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Research on leakage area detection method in water distribution network based on gray wolf optimization

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ABSTRACT

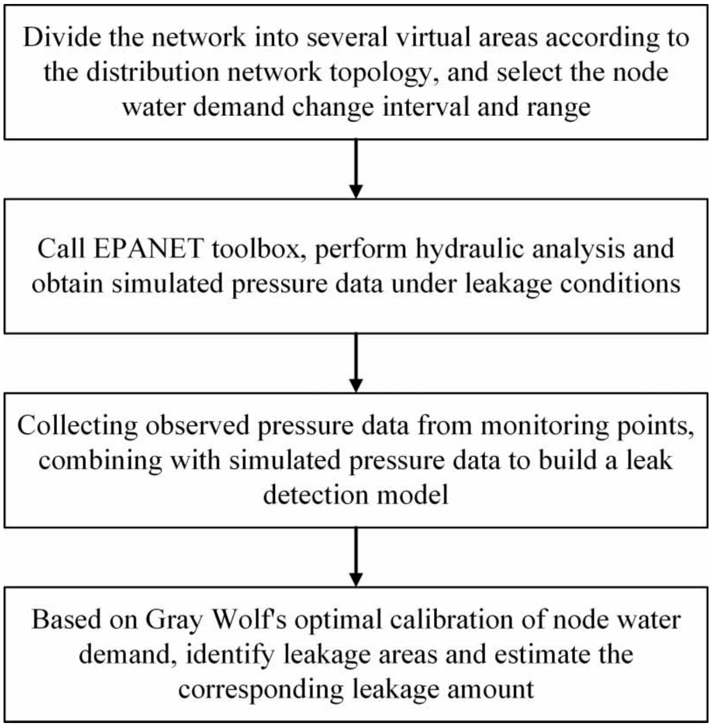
Leakage in a water distribution network (WDN) leads to a large amount of water loss and water pipe pollution and affects residents' domestic water supply. Therefore, network leakage detection significantly saves water resources. The traditional model approach has ample search space in solving large distribution network applications, a challenging and complex leakage detection process and a low detection accuracy. For the above problems, this study proposes a new method of leakage area detection based on gray wolf optimization (GWO). First, the extensive WDN is divided into several virtual areas. Then, the leakage is simulated by the additional water demand of nodes, and the node demand of the distribution network is calibrated based on the GWO algorithm. Finally, the leakage area is identified, and the size of the leakage in that area is estimated. The method was experimented on in two cases, simulating single-point leakage and multi-point simultaneous leakage, respectively. The results show that the method estimates the size of leakage in the corresponding area based on accurate identification of leakage areas, and the detection error of leakage is within 17.14%. The method provides water workers with guidance on leak detection, significantly reducing staff time to repair pipes.

Key words: gray wolf optimization algorithm, leakage area, leakage detection, water distribution network

HIGHLIGHTS

- Use a small number of monitoring sensors to detect the leakage status of pipeline networks, identify leakage areas and estimate the leakage amount.
- A multi-leakage point detection method based on gray wolf optimization is proposed, which can effectively simulate the actual pipe network leakage situation.
- A method of dividing multiple virtual areas for leak detection is proposed, which improves the accuracy of leak detection.

GRAPHICAL ABSTRACT



1. INTRODUCTION

Water is a vital resource for human survival, and population growth and climate change are leading to severe water shortages. By 2030, water demand is expected to increase by 40% compared with 2017 (Endo *et al.* 2017). As the overall size of urban water distribution networks continues to expand, water distribution network (WDN) systems thus serve the vital task of transporting water for residential use. However, urban pipes are prone to ageing when buried underground for years. Leakage can easily occur at pipes and their connections, affecting residents' domestic water use and leading to water loss and energy loss. Therefore, researchers and water workers have been widely concerned about the leakage of water distribution networks in the past decades (Pérez *et al.* 2011; Fang *et al.* 2019; Xie *et al.* 2019).

Commonly used leak detection methods can be summarized as hardware- and model-based methods. The key to hardware-based methods lies in the mutual correlation technique, where specific sensors are placed at both ends of the pipe for leak detection (Hu *et al.* 2021). Due to the complex environment and low signal-to-noise ratio of the actual leakage situation, it is sometimes difficult to collect the leakage signal effectively. Therefore, researchers usually use wave decomposition and transformation techniques to reduce or eliminate the noise of the leakage signal (Brennan *et al.* 2019). Brennan *et al.* (2019) demonstrated that accurate time-delay estimates could also be obtained by using polar co-correlation on simulated and measured data as long as the excess zeros in the noise data are retained. The results show that severe shear has no significant effect on normalized co-cause failure and the location of leaks. This result has important implications for the development of leak noise correlators. Cody *et al.* (2020) addressed the problem of detecting and locating leaks in water distribution pipes using linear prediction techniques. The method uses data-driven pipeline anomaly detection and features extracted from linear programming coefficients representing the underlying acoustic signal. The results show that shorter segments of the linear programming (LP) reconstructed signal can achieve similar levels of accuracy as using longer segments of the original time series, a key advantage in long-term online implementation applications. Gao *et al.* (2006) compared the ability of various time-delay estimators using intercorrelation to localize plastic pipe leaks. The results showed that the error of random noise on the signal measurement was insignificant relative to the resolution of the time-delay estimator for the low-pass filtering characteristics of the pipe. As mentioned above, wave decomposition and transformation techniques are important for signal extraction and noise cancelation. However, the signal measured at the sensor is distorted by wave attenuation and interference in the propagation path. As a result, the leakage signal of small-scale leakage tends to be drowned in the background noise and is difficult to detect. Conversely, model-based approaches are promising and can provide near-complete leakage control solutions for all types of leakage (Vítkovský *et al.* 2000; Zhang *et al.* 2016; Sophocleous *et al.* 2017).

