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Research on Predicting Leakage Aperture of Water Pipelines Based on IGWO-BP Model

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Abstract. This study presents an innovative method for predicting coal water supply pipeline leakage aperture sizes. Firstly, an Improved Grey Wolf Optimization (IGWO) algorithm is introduced, which combines Bernoulli chaotic initialization, elliptical convergence parameters, and dynamic weight updates. The algorithm's optimization capabilities are enhanced by IGWO. Secondly, the effectiveness of IGWO is validated through benchmark tests. Finally, IGWO is applied to optimize the initial structural parameters of a Backpropagation (BP) neural network. The effectiveness of IGWO-BP is verified using laboratory pipeline infrasound leakage signals. The optimized IGWO-BP model demonstrates superior performance in predicting leakage apertures, with a substantial 69.12% reduction in mean absolute percentage error (MAPE) and a 66.96% decrease in mean square error (MSE) compared to traditional BP models, offering valuable insights for future leak remediation efforts.

Keywords. Coal water supply pipeline, Leak detection, Gray Wolf algorithm, Infrasound sensing, Neural network

1. Introduction

Coal water supply pipeline are essential for urban development. yet their expansion has led to occasional leaks and failures, causing economic losses and safety concerns [1-2]. Managing these variable leaks requires real-time monitoring.

Preference [1-2] detects pressure changes in the pipe network using high-frequency pressure sensors, and identifies leakage conditions in the pipe network using negative pressure waves; Ahmad et al. [3] used continuous wavelet transform to obtain acoustic image features from time series acoustic emission signals, and then identified the pipeline leakage state through neural network; Mujtaba et al. [4] identified the fault category of specific gas pipeline through shallow neural network classifier (SNNC); Zhang Yong et al. [5] optimized Elman neural network by genetic algorithm (GA) and applied it to pipeline leakage identification.

However, prior research concentrates on detecting and categorizing pipeline leaks, leaving leak size prediction and its connection to pipeline parameters unexplored, and it is still a difficult problem to further establish the mapping model. This study enhances

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the ***GreyWolfOptimization*** (GWO) algorithm, creating IGWO. Using BP neural network model to predict leakage.

2. Methods

2.1. Algorithm principle

The GWO Algorithm draws inspiration from grey wolf behavior in nature, categorizing the population into $\boldsymbol{\alpha}$, $\boldsymbol{\beta}$, $\boldsymbol{\delta}$, and ω wolves based on fitness. The $\boldsymbol{\omega}$ wolf simulates global optimization by approaching the $\boldsymbol{\alpha}$, $\boldsymbol{\beta}$, and $\boldsymbol{\delta}$ wolves during the hunt.

2.1.1. Population initialization improvement

In GWO, random population initialization can lead to uneven distributions. To enhance algorithmic speed and quality, we introduced Bernoulli chaos mapping for population initialization, offering a more uniform distribution within the solution space. The expression for this initialization is as follows:

$$x_{n+1} = \begin{cases} \dfrac{x_n}{1-\lambda}, 0 \le x_n \le 1-\lambda \\ \dfrac{x_n - 1 + \lambda}{\lambda}, 1-\lambda < x_n \le 1 \end{cases} \quad (\lambda = 0.4) \tag{1}$$

Figure 1 illustrates the distribution of the Bernoulli chaos mapping sequence, demonstrating a uniform distribution with consistent density across different mapping values. This application of Bernoulli chaos mapping during GWO initialization enhances population distribution in the solution space, improving convergence speed.

2.1.2. Convergence parameter update strategy improvement

In the GWO algorithm, the convergence factor '**A**' adapts to the control parameter '**a**'. When |**A**| > 1, the wolf pack explores the entire hunting area, while |**A**| < 1 leads to continuous surrounding of the optimal prey. The GWO Algorithm describes '**a**' as linearly decreasing, but Cao Ke et al. [6] have shown that different '**a**' update strategies significantly affect GWO's global and local search capabilities. This paper introduces an '**a**' update strategy based on a four-part ellipse's regular variation pattern (Equation 2), enhancing global and local convergence and algorithm accuracy.

$$a = 2 \cdot \sqrt{1 - \frac{t^2}{t_{\max}^2}} \tag{2}$$

Figure 2 illustrates the updated convergence parameter strategy's characteristics: slow decay in early iterations for improved global exploration, followed by accelerated decay in later iterations for enhanced local search precision.

