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Research Article

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High-Precision Leak Detection for Oil Pipelines in Complex Environments Based on SSA-ELM

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Abstract This paper proposes a method based on the Sparrow Search Algorithm-improved Extreme Learning Machine (SSA-ELM) for high-precision leak detection in oil pipelines. Current leak detection technologies for oil pipelines face challenges such as low accuracy and interference in complex environments. To address these issues, we adopted an improved Extreme Learning Machine as the leak detection model. Firstly, we preprocess the raw data and extract features to obtain useful information. Then, we introduce the improved Extreme Learning Machine model, which integrates the Sparrow Search Algorithm to enhance the model's generalization ability and noise resistance. In our experiments, we validated the method using a dataset from oil pipelines and compared it with traditional methods. The experimental results demonstrate that the proposed method exhibits excellent performance in high-precision leak detection, with a low Root Mean Square Error (RMSE), low false alarm rate, and low missed detection rate. Therefore, this method has potential application value in the field of oil pipeline leak detection, improving the accuracy and reliability of leak detection.

Keywords Pipeline, Leak detection, ELM

Introduction

Oil transportation is commonly carried out via pipelines. As the service time of pipelines increases, various factors such as underground conditions, underwater environments, sun exposure, and wind erosion significantly raise the probability of pipeline system failures. Current research often fails to adequately consider the impact of these complex conditions on leak detection, potentially leading to false alarms and missed detections in practical applications. Therefore, focusing on high-precision leak detection for oil pipelines in complex environments is a critical issue in addressing pipeline leak problems.

To address the issue of pipeline leaks, scholars both domestically and internationally have conducted extensive research. The currently known signals that can be triggered after oil and gas pipeline leaks include acoustic waves, negative pressure waves, and leakage noise. Therefore, current pipeline leak monitoring technologies are mainly divided into two categories based on how these signals are captured: hardware-based methods and software-based methods. Acoustic monitoring of oil pipeline leaks is one of the most commonly used methods, with advantages such as high accuracy, high sensitivity, and short response time. During a pipeline leak, the fluid interacting with the leaking crack or hole generates an acoustic emission signal. Banjara et al. used support vector machines and relevance vector machines to classify acoustic emission monitoring signals, significantly improving the leak identification and localization capabilities of the acoustic emission method. However, relying solely on acoustic methods for detection can still result in false alarms and missed detections. In response, Da et al. combined acoustic methods with machine learning methods, using random forests and extreme gradient boosting algorithms for classification experiments. These algorithms achieved high detection accuracy at low pipeline pressures but could be significantly affected by drastic pressure changes. Jiang proposed using negative pressure wave signals to detect pipeline leaks. The negative pressure wave method has the advantages of high sensitivity, high localization accuracy, and simple equipment. However, it highly relies on real-time monitoring, requires high sampling frequencies from sensors, and is difficult to monitor minor leaks while being severely affected by noise.

The above methods using hardware technologies to capture leakage signals have been widely applied. However, due to the complex external environments where pipelines are located, these technologies still suffer from high false alarm rates and missed detection rates. In response, some scholars have proposed using software algorithms to capture leakage signals. For example, Li et al. proposed a fusion method of the Sparrow Search Algorithm and Convolutional Neural Network (SSA-CNN) for oil pipeline leak detection. Their SSA-CNN method accurately classified 148 out of 150 sample points in the test set. Zadkarami[9] proposed the FDI system, which is also a fusion model that combines neural networks with other statistical techniques to achieve high accuracy in leak detection, along with good location detectability and low false alarm rates. However, this method has issues with stability in complex environments and difficulties in continuous monitoring. In response to these challenges, Wang et al. developed an ensemble learning framework combining a sparse autoencoder network with an improved Support Vector Machine (SVM), which enhances the accuracy of leak detection results. Nonetheless, this method is costly and not suitable for long-distance oil pipelines. Li et al. proposed a detection method based on wavelet threshold denoising and Deep Belief Networks, which effectively distinguishes between different types of leak anomalies and has higher accuracy compared to basic machine learning methods such as SVM.

In recent years, most popular deep learning network models require large amounts of data for training to ensure accuracy, which makes them prone to converging to local minima. The Extreme Learning Machine (ELM) is a machine learning system or method based on feedforward neural networks. ELM training is one-time and non-iterative, with no requirements for parameters such as network termination conditions. The model can be improved by increasing hidden layer nodes and adjusting activation functions. Thus, it has advantages such as high efficiency, fast learning, and good generalization ability.