The modeling method is a crucial detection technique in the leakage detection method. Its basic principle is to construct a hydraulic model to simulate the operation of the pipeline, and the model simulation to obtain characteristic data under different leakage conditions, and formulate and solve the inverse problem based on the steady-state model by minimizing the difference between the actual and simulated values (Vítkovský *et al.* 2001; Blocher *et al.* 2020). The method was first proposed by Pudar & Liggett (1992) to solve the inverse problem of pipeline network leakage using parameter identification. In order to try to locate the leakage using pressure data, the method represents the equivalent orifice area of possible leakage as an unknown quantity. The results show that the method can represent the location of the most likely leaky node with probability, although the error is significant. Wu *et al.* (2010) further proposed a leak detection method that calibrates the nodal injector coefficients. The method considers the pressure changes in the pipeline network due to leakage. The simulated leakage amount is related to the node pressure and is solved using a genetic algorithm (GA). The results show that the method can reduce the leakage area to several leakage nodes and their connected nearby pipes. Berglund *et al.* (2017) identify linear combinations of individual simulated leaks capable of simulating pressure variations between normal operating conditions and the leaky pipe network, i.e., the interaction of multiple leaks assumed to be nonlinear can be approximated as linear. The method considers mathematical programming to describe the leakage characteristics of the pipe network efficiently. The results show an approximately linear relationship between the pressure variation and the amount of leakage for leakage coefficients below 20 (two leaks) and 7 (five leaks). Sanz *et al.* (2015) proposed comparison of the calibration parameters with their historical values and determination of the presence of leakage in the pipeline network based on the variation of the parameters. The results show that even considering a small number of sensors, leakage losses that affect the parameter more than the uncertainty of the parameter can be located within 200 m. Hajibandeh & Nazif (2018) considered the different probabilities of leakage occurring for different leakage amounts during the leakage detection process, i.e., areas with high operating pressure are more prone to severe leakage. The results showed that the method could accurately find the leak location or its adjacent joint location. However, the traditional modeling method has an ample search space applied to large distribution networks during the solution process. The leakage detection process is complicated, with low detection accuracy (Zhang *et al.* 2016). Therefore, developing a practical leak detection technology is an urgent task nowadays.

In response to the above questions, a new method of leak detection based on gray wolf optimization (GWO) is proposed in this study. In order to achieve the leakage area identification, the leakage is represented as a combination of leakage of different water demand types. The nodal water demand calibration process is completed based on the GWO algorithm to minimize the difference between the observed and simulated pressures. Finally, the leakage area of the network is identified, and the leakage volume of the corresponding area is estimated. Unlike most previous methods, this method can detect large-scale network leaks, and the number of simultaneous leaks during the simulated leak is unknown.

2. METHODOLOGY

The current study proposes a method to identify leakage areas in the distribution network, which treats the leakage detection problem as an inverse problem-solving process of parameter identification, i.e., a calibration process. The calibration process is achieved through GWO. In particular, this study uses a small number of monitoring sensors to detect the leakage status of the pipe network and identify the leakage areas and estimate the corresponding leakage volume.

2.1. Calibration process

Leakage at any location in the distribution network will result in pressure changes in the network, and these changes depend on the leakage area and its corresponding leakage volume. Therefore, in this study, these pressure changes are used to calibrate the water demand at the network nodes, identify the network's leakage areas and estimate the leakage volume of the corresponding areas. The flow of the leakage detection method is shown in Figure 1.

The method consists of several steps: first, the network is divided into several virtual areas based on the topology of the distribution network and the location of the monitoring points. Secondly, the leakage is represented as a combination of leakage of water demand types, and the leakage is simulated with the additional water demand of nodes. The EPANET Toolbox is called to perform hydraulic analysis and obtain simulated pressure data. Finally, the GWO is used to construct a leakage detection model to estimate the leakage size in each area.