2.1.3. Adaptive location update strategy improvement

In the GWO algorithm, all grey wolves equally influence position updates, despite their differing characteristics. This uniformity leads to slower convergence. Additionally, $\boldsymbol{\alpha}$,

β, and ***δ*** wolves only update when superior solutions are found, potentially causing global optima challenges if they get stuck locally.

To address these issues, this paper combines dynamic weight update strategies from references [6] and [7], proposing an adaptive dynamic weight position update strategy (Equation 3) that considers adaptivity and fitness.

$$\mathbf{X}(t+1)=\left(\frac{2t}{t_{\max}}+1\right)\cdot\frac{\omega_{\alpha}W_1\mathbf{X}_1+\omega_{\beta}W_2\mathbf{X}_2+\omega_{i}W_3\mathbf{X}_3}{3} \tag{3}$$

In Equation (3), 'W_i' represents the current positional weights of individual grey wolves concerning the ***α***, ***β***, and ***δ*** wolves. 'f_j' denotes the fitness values of the ***α***, ***β***, and ***δ*** wolves. This equation defines update grey wolf's position in each iteration, dynamically adjusting the weights based on fitness values and leadership tiers, enhancing global and local search capabilities in the GWO algorithm.

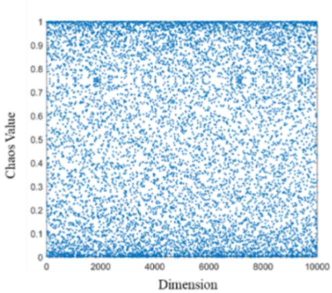

Figure 1. Bernoulli Chaos Sequence Distribution

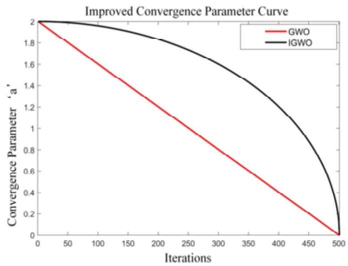

Figure 2. Convergence Parameter Curve.

2.2. Simulation

Eight test functions (Table 1) were chosen to evaluate the IGWO against GWO and other metaheuristic methods. All algorithms employed a population size of 30 and a maximum of 500 iterations, with 20 independent runs, and the most representative outcome were selected for comparison.

Table 1. Benchmark Function Table (Dimension=30, Solution=0)

Function	Expression	Function	Expression
F1	$f_1(x)=\sum_{i=1}^{n}X_i^2$	F5	$f_5(x)=\sum_{i=1}^{n}(\lvert x_i+0.5\rvert)^2$
F2	$f_2(x)=\sum_{i=1}^{n}\lvert X_i\rvert+\prod_{i=1}^{n}\lvert X_i\rvert$	F6	$f_6(x)=\sum_{i=1}^{n}\left[x_i^2-10\cos(2\pi x_i)+10\right]$
F3	$f_3(x)=\max_i\left\{\lvert x_i\rvert,1\le i\le n\right\}$	F7	$f_7(x)=\frac{1}{4000}\sum_{i=1}^{n}x_i^2-\prod_{i=1}^{n}\cos\frac{x_i}{\sqrt{i}}+1$
F4	$f_4(x)=\sum_{i=1}^{n-1}\left[100(x_i+1-x_i^2)^2+(x_i-1)^2\right]$	F8	$f_8(x)=20\exp\left[-0.2\frac{1}{n}\sum_{i=1}^{n}x_i^2\right]-\exp\left[\frac{1}{n}\sum_{i=1}^{n}\cos(2\pi x_i)\right]+e+20$

2.3. Experiment

The BP neural network, trained via error backpropagation, is a widely employed model. In heating pipeline leakage prediction, the study integrates IGWO to optimize the BP network, enhancing convergence and prediction accuracy (Figure 6).

The laboratory's pipeline leakage detection platform comprises submersible pumps, variable frequency drives, subsonic sensors, and pressure sensors. The 107-meter DN80 diameter pipeline operates at 0.3MPa pressure. Five ball valves, with 2mm to 8mm aperture plugs, simulate leaks. CASI subsonic sensors (1kHz) connect to a digital instrument via UDP. Pressure sensors and electromagnetic flow meters transmit data to the monitoring host through Modbus communication.

