loop, is adopted in this paper to illustrate the application of the proposed scheme and its performance under different Settings. The network consists of 19 nodes, 40 pipes, 3 reservoirs and 1 water pump. Pipe diameter is 200mm-400mm, and node basic demand is 12.5L /s-63.1L/s and $N_{pipe} = 40$.

It is assumed that the potential burst area is the entire network, that is, every pipeline in the network is the potential location of the leakage. The placement positions of different sensors include three different situations of the number of sensors N_m in the pipe network, as shown in Table 1 (Zhou et al.,2019) and marked in the Fig. 6.

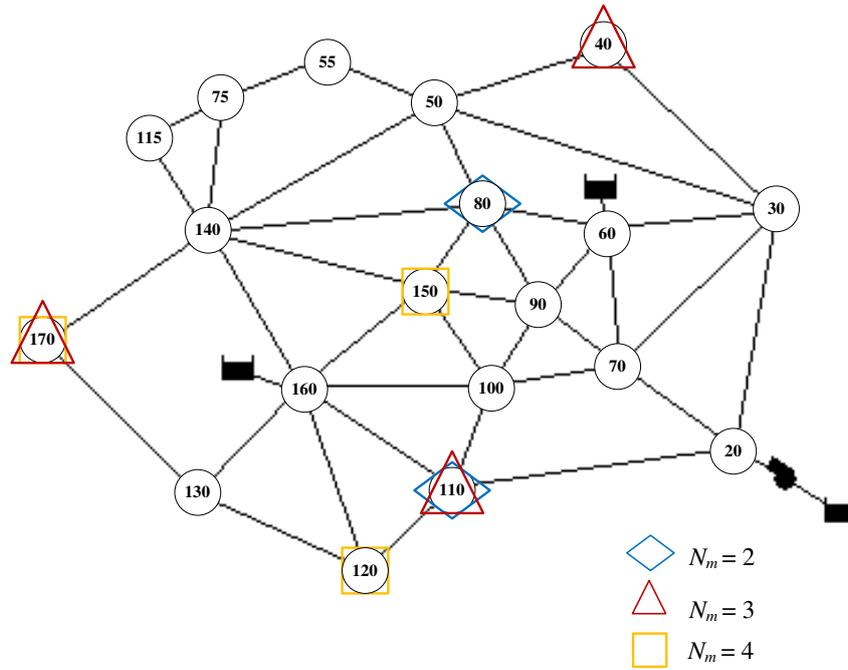


Fig. 6 Anytown network layout and different number of sensor locations.

For a water supply pipe network, in actual applications, the sensor layout is not unique. Therefore, the experiment has conducted research on various sensor layouts. In the analysis, the number of sensors is changed to a different value each time, while the other parameters are left as default. In addition, for the problem that data set noise has a great influence on the model accuracy, 30-40dBz Gaussian white noise is added to the dataset and test set to verify the application type of the framework. The results of different sensor arrangements are shown in Table 1.

The result of the classification process under different N_m values are presented in Fig. 7. It can be seen that the accuracy increases with the growth of the number of sensors. In the case of adding noise, when $N_m = 2$, the class accuracy is 0.76, However, the class accuracy become higher than 0.9 if $N_m = 3$. This indicates that the number and location of sensors are related to the leak detection results of the framework.