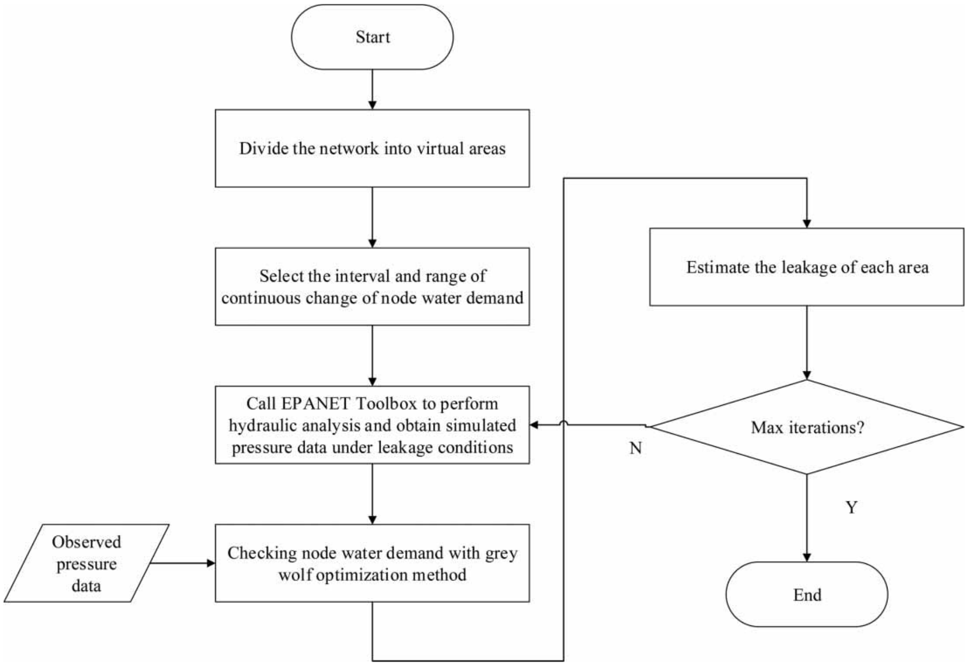


Figure 1 | Leakage detection method in WDN.

Specifically, to minimize the difference between the pipe network's simulated and observed pressure data, the objective function is expressed as shown in the following equation:

$$f(x) = \sum_{np=1}^{NP} w_{np} \left| \frac{Psim_{np} - Pobs_{np}}{Pobs_{np}} \right| \tag{1}$$

where $f(x)$ denotes the objective function, np denotes the node pressure counter, and NP denotes the total number of modeled pressure monitoring points in the pipe network. $Psim_{np}$ is expressed as the np node's simulated pressure data, $Pobs_{np}$ denotes the np node's observed pressure data, and w_{np} denotes the dimensionless coefficient corresponding to the pressure at the np node, calculated by the following equation:

$$w_{np} = \frac{Pobs_{np}}{\sum Pobs_{np}} \tag{2}$$

In order to calculate the actual leakage in each area, we need to calculate and integrate the leakage in each leakage location in that area. Therefore, we propose the following equation:

$$Q_z = \Sigma_{n=1}^{N_z} q_{z,n},\ n \in \{1,\ \ldots,\ N_z\} \tag{3}$$

Q_z denotes the total leakage in calculation area z, $q_{z,n}$ denotes the leakage of leakage node n in area z, n denotes the leakage node index and N_z denotes the total number of leakage nodes in area z.

In the calibration process, each leakage node's amount continuously varies at certain demand intervals, and Equation (4) is proposed:

$$0 \leq \Delta q_n \leq Q_{L},\ n \in \{1,\ \ldots,\ N\} \tag{4}$$

where Δq_n denotes the change interval of node demand, Q_L denotes the maximum change demand of nodes and N denotes the total number of leaky nodes in the pipe network.

2.2. Optimization process

GWO is a novel population intelligence optimization algorithm proposed by Mirjalili *et al.* (2014), and which is an optimization method that simulates the prey predation process of gray wolves. The GWO algorithm has a simple structure, with few parameters to be adjusted. It is easy to implement, in which there are convergence factors that can be adaptively adjusted and an information feedback mechanism that can balance local optimum and global search. The results show that the GWO algorithm has high performance in solving unknown, challenging search spaces and can effectively balance exploration and exploitation capabilities (Ansari *et al.* 2020; Vashishtha & Kumar 2022).

Like other optimization methods, this algorithm simulates the predatory behavior of gray wolf packs by basing on the wolf pack. The mechanism of body collaboration is used to achieve optimization. Four types of gray wolves, the alpha, beta, delta and omega, were used to simulate the leadership hierarchy and hunting mechanism in nature. In addition, three main steps of searching for prey, surrounding prey and attacking prey are implemented for optimization (see Figure 2 for the specific steps).

The concept of the gray wolf individuals in this study's optimization problem is the combination of leakage of different water demand types, and the size of the fitness function is the size of the objective function value. During each iteration, the three gray wolves with the smallest fitness value among the current individuals are retained. Then the positions of other gray wolf individuals are updated based on their position information to obtain finally the optimal solution. Therefore, each gray wolf individual is represented as a leakage matrix as in Equation (5):

$$X^w = [l_1, l_2, \ldots, l_j], j \in \{1, \ldots, J\} \tag{5}$$

X^w denotes the leakage matrix of the w gray wolf individual; l_j denotes the leakage volume of the j node of the simulated pipe network and J is the total number of nodes of the pipe network.

