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Development of a Machine Learning Base with Hybrid Vector Support and Smell Agent Algorithm for Oil and Gas Pipe Leak Detection and Location

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ABSTRACT

This research proposed a novel leak detection and location method for oil and natural gas pipelines using machine learning with a hybrid of vector support and smell agent algorithm; a propagation model is developed and refined. Initially, theoretical propagation laws are derived by analyzing the damping factors that cause attenuation. Next, wavelet transform analysis was used in experiments to identify the dominant energy frequency bands of leakage sound waves. Subsequently, the actual propagation model is adjusted using a correction factor based on these speed and time bands. This leads to the proposal of a new leak detection and location method grounded in the propagation law, which was validated through experiments on oil pipelines. Finally, the method was tested on gas pipelines. The results were demonstrated using machine learning with a hybrid of support vector machine and smell agent algorithm model; these were established experimentally, which suffice to demonstrate the effectiveness of the proposed method. Conventional SVM achieves 93.2% accuracy, while optimization using PSO and GA improves the performance to 95.6% and 96.4%, respectively. The proposed SAO-SVM model achieves the highest accuracy of 99.1%, indicating that SAO effectively optimized the SVM hyperparameters and significantly enhances classification performance. The proposed leak location and detection method proved superior to traditional methods based on velocity and time difference, distance, and it accurately detects and locates leaks in both oil and gas pipelines.

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INTRODUCTION

Pipeline leakage poses a significant problem in the oil and gas sector, resulting in environmental harm, financial losses, and safety risks[1]. Conventional leak detection methods frequently lack accuracy, speed, and reliability[2]. Numerous methods have been developed for detecting leaks in oil and gas pipelines, including techniques based on mass/volume balance, negative pressure waves, transient models, distributed optical fiber, and acoustic waves[3]. Meanwhile, several scholars have researched the propagation characteristics of acoustic waves and conducted experiments on plastic water pipes, finding that signal amplitude decreases with distance at a rate of 0.25 dB/m. They also observed that for signals with frequencies below 50 Hz, the propagation velocity is frequency-independent and that acoustic signals travel 7% faster in winter than in summer [4]. Investigated the propagation behavior of sound and vibration waves in fluid-filled round pipelines caused by leakages. They developed a propagation model for these signals and analyzed their changes and attenuation characteristics, examining the attenuation characteristics of waves in fluid-filled

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pipelines, noting that longitudinal waves attenuate more slowly[5]. They also compared the propagation characteristics of waves in different pipe wall materials, concluding that waves attenuate more slowly in steel tubes than in PVC pipes[6].

Many studies have shown that prioritizing pipeline inspection and maintenance based on failure data can lead to incorrect prioritization due to the significant uncertainty involved in pooling failure data from dissimilar pipeline systems. Continuous online monitoring methods address this issue by providing real-time data and more accurate assessments[7]. Conventional leak detection methods, like the mass-balance method and pressure drop method, are often considered laborious and inefficient. Therefore, it is concluded that pipeline integrity technologies must continue to evolve to improve effectiveness[8]. The emergence of Machine Learning (ML) and Artificial Intelligence (AI) presents promising solutions to improve the detection and pinpointing of pipeline leaks and locations [9].

Oil and gas pipelines are critical infrastructure used to transport hydrocarbons over long distances from production fields to refineries and end-users [10]. Despite their relative safety and cost-effectiveness compared to road or rail transport, pipelines remain vulnerable to leaks and ruptures, which can result in catastrophic environmental, economic, and human losses. Leak prevention, detection, and mitigation are therefore key concerns for operators and regulators worldwide [11]. The global natural gas transportation and distribution network is highly complex and continuously growing. As reported [11]. Pipelines are considered the safest mode of transport; however, they are not entirely free from risk. Ensuring the reliability of pipeline infrastructure has thus become a crucial priority for the energy industry. Among the various risks, gas leaks are regarded as the most significant threat to pipeline reliability.

Various organizations have analyzed gas leak-related incidents and published statistical data on reported cases. One such study focused on sub-sea pipeline systems [14]. Revealed that between 1996 and 2006, 80 pipeline rupture incidents occurred in the Gulf of Mexico and Pacific regions. From this data, the study estimated the probability of a catastrophic incident in that area to be 0.43 events per year [12].