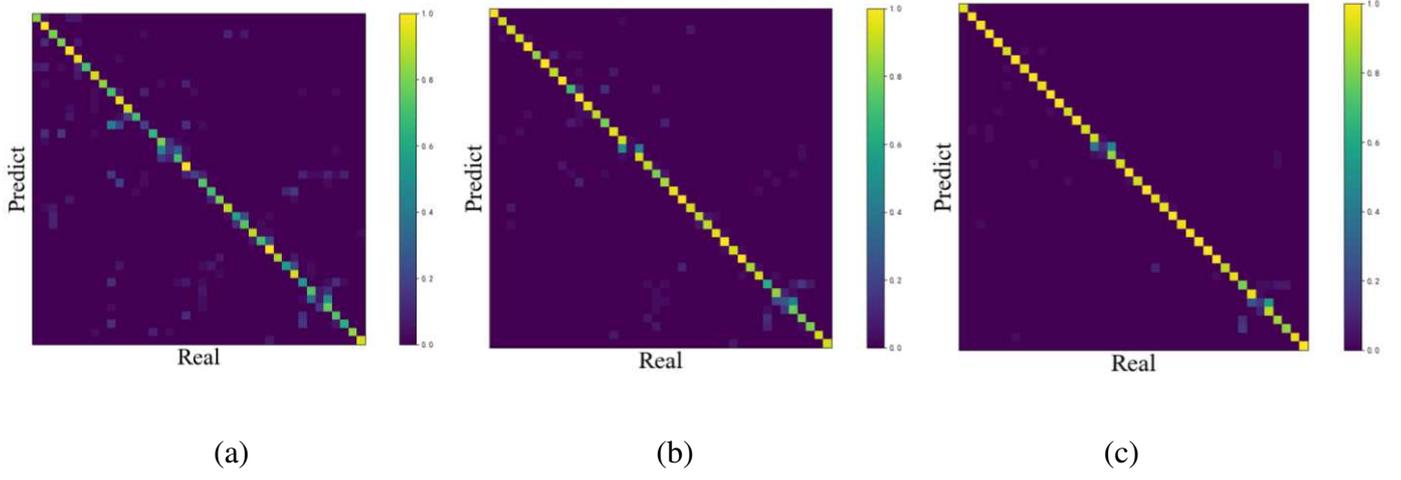


Fig. 7 The confusion matrix for predicting leaky pipelines with different number of sensors, (a) for two sensors; (b) for three sensors; (c) for four sensors.

The result of the regression process under different N_m values are presented in Fig. 8. The abscissa is the actual leak location, and the ordinate is the leak location predicted by the framework. As can be seen from the figure, scattered points are mostly distributed on the diagonal. This shows that the location of the leakage point on the pipeline is mostly correct. Similarly, the positioning results under different N_m values were compared. As the number of sensors increases, the positioning capability of the framework improves.

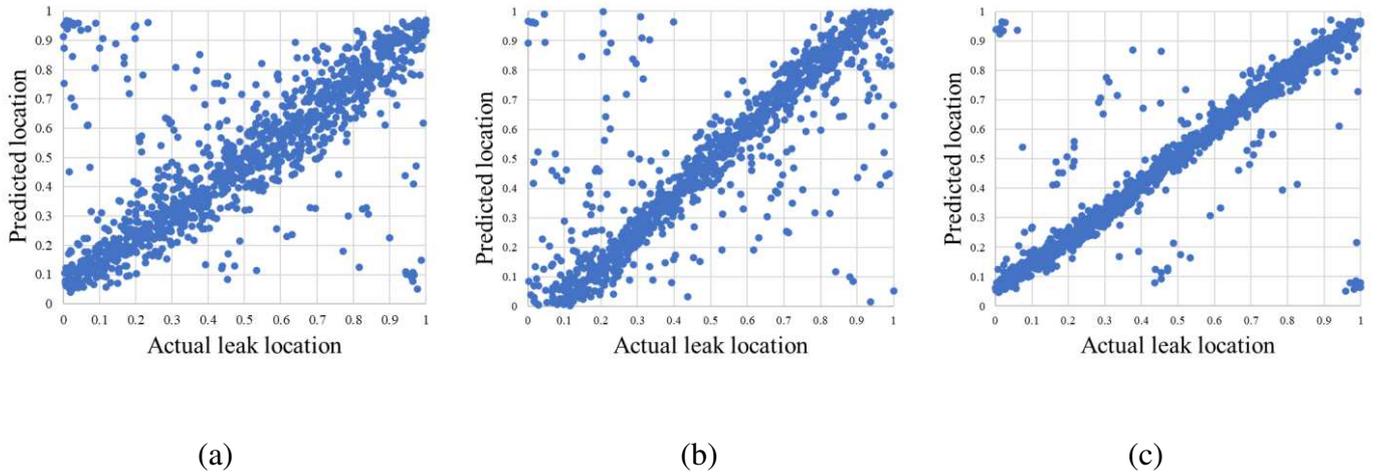


Fig. 8 Scatter plot of predicted and actual positions with different number of sensors, (a) for two sensors; (b) for three sensors; (c) for four sensors.