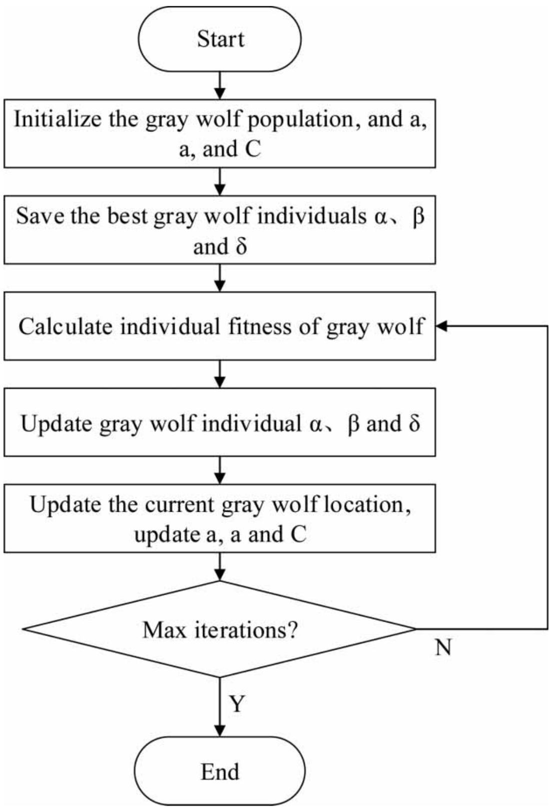


Figure 2 | Flow chart of GWO process.

The leakage amount in each node is updated in each iteration according to the following equations:

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \tag{6}$$

$$\begin{cases} \vec{X}_1 = \vec{X}_a - A_1 \cdot \vec{D}_\alpha \\ \vec{X}_2 = \vec{X}_\beta - A_2 \cdot \vec{D}_\beta \\ \vec{X}_3 = \vec{X}_\delta - A_3 \cdot \vec{D}_\delta \end{cases} \tag{7}$$

$\vec{X}(t+1)$ denotes the updated leakage matrix of the w gray wolf, where t is the number of generations of the current iteration; $\vec{X}_1$, $\vec{X}_2$ and $\vec{X}_3$ define the step length and direction of the wolf pack w individuals toward α, β and δ, respectively; $\vec{X}_a$, $\vec{X}_\beta$ and $\vec{X}_\delta$ represent the current leakage matrices of α, β and δ, respectively; A is the coefficient vector.

During the hunting process, the algorithm considers α, β and δ to be more aware of the location of the prey and uses these three positions to determine the location of the prey. The behavior of the gray wolf to round up the prey is defined by the following equation:

$$\vec{D} = |\vec{C} \cdot \vec{X}_p(t) - \vec{X}(t)| \tag{8}$$

$\vec{D}$ is denoted as the distance between individual gray wolves and their prey, where t is the number of generations of the current iteration, $\vec{C}$ is the coefficient vector and $\vec{X}_p(t)$ and $\vec{X}(t)$ are the position vector of the prey and the position vector of the individual gray wolf, respectively.

3. RESULTS AND DISCUSSION

In this section, we will study the method's performance in two cases of pipe networks. The first is the publicly available simple pipe network model Hanoi network, and the second is the publicly available NET3 benchmark model pipe network by Rossman's team. The hydraulic model of the network is used to simulate each scenario, collect the field pressure data and compare it with the pressure of the model-simulated leakage, which determines the pipe network's actual leakage.

3.1. Case 1: Hanoi network

The Hanoi network is an example of a typical WDN, initially proposed by Fujiwara & Khang (1990) and built on the planned backbone network in Hanoi, Vietnam. The Hanoi network contains 31 water nodes, 34 pipes and one pump. The total demand of the system is about 5,556 L/s and the total pipe length is 36.61 km. The network was analyzed in a single steady state without delayed simulation, with simulated leakage in litres per second.

As shown in Figure 3, the purpose of the experiment is to test the advantages of the GWO method. The red triangles indicate the locations of installed pressure monitoring points, and the blue circles serve to simulate leakage events at different locations. We simulated leakage at the five different locations 7, 13, 21, 26 and 29, all with a leakage of 20 L/s. Table 1 gives the comparison results of three algorithms, GA, ant colony optimization (ACO) and GWO, for leak location, and calculates their accuracy for simulating 100 leak experiments at each leak location. The experimental results show that the GWO method has the highest average accuracy in the leakage experiments and shows high performance in solving the problem of the large search space.

In the optimization process, the solution to each optimization problem is abstracted as the individual gray wolves in the population. In this case, the number of gray wolf populations is set to 80 and the maximum number of iterations is set to 50. Also, we mention that the GWO requires fewer parameters to be adjusted. This is because the two main adjustment parameters, a and C, are adaptive and do not need to be set artificially. They are shown in Table 2.

We have implemented a virtual area identification method, the idea of which comes from the research of Moasheri *et al.* (2021). Based on the geographic location of the network and the measurement field tools, they divide the network area into several virtual areas and then estimate the leakage probability of the virtual areas. Similarly, we divide the network evenly into several virtual areas based on the topology of the network, with a similar number of water-using nodes in each virtual area. To investigate the effect of the division method of virtual areas on the detection results, two different sets of virtual areas are designed. Figure 4(a) and 4(b) indicate the horizontal division and the vertical division. This also includes three pressure monitoring points and four virtual areas, denoted as red triangles and areas delimited by red boundaries.