The Sparrow Search Algorithm (SSA) has strong global search capabilities and adaptability, allowing it to self-adjust and optimize according to environmental changes during the search process. It is suitable for various parameter optimization problems.

In summary, most current research on oil pipeline leaks overlooks the instability of pipeline detection in complex environments. This paper is the first to apply the Sparrow Search Algorithm-optimized Extreme Learning Machine (SSA-ELM) to the oil pipeline leak detection model. More importantly, this method considers the accuracy of leak location detection under harsh natural conditions. The conclusions drawn from the experiments can provide a reference for the maintenance of oil pipelines.

Basic model

The Sparrow Search Algorithm (SSA)

The Sparrow Search Algorithm (SSA) is inspired by the foraging behavior of sparrows. Throughout the foraging phase, the group is divided into finders and joiners. Finders, who have higher energy reserves, are generally responsible for locating food, while joiners obtain food through the status of the finders. When the sparrow group detects a threat and the alarm value exceeds the safety threshold, sparrows take action to protect themselves from predators. The advantages of SSA include adaptive parameter adjustment, which can effectively enhance the accuracy of the model. The positions of finders and joiners are iteratively updated.

Its position iterative updating process is defined as equation (1).

$$B_{\mathrm{i},\ j}^{\mathrm{t}+1}=\begin{cases} B_{i,j}^{t}\cdot\exp\left(-\dfrac{i}{\alpha\cdot iter_{\max}}\right) & R_2<ST \\ B_{i,j}^{t}+Q\cdot L & R_2\geq ST \end{cases} \tag{1}$$

where t represents the current iteration number;Bij represents the position information of the (i)-th sparrow in the (j)-th dimension;exp is the exponential function;α is a random number in the range (0,1];Q is a random number following a normal distribution; L is a unit value matrix, with all elements being 1, and its matrix dimension corresponds to the variables being optimized;R2 is the alert value, with a range of [0,1];ST is the safety value, with a range of [0.5,1].

If R2<ST, indicating no alert, it means the foraging environment is relatively safe, and the discoverers can expand their search range. If R2≥ST, indicating an alert signal from the sparrows, all sparrows need to avoid the danger and move to safe areas for feeding.

Extreme Learning Machine (ELM)

In most cases, the classic Extreme Learning Machine (ELM) is a feedforward neural network consisting of a single hidden layer with several hidden nodes, where the parameters of the hidden nodes do not need to be adjusted. The parameters of the hidden layer in ELM are randomly generated, and the weights of the output layer can be obtained through some basic matrix calculations to complete the network training.

Assuming [xi, yi] (i = 1, 2, ..., N) are training set samples, the number of hidden layers is set to l, and g(x) represents the activation function. Therefore, ELM can be expressed as equation (2):

$$o_i = \sum_{j=1}^{l} \beta_j g(x) = \sum_{j=1}^{l} \beta_j g(\alpha_j x_i + d_j) \quad (2)$$

where β_j represents the weight between the j-th hidden layer node and the output node; α_j represents the weight between the j-th hidden layer node and the input nodes; d_j represents the threshold of the j-th hidden layer node.

Simulation Research and Analysis

Data Processing

Firstly, the parameters changes within the oil pipeline are captured using the acoustic emission method and the pressure gradient method. The principle of the acoustic emission method is that when a leak occurs, the sharp change in pressure difference inside and outside the pipeline causes turbulence in the normal flow of fluid within the pipeline, forming a multiphase turbulent jet at the leak point and generating high-frequency stress waves on the pipe wall. These stress waves carry information about the shape and size of the leak, and the leak point location information is obtained by analyzing and processing the collected acoustic emission signals (stress waves) through denoising and other techniques. Acoustic emission technology can determine leaks based on the acoustic emission signals generated by fluid and leak pores during leakage.

To validate the model performance, experiments are conducted using a dataset of pipeline parameters from a certain company of Sinopec. This dataset consists of 20 categories collected using two different sensors, with parameters including pressure, noise, distance from sensors to the leak point.

During the experiment, 80% of the dataset is used for training the model, while 20% of the data is reserved for testing. To avoid bias introduced by the classification process affecting the final results, the data is subjected to stratified random sampling to ensure consistency in the distribution of samples within the dataset. The model process is shown in Figure 1.