Table 1 Leakage location accuracy under different conditions

Optimal Meter Locations	Number of sensors	Accuracy	Accuracy(with noise)
Node 170,150,30,120	4	0.94	0.89
Node 10,40,170	3	0.92	0.86

Training epoch indicates the number of times that network repeatedly learns the same training dataset. The default training epoch used in our study is 200. The effects of training epoch are presented in Fig. 9. As shown in Fig. 9a and Fig. 9b. The class loss and the local loss of model decreases with the iteration and finally stabilizes. As shown in Fig. 9c, Proposed framework can achieve good results ($acc > 0.80$) after 45 training epochs, with minor improvement ($acc > 0.90$) if over 75 training epochs is used. The regression MSE changes are shown in Fig. 9d, the MSE tends to be stable after a period of oscillation, and is tend to be 0 during the training. In other words, most of these leaks are accurately located.

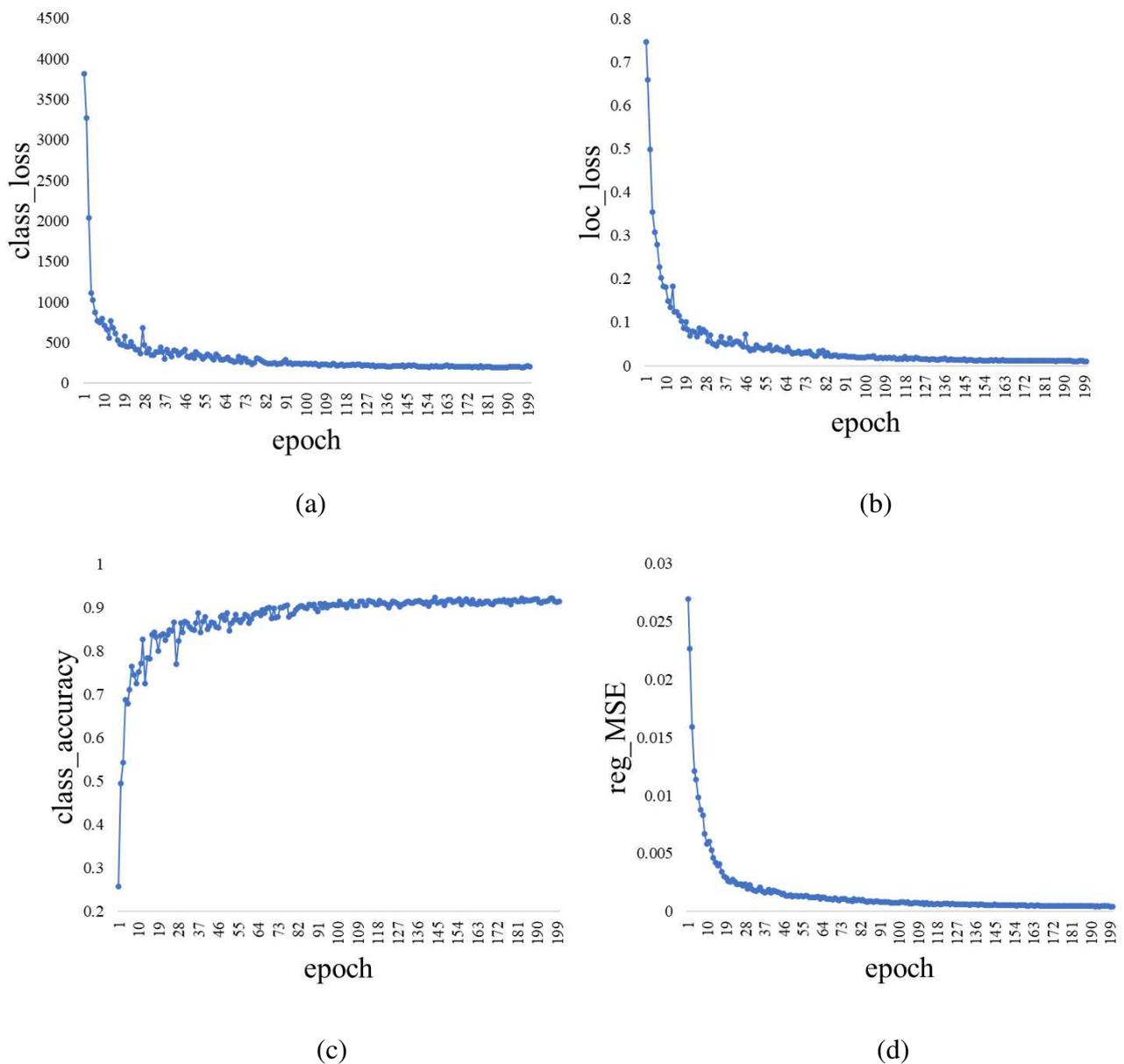


Fig. 9 Curves of various indicators, (a) Classification loss curve; (b) Regression loss curve; (c) Classification accuracy curve; (d) Regression MSE curve