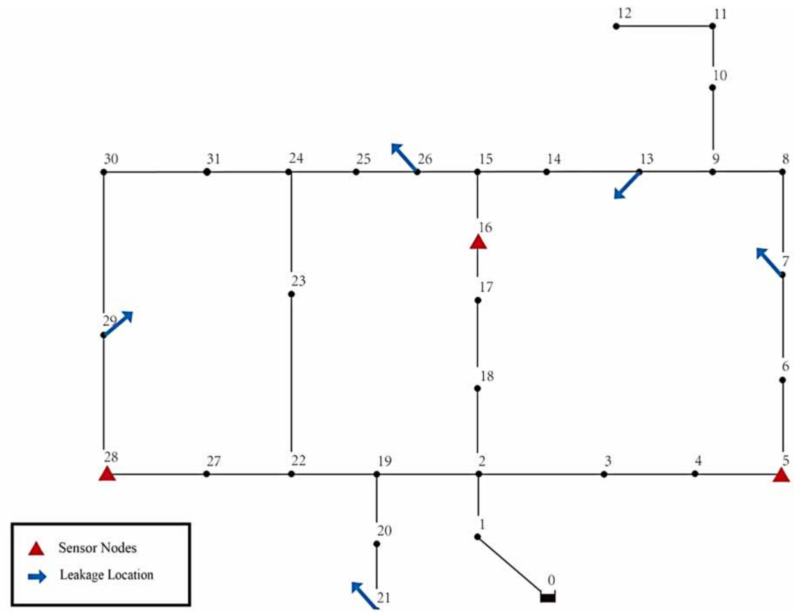


Figure 3 | Hanoi Network topology and simulation of leakage at different locations.

Table 1 | Accuracy of different optimization methods in the Hanoi network

Leakage location	7	13	21	26	29	Average accuracy (%)
GA (%)	82	77	66	81	76	76.4
ACO (%)	78	71	65	76	76	73.2
GWO (%)	96	91	85	92	99	91.2

Table 2 | Parameter values of the detection model in the case study

Parameters	Number of gray wolves	Max iterations	$r1$	$r2$	a	Δq (L/s)
Value	80	50	[0,1]	[0,1]	$2 \rightarrow 0$	1

Both networks (a) and (b) have been used to study the proposed method under two operating conditions in this case. The two operating conditions represent one leakage and three simultaneous leaks, as marked by the green and blue arrows in Figure 4. The first condition simulated node 30 with a leak of 15 L/s. The second condition simulated three simultaneous leaks at nodes 7, 14 and 27 with leakages of 13, 7 and 10 L/s. It is assumed that the total leakage of the pipe network is known, and the reservoir is directly connected to the network from a single node (Maghrebi *et al.* 2014). Leakage under all operating conditions is considered a variation in demand between 0 and 20 L/s with an interval of 1 L/s and leakage within 0.36% of the total water demand. The results of the ten independent experimental tests in the first case study are given in Tables 3 and 4, and the results are expressed as the estimated leakage in the corresponding areas.

The results show that the detection model can accurately simulate leakage assuming only one leakage in the network. Each experiment identifies a 15 L/s leakage occurring in the simulated leakage area I. Assuming multiple leaks in the network, the detection model identifies the occurrence of leaks in the simulated leaky areas I and III of the network (a), and the occurrence of leaks in the simulated leaky areas II and IV of the network (b). In addition, the third and eighth experiments of network (a) identified leakage in area II, and the fifth and sixth experiments of network (b) identified leakage in area III. This is because the detection model locates the upstream and downstream nodes of the actual leakage, which are classified as other leakage regions.

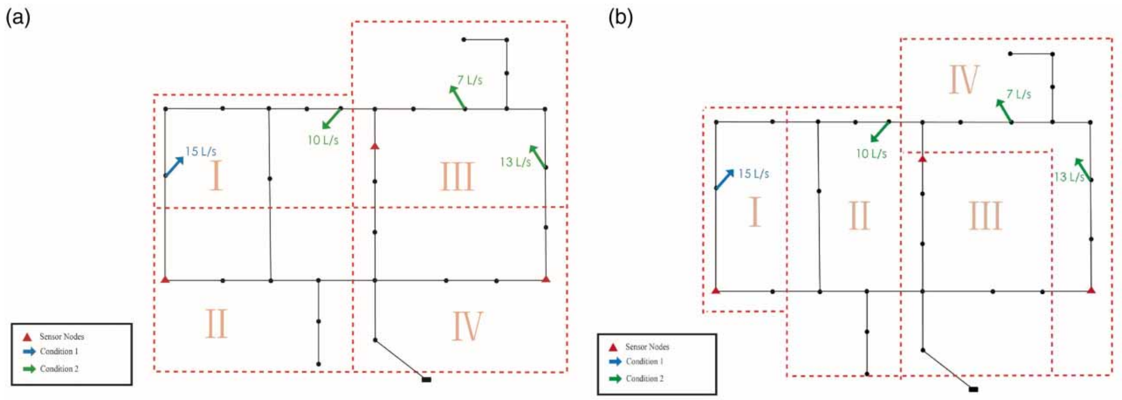


Figure 4 | Both networks' divisions (a) and (b) representing horizontal division and vertical division into four virtual areas.