The BP neural network consists of 7 input nodes, 12 hidden layer nodes, and 1 output node. Training runs for 200 epochs, aiming for 0.001 precision, with a 0.01 learning rate. Each optimization algorithm employs a 30-member population for 500 iterations, repeated 30 times for representative results.

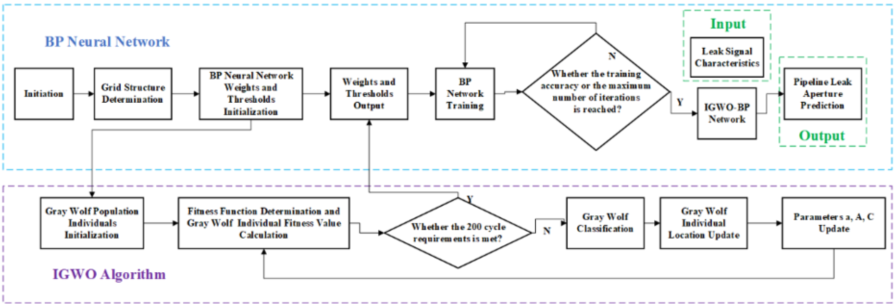

Figure 3. Process of IGWO-BP Neural Network.

3. Results

3.1. Simulation result

The convergence curves of these four algorithms across the eight test functions are illustrated in Figure 4, and the summarized results are presented in Table 2. Results clearly show that the two improvement strategies presented in this study have significantly elevated the GWO algorithm's performance. IGWO outperforms other algorithms in convergence precision and global optimization, as indicated by average results. Furthermore, IGWO exhibits good robustness, as observed in standard deviations. Thus, IGWO stands as a superior optimization approach.

Table 2. Test results

Model	GWO		PSO		TLBO		IGWO	
	Mean	σ	Mean	σ	Mean	σ	Mean	σ
F1	1E-27	1E-27	8E-04	7E-04	1E-90	1E-90	**0**	**0**
F2	7E-17	3E-17	7E-01	3E-01	9E-46	7E-46	**1E-282**	**0**
F3	1E-06	1E-06	3E-01	1E-01	2E-37	2E-37	**1E-276**	**0**
F4	3E+01	9E-01	**2E+01**	1E+01	2E+01	4E-01	2.86	**1E-02**
F5	7E-01	4E-01	7E-04	8E-04	**1E-05**	**1E-05**	6E-00	5E-01
F6	4E-00	2E-00	2E+01	6E-00	1E+01	7E-00	**0**	**0**
F7	**0**	**0**	2E-03	3E-03	0	0	**0**	**0**
F8	1E-13	1E-14	1E-00	5E-01	4E-15	0	**8E-16**	**0**

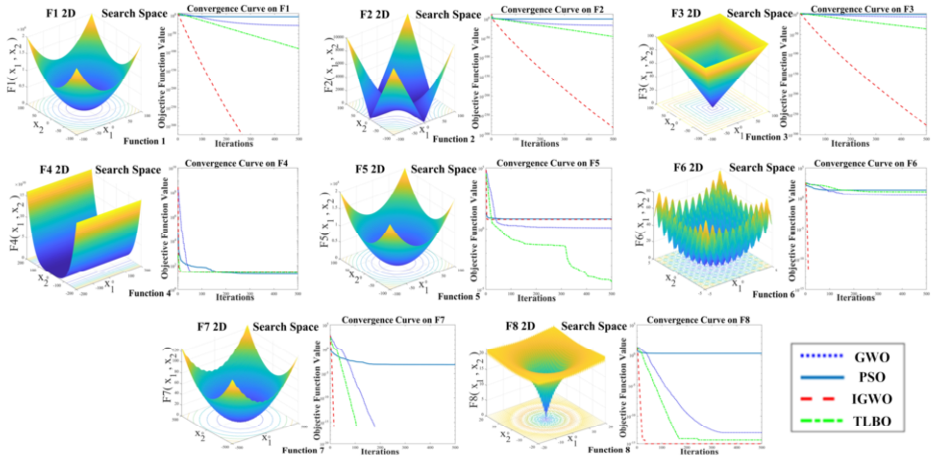

Figure 4. Comparison of Benchmark Test Function Graph and Convergence Curve.