4.2 Case2

A relatively complex network Net3 was used to test the reliability of the framework. The network layout, as shown by 117 pipelines, 92 contacts and 2 reservoirs and of 3 pools. Assumes that the potential attack area for the entire network. Pipe diameter is 202mm-2514mm, the pipe length is 3m-3000m, and $N_{pipe} = 117$. There are four pressure sensors and they are marked with red dots in the Fig. 9 (Li Et al.,2019).

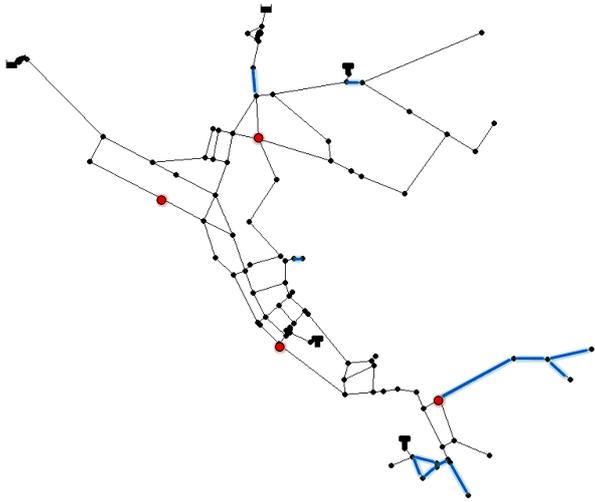


Fig. 10 Location of sensors and location of pipeline segment with poor detection effect.

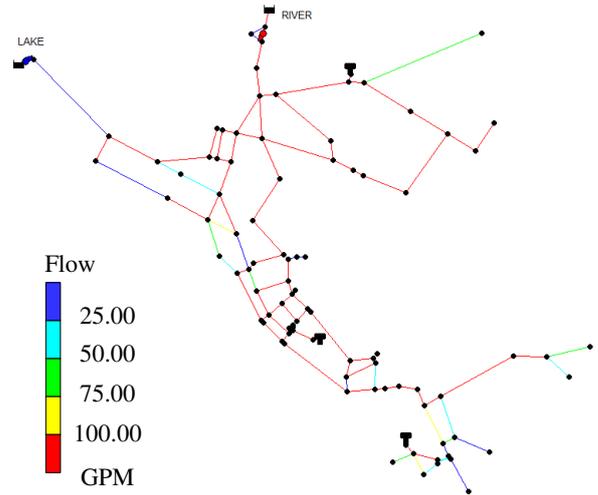


Fig. 11 Net3 Water flow distribution diagram

Each pipe in the network was analyzed, for the pipe section with poor positioning accuracy, they are marked with blue in Fig .10. The hydraulic analysis of net3 pipe network is carried out, running results are shown in Fig .10. The blue section has a low flow rate, which is about 0.3-2.3 L/s, while pipes with relatively large flow that about 6.3-828L/s are marked in red. By comparing Fig. 10 and Fig. 11, it can be seen that for the pipe section with small flow rate, the positioning accuracy is relatively reduced. Because when the pipeline flow is small, the pressure in the pipeline will be lower, and the corresponding pressure difference caused by leakage will be relatively small, which will affect the positioning effect.

Classification results for Net3 is shown in Fig.12a, the abscissa is the actual leaking pipeline, and the ordinate is the predicted leaking pipeline. Predictions of leaky pipes are mostly correct. It can be shown in Fig. 12b, as the number of iterations increases, the accuracy can reach more than 0.90.