Table 3 | Results of ten independent experimental tests in the first case study

Division method	Experimental conditions			1	2	3	4	5	6	7	8	9	10
a	1	I	15	15	15	15	15	15	15	15	15	15	15
	2	I	10	10	10	8	12	10	10	8	7	10	11
		II	0	0	0	3	0	0	0	0	4	0	0
		III	20	20	20	19	18	20	20	22	19	20	19
b	1	I	15	15	15	15	15	15	15	15	15	15	15
	2	II	10	10	10	10	12	12	10	14	10	10	11
		III	0	0	0	0	0	1	1	0	0	0	0
		IV	20	20	20	20	18	17	19	16	20	20	19

Table 4 | Leakage detection results in the first case study

	Experimental conditions			Detection result		
Division method		Leakage area	Leakage amount (L/s)	Leakage area	Leakage amount (L/s)	Error
a	1	I	15	I	15	0
	2	I	10	I	10.125	1.25%
		III	20	III	19.875	0.63%
b	1	I	15	I	15	0
	2	II	10	II	10.875	8.75%
		IV	20	IV	19.125	4.37%

In Table 4, a summary of the experimental results simulating both conditions of the above networks (a) and (b) is given. The leakage area is the detection result with the most frequent occurrence under ten independent experiments, and the leakage amount is the average value of the leakage amounts for the correctly identified leakage area in ten independent tests. The error calculates the magnitude of the direct difference between the simulated leakage amounts and the detection results. An error of zero means that the leakage estimated by the detection model is equal to the leakage simulated by the experimental condition in all results where the leakage area is correctly identified. The results show that both the network divided horizontally (a) and vertically (b) were able to correctly identify the leakage areas, and the error in the estimated leakage was within 8.75%. Therefore, the way the virtual area is divided is not unique and has no necessary impact on the good or bad detection results.

3.2. Case 2: NET3 network

The EPANET NET3 benchmark network was selected as the pipe network model for this case (Rossman 2000), with a complex topology that can be used to simulate a real-life complex pipe network. The NET3 network contains 92 connection nodes, 117 pipes, two water sources, two pumps and three basins as physical components. The total inlet flow, total node demand and total pipe length of the network are 828.95 L/s, 192.28 L/s and 65.7 km. The network was analyzed in a steady state and included five pressure monitoring points and seven virtual areas. The proposed areas are shown in Figure 5 as red triangles and areas delineated by boundaries in red, respectively.

In this case, the network has been used to study the proposed method under different operating conditions, including one, three and five simultaneous leakages. In these service condition experiments, five pressure monitoring points were placed at 111, 157, 213, 269 and 273, as shown in the red triangles of the figure. Figure 5 shows the Working Condition 1 simulation. The leakage at a single node of the pipe network is 5 L/s, indicated by the black arrow. Conditions 2 and 3 indicate three and five simultaneous leaks, respectively. The green arrows indicate the three leakage amounts of 4 and 6 L/s for area V and 5 L/s for area VII. Five simultaneous leakage simulations of 7 and 8 L/s in area II, 4 and 6 L/s in area III and 5 L/s in area VI are indicated by blue arrows. Assuming that the total network leakage is known, that the river is directly connected to the network from a single node, and that the lake water supply valve is closed, the node leakage for all operating conditions is considered to vary between 0 and 10 L/s with an interval of 1 L/s. Leakage is within 5.2% of total water demand. In the optimization process, the number of gray wolf individuals is set to 100, the maximum number of iterations is set to 50 and the rest of the parameters are the same as the first case network. The results of the ten independent experimental tests in the second case study are given in Tables 5 and 6, and the results are expressed as the estimated leakage in the corresponding areas.

The results show that the detection model can accurately identify that the leakage occurs in area I assuming only one leakage in the network. Assuming that the network is leaking in two areas, the model identifies the leaking area and estimates the amount of leakage in the leaking area in all seven experiments. The estimated leakage amount is consistently above or below the actual leakage amount in the area. In contrast, three leaky areas were identified in three experiments. This is because the detection model locates nodes near the actual leak. These nodes are often upstream and downstream of the actual leaky nodes, and therefore meet our expectations. However, the detection model still detected the areas with leakage. Similarly, in the second, sixth and ninth experiments of Condition 3, the detection model additionally identified area IV as leaking, with the amount of leakage ranging from about 1 to 2 L/s.

Specifically, under the assumption that there is one leakage in the network, the model identifies the leakage area of the network as area I and estimates the leakage volume of the corresponding area as 5 L/s. The model can accurately identify