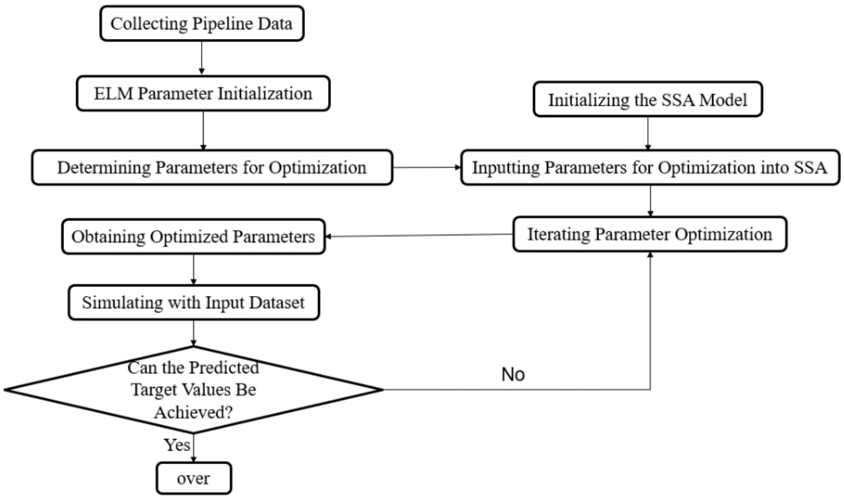

Figure 1: Flowchart of the SSA-ELM Model

Analysis of Simulation Results

To verify the effectiveness of SSA-ELM in pipeline leakage research, experiments were conducted comparing it with traditional models such as CNN and BP neural networks. Simulations were performed using the same dataset, and the results showed that SSA-ELM has significant advantages in prediction. The root mean square error (RMSE) of the three models is shown in Figure 2.

The improved SSA-ELM demonstrates a clear advantage in the accuracy of oil pipeline leakage detection. Its model accuracy steadily improves with different optimization iterations and surpasses that of traditional models like CNN and BPNN, which rely on the number of iterations.

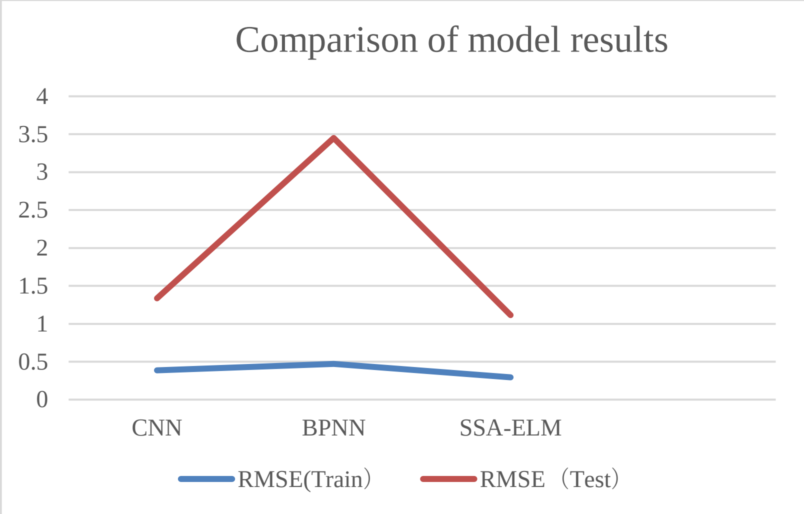

Figure 2: Comparison of model results

Conclusion

This paper is based on SSA-ELM and focuses on high-precision leak detection in oil pipelines through research and experimental verification. Through the analysis and comparative experiments on the oil pipeline dataset, the following conclusions are drawn:

1. Improved Extreme Learning Machine (ELM) exhibits excellent performance in leak detection in oil pipelines. By introducing the idea of local weighting and regularization techniques, the improved ELM can enhance its generalization ability and noise resistance, effectively coping with noise interference in complex environments.
2. The proposed method achieves significant results in high-precision leak detection. Compared to traditional methods, the improved ELM method demonstrates noticeable advantages in detection accuracy.
3. The results of this study indicate that the improved ELM method has potential application value in the field of leak detection in oil pipelines. It can enhance the accuracy and reliability of leak detection, providing an effective means for the safe operation of oil pipelines.
4. However, it should be noted that leak detection in oil pipelines is a complex and challenging problem, and there are still areas for improvement and further research directions. For example, further optimization of parameter selection and model training strategies for the improved ELM method, as well as integration with other technical means and data sources for comprehensive application, will be the direction of future research.
5. In summary, the research results of this paper demonstrate that methods based on improved ELM have good potential for application in high-precision leak detection in oil pipelines, providing valuable references and guidance for research and practice in related fields.

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