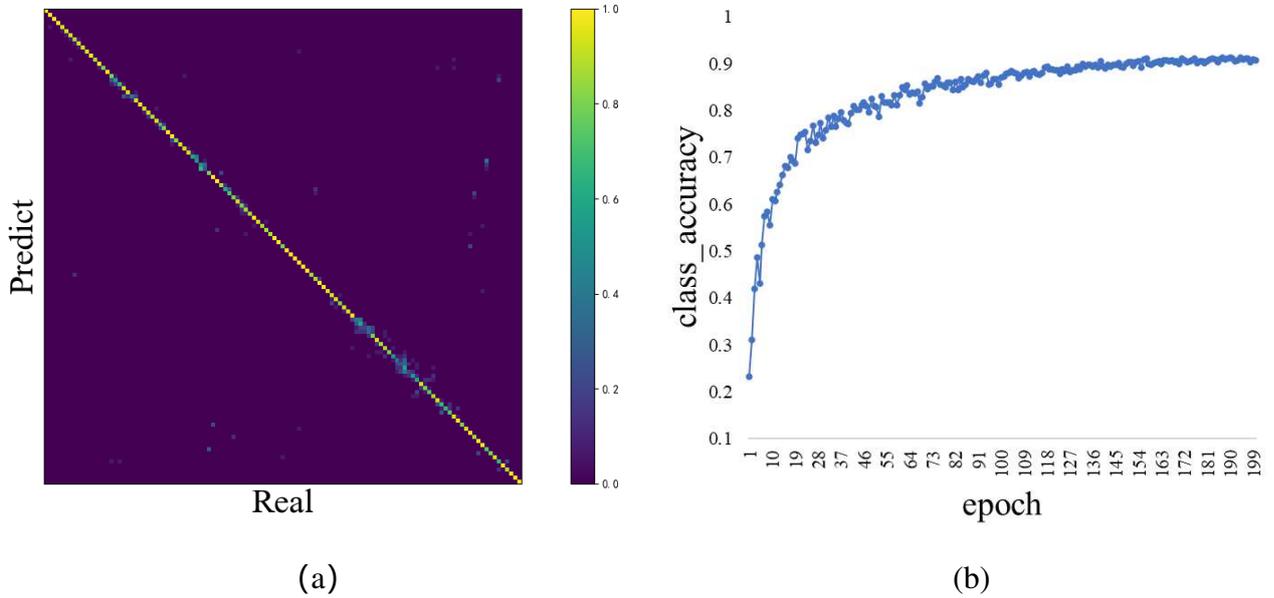


Fig. 12 (a) Classification confusion matrix; (b) Classification accuracy curve;

Regression loss curve without multi-supervision is shown in Fig. 13a, while the regression loss curve under multi-supervision is shown in Fig. 13b. It can be seen from the figure that the convergence speed of the model is faster when adding multi-supervision.