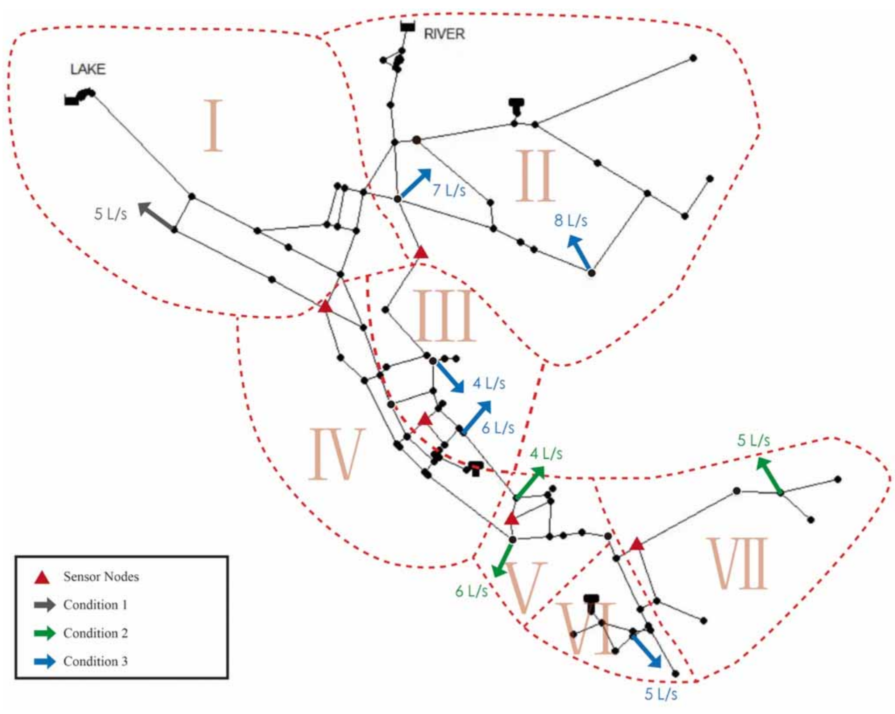


Figure 5 | Network for the second case study (red triangles and green boxes indicate monitoring points and simulated leakage nodes).

Table 5 | Results of ten independent experimental conditions 1 and 2 in the second case study

Conditions	Experimental conditions		1	2	3	4	5	6	7	8	9	10
1	I	5	5	5	5	5	5	5	5	5	5	5
2	V	10	11	11	11	12	10	10	10	10	11	11
	VI	0	1	0	0	0	1	0	1	0	0	0
	VII	5	3	4	4	3	4	5	4	5	4	4
3	II	15	16	15	14	16	11	12	15	15	16	11
	III	10	9	9	11	9	14	11	10	10	7	14
	IV	0	0	1	0	0	0	2	0	0	2	0
	VI	5	5	5	5	5	5	5	5	5	5	5

Table 6 | Leakage detection results in the second case study

Experimental conditions			Detection result		
	Leakage area	Leakage amount (L/s)	Leakage area	Leakage amount (L/s)	Error
1	I	5	I	5	0
2	V	10	V	10.857	8.57%
	VII	5	VII	3.857	17.14%
3	II	15	II	14	6.67%
	III	10	III	11	10%
	VI	5	VI	5	0

the leakage area and estimate the corresponding leakage amount, and the calculation error of the leakage amount is 0. This means that in all the results of correctly identifying the leakage area, the leakage estimated by the detection model equals the leakage simulated by the experimental conditions. Under the assumption that the network has three and five leakage areas, the model can accurately identify the leakage areas as V and VII and II, III and VI, respectively, and estimate the corresponding leakage amounts as 10.857 and 3.857 L/s and 14, 11 and 5 L/s, respectively. The leakage in area II is more severe, but the error is within a certain range. This is because the hydraulic model more accurately simulates the situation where there is a large amount of leakage in the network. The pressure changes in the network caused by large leakage are more obvious. The results demonstrate that the model can not only identify areas of leakage in the network but also assess the severity of leakage in each area, guiding staff in developing a leak detection plan.

It should be noted that in the case of simulating multiple leaks in the pipe network, the detection results are subject to errors. These errors are unavoidable and will be detected for each leaky area in the network. The errors arise because the model can detect nodes near the leak location. These nodes are more upstream and downstream nodes of the leaky nodes and are divided into adjacent leaky areas. In particular, detecting only one leak in a single area was good regardless of several leaks in the network. This may be since the pressure variation due to a single leak in an area is better identified and easily detected. It is noteworthy that area VI of the five leakage conditions and areas II and III of the simulated leakage are also not in adjacent spatial locations, and the leakage in area II is more severe than in area III. The test results show that the leakage amount of area II is more significant than that of area III with the same number of leaks, which can determine the area of relatively serious pipe network leakage, as shown in Figure 5.

4. CONCLUSION

This paper proposes a new method for leaky area detection based on GWO. The method is based on the calibration of the demand of the pipe network nodes by GWO and is evaluated on two simulation models. In this method, the WDN is divided into several virtual areas, and the network leakage is simulated with a combination of different leakage types of water demand. The pressure variation of the network is calibrated based on the model approach to identify leakage areas and estimate the corresponding leakage volume. The results show that the method can accurately identify the leakage areas and estimate the leakage volume in a single leakage scenario. When there are multiple leakage cases in the network, the method produces errors in estimating leakage in the leakage areas. Likewise, with errors consistently below 17.14%, it can still identify leaky areas and detect the severity between them. It provides a reference for the later field maintenance workers so that a reasonable and practical maintenance plan can be developed.

This paper considers only leakage detection experiments based on an accurate hydraulic model. The hydraulic model calibration part will be further considered in future studies to simulate the leakage of pipe networks more accurately. In addition, the single nature of the data is also a challenge to the leakage detection method. Further research can be conducted later to add the leakage area identification of flow monitoring points to improve the model detection accuracy.

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DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

CONFLICT OF INTEREST

The authors declare there is no conflict.

REFERENCES

Ansari, M. M., Guo, C., Shaikh, M. S., Chopra, N., Haq, I. & Shen, L. 2020 Planning for distribution system with grey wolf optimization method. *Journal of Electrical Engineering & Technology* **15** (4), 1485–1499.