3.2. Experiment result

In experiments, we recorded pipeline wall pressures (0.05MPa to 0.3MPa) and collected 500 signal sets (2mm to 8mm apertures) with a 7:3 training-to-testing ratio. "db6" wavelet analysis reduced noise. Figures 5 shows denoised leakage signals.

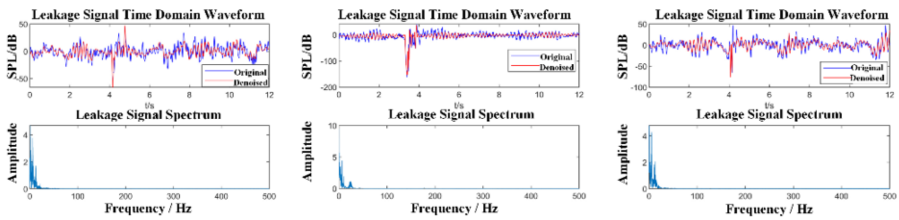

Figure 5. Different working conditions leakage signals.

Comparative analysis shows pipeline pressure and leakage aperture primarily shape subsonic signals. Thus, pressure is a crucial input, and leakage signals span 0-30Hz with varying frequencies. The model uses 3 temporal, 2 shape, and 1 frequency features, alongside normalized pressure, to predict leakage aperture.

Figure 6 displays error distribution comparisons among the five neural network models for leakage aperture prediction. The unoptimized BP network exhibits significant prediction errors and instability. In contrast, the IGWO-BP model maintains errors within ±0.1mm, showcasing superior precision and robustness. This is credited to the favorable impact of the IGWO algorithm on BP network structural optimization. While the GWO-BP, TLBO-BP, and PSO-BP models improve upon BP, they still fall short of IGWO-BP, highlighting IGWO's superior global optimization and local search accuracy.

To enable a more intuitive comparison of predictive accuracy, this study introduces two evaluation metrics: MAPE and MSE. Table 3 presents a comparative assessment of precision among the five predictive models. Under identical experimental conditions, the IGWO-BP predictive model outperforms the other five models with the lowest MAPE and MSE. It reduces MAPE by 69.12% and MSE by 66.96% compared to the BP model and decreases MAPE by 34.78% and MSE by 39.25% compared to the GWO-BP model.

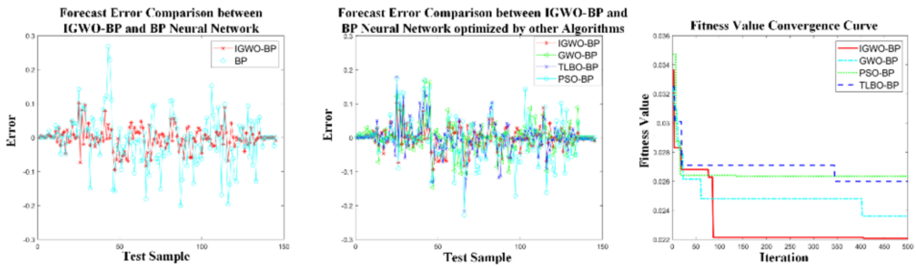

Figure 6. IGWO-BP and other BP neural networks prediction error comparison and fitness value convergence curve.

Table 3. Comparison of MAPE and MSE of each prediction model.

Model	MAPE	MSE
BP	0.28283	0.0043105
PSO-BP	0.23032	0.0034505
GWO-BP	0.13397	0.002344
TLBO-BP	0.16214	0.0032437
IGWO-BP	0.087374	0.001424

The fitness convergence curves in Figure 6 show rapid convergence for all optimization algorithms, with IGWO-BP exhibiting the most significant improvement (34.7%). It avoids local optima, in contrast to PSO-BP, which ceases to converge after 130 iterations. This underscores IGWO's superior predictive accuracy enhancement for the BP neural network.

4. Conclusion

This paper introduces the IGWO-BP method, combining IGWO with BP Neural Network to predict coal water supply pipeline leakage aperture. It demonstrates superior accuracy and robustness compared to other methods, offering stability and efficiency in model optimization.

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