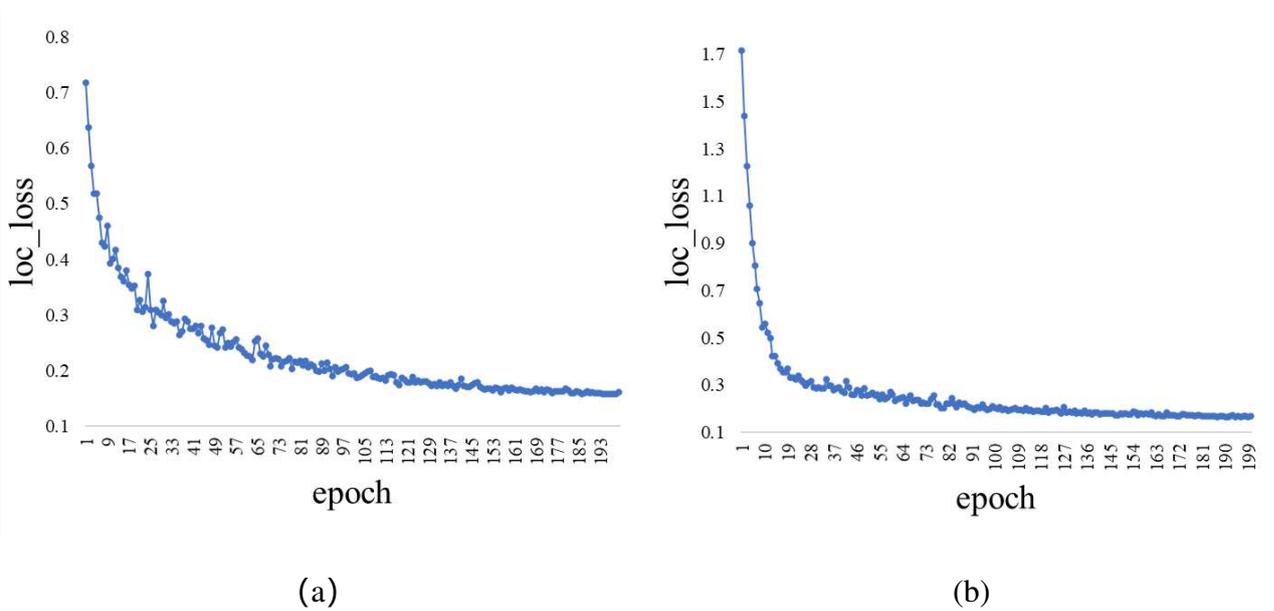


Fig. 13 (a) Regression loss curve without multi-supervision; (b) Regression loss curve under multi-supervision.

The regression results are shown in Table 2. It shows the location results of partial pipeline leakage points. It can be seen that for most of the leakage points, the predicted location is close to the actual leak location.

Table 2 Real and predicted locations of partial leaks

real	predict	real	predict	real	predict
0.27128771	0.25215074	0.27490038	0.24260521	0.33107056	0.31154203
0.4412435	0.45087796	0.48991961	0.06277874	0.52721745	0.50581014
0.55113812	0.5669899	0.564552317	0.58035916	0.60775638	0.5967347
0.60789598	0.2966982	0.613707242	0.6844515	0.681601759	0.6904852
0.751500710	0.7499844	0.755020817	0.74956125	0.7866898625	0.77491295
0.881704730	0.09208471	0.8868529427	0.89258546	0.8925854680	0.88554525
0.907860761	0.89181936	0.9375532263	0.90601635	0.009070198	0.049300946

5 Discussions

The proposed framework is verified by two pipe networks. Case 1 is a pipe network of Anytown with 40 pipelines and 19 nodes. It is applied to an analysis of different sensor layout schemes. As the number of sensors increases, so does the positioning capability. In the case of using four sensors, the positioning accuracy of the pipeline can reach 0.94, and the MSE of the specific location of the leakage point is 0.000435. With the addition of 30-40dB noise, the positioning accuracy of the pipeline can reach 0.89. With the addition of noise signals, the framework performs well. Case 2 is a pipe network Net3 with 117 pipelines and 92 nodes. The positioning accuracy of the pipeline can reach 0.91, the MSE of the specific location of the leakage point is 0.0009177. The pipelines whose positioning of the pipeline progress is below 0.80 are analyzed. Most of them are pipe sections with small traffic in the pipe network. The smaller the flow rate makes the pressure of the pipe section smaller, so the characteristics of leakage are not obvious. In addition, experiments have shown that when the multi-supervision module is added, the network converges faster. For the precise positioning results, real and predicted locations of partial leaks are listed to visually see the accuracy of the positioning.

6 Conclusions

A leakage localization method for urban water supply pipe network based on ResNet network is proposed. Use WNTR to generate pressure difference data. After ResNet extracts the characteristics of the leakage

pressure difference change, classification and regression are performed respectively, and a multi-supervision mechanism is introduced in the regression process to accelerate the convergence of the model. Predict leaking pipelines through the classification process. Predict the specific location of the leak on the pipeline through the regression process. The proposed framework for accurate leak detection was applied to two water distribution pipe network cases. Experiments show that the method has reached a certain detection accuracy. In the current research, there is a lack of research on locating to the specific location of specific pipe sections for leak detection of water supply pipe network. This research proposes a possibility for precise location. In the next research work, more optimization methods can be adopted to improve the neural network structure; when the experimental conditions permit, test on more complex pipe networks and compare with current work.

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Authors Contributions

All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by J Li, WJ Zheng and CG Lu. The first draft of the manuscript was written by WJ Zheng and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

Competing Interests

None.

Availability of data and materials

All authors make sure that all data and materials as well as software application or custom code support the published claims and comply with field standards.

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