Berglund, A., Areti, V. S., Brill, D. & Mahinthakumar, G. 2017 Successive linear approximation methods for leak detection in water distribution systems. *Journal of Water Resources Planning and Management* **143** (8), 04017042.

Blocher, C., Pecci, F. & Stoianov, I. 2020 Localizing leakage hotspots in water distribution networks via the regularization of an inverse problem. *Journal of Hydraulic Engineering* **146** (4), 04020025.

Brennan, M. J., Gao, Y., Ayala, P. C. Almeida, F. C. L., Joseph, P. F. & Paschoalini, A. T. 2019 Amplitude distortion of measured leak noise signals caused by instrumentation: effects on leak detection in water pipes using the cross-correlation method. *Journal of Sound and Vibration* **461**, 114905.

Cody, R. A., Dey, P. & Narasimhan, S. 2020 Linear prediction for leak detection in water distribution networks. *Journal of Pipeline Systems Engineering and Practice* **11** (1), 04019043.

Endo, A., Tsurita, I., Burnett, K. & Orencio, P. M. 2017 A review of the current state of research on the water, energy, and food nexus. *Journal of Hydrology: Regional Studies* **11**, 20–30.

Fang, Q. S., Zhang, J. X., Xie, C. L. & Yang, Y. L. 2019 Detection of multiple leakage points in water distribution networks based on convolutional neural networks. *Water Supply* **19** (8), 2231–2239.

Fujiwara, O. & Khang, D. B. 1990 A two-phase decomposition method for optimal design of looped water distribution networks. *Water Resources Research* **26** (4), 539–549.

Gao, Y., Brennan, M. J. & Joseph, P. F. 2006 A comparison of time delay estimators for the detection of leak noise signals in plastic water distribution pipes. *Journal of Sound and Vibration* **292** (3–5), 552–570.

Hajibandeh, E. & Nazif, S. 2018 Pressure zoning approach for leak detection in water distribution systems based on a multi objective ant colony optimization. *Water Resources Management* **32** (7), 2287–2300.

Hu, Z., Tariq, S. & Zayed, T. 2021 A comprehensive review of acoustic based leak localization method in pressurized pipelines. *Mechanical Systems and Signal Processing* **161**, 107994.

Maghrebi, M. F., Aghaebrahimi, M. R., Taherian, H. & Attari, M. 2014 Determining the amount and location of leakage in water supply networks using a neural network improved by the bat optimization algorithm. *Journal of Civil Engineering and Urbanism* **4** (3), 322–327.

Mirjalili, S., Mirjalili, S. M. & Lewis, A. 2014 Grey Wolf Optimizer. *Advances in Engineering Software* **69**, 46–61.

Moasheri, R., Ghazizadeh, M. J. & Tashayoei, M. 2021 Leakage detection in water networks by a calibration method. *Flow Measurement and Instrumentation* **80**, 101995.

Pérez, R., Puig, V., Pascual, J., Quevedo, J., Landeros, E. & Peralta, A. 2011 Methodology for leakage isolation using pressure sensitivity analysis in water distribution networks. *Control Engineering Practice* **19** (10), 1157–1167.

Pudar, R. S. & Liggett, J. A. 1992 Leaks in pipe networks. *Journal of Hydraulic Engineering* **118** (7), 1031–1046.

Rossman, L. A. 2000 *EPANET 2: Users Manual*. EPA/600/R-00/057, US Environmental Protection Agency, Cincinnati, OH, USA.

Sanz, G., Pérez, R., Kapelan, Z. & Savic, D. 2015 Leak detection and localization through demand components calibration. *Journal of Water Resources Planning and Management* **142** (2), 04015057.

Sophocleous, S., Savić, D. A., Kapelan, Z. & Giustolisi, O. 2017 A two-stage calibration for detection of leakage hotspots in a real water distribution network. *Procedia Engineering* **186**, 168–176.

Vashishtha, G. & Kumar, R. 2022 An amended grey wolf optimization with mutation strategy to diagnose bucket defects in Pelton wheel. *Measurement* **187**, 110272.

Vítkovský, J., Simpson, A. & Lambert, M. 2000 Leak detection and calibration using transients and genetic algorithms. *Journal of Water Resources Planning and Management* **126** (5), 262–265.

Vítkovský, J. P., Simpson, A. R., Lambert, M. F. & Wang, X. J. 2001 An experimental verification of the inverse transient technique. In: *Proceedings of 6th Conference on Hydraulics in Civil Engineering*, Institution of Engineers, Barton, ACT, Australia, pp. 373–380.

Wu, Z. Y., Sage, P. & Turtle, D. 2010 Pressure-dependent leak detection model and its application to a district water system. *Journal of Water Resources Planning and Management* **136** (1), 116–128.

Xie, C. L., Fang, Q. S., Zhang, H. Y. & Zhang, J. X. 2019 Optimal layout of pressure monitoring points in water supply network based on Optics. *E3S Web of Conferences* **79**, 01015.

Zhang, Q., Wu, Z. Y., Zhao, M. & Qi, J. Y. 2016 Leakage zone identification in large-scale water distribution systems using multiclass support vector machines. *Journal of Water Resources Planning and Management* **142** (11), 04016042.

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