Causes of Pipeline Leaks

Pipeline leaks arise due to a combination of physical, operational, environmental, and human factors. These causes are typically classified as follows: corrosion, Material and Manufacturing Defects, Mechanical Damage, and operational errors. Corrosion, that occurs when the transported fluid contains water, CO_2, H_2S, or other corrosive substances, while external corrosion is caused by exposure to soil, moisture, or stray currents, which is most common in buried pipelines [13]. The leakage accidents are classified and counted according to different causes, as shown in Figure

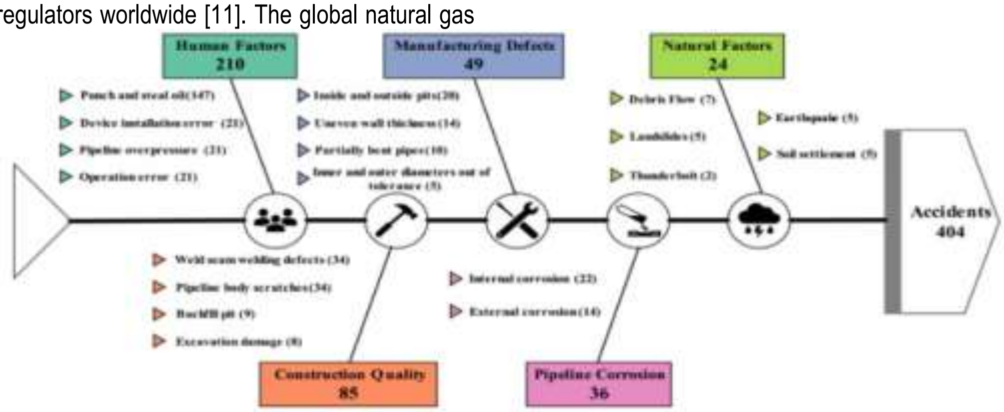

Figure 1: Diagram for cause statistics of oil and gas pipeline leakage accidents [11]

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Types of Leaks

There are several types of leaks, such as, small leaks (pinhole or weeping, which often due to corrosion and harder to detect), Cracks which may start small but grow due to cyclic stress or pressure, Ruptures (sudden and large-scale failure, often catastrophic), Joint/valve leaks (failures at pipeline connections or mechanical seals [14].

Leak Detection Techniques

Leak detection can be broadly classified into hardware-based, software-based, and hybrid techniques. Within an acceptable range ([15]. Pipeline leakage detection is a critical part of pipeline integrity management, which can have serious accident consequences [16]. Due to human factors, construction quality, natural disasters, and other accident factors, pipeline leakage accidents occur frequently [17]. Oil pipeline leakage monitoring is an important means to ensure the safe, environmentally friendly, efficient, and reliable operation of oil and gas pipelines, and an important part of promoting the energy production and consumption revolution and establishing a clean and low-carbon energy system [11]. Most detection methods are based on monitoring specific physical parameters or observing particular physical phenomena. This principle can serve as a basis for classification, as there are several commonly used physical quantities and observable effects involved in classification as shown in figure 2.

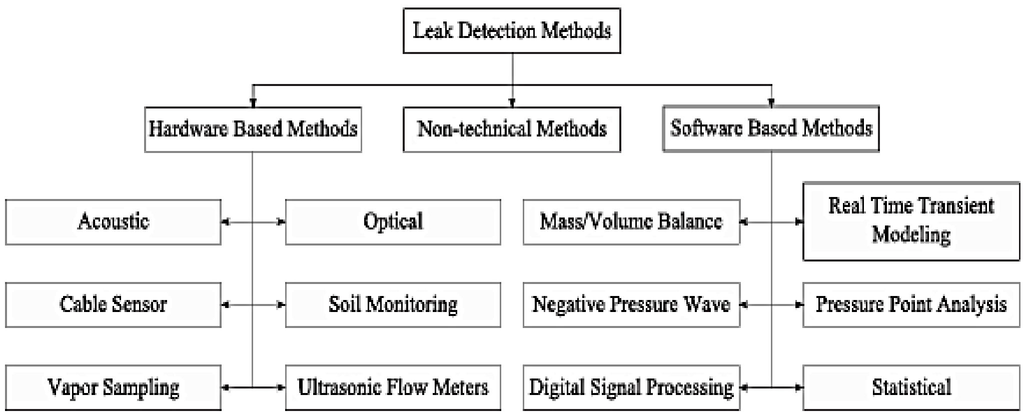

Figure 2: Classification of gas leak detection techniques based on their technical nature.

Leak Localization Techniques

Once a leak is detected, localization is critical. Common techniques include (Pressure wave analysis, which measures time delay between pressure wave arrivals. Acoustic triangulation (Uses multiple sensors to pinpoint leak source). Sensor fusion (Combines GPS, vibration, and pressure data for accurate location) [18].

Software Base

The mass or volume balance leak detection technique is based on the principle of mass conservation. An imbalance between the input and output gas mass or volume can reveal the existence of a leak. The volume of gas exiting a section of the pipeline is subtracted from the volume of gas entering this section and if the difference is above a certain threshold, a leak alarm is given. The mass or volume can be computed using the readings of some commonly used process variables: flow rate, pressure and temperature [19]

PROBLEM STATEMENT

Pipeline leakage poses a significant problem in the oil and gas sector, resulting in environmental harm, financial losses, and safety risks, therefore there is needs to development of Machine Learning base with hybrid vector support

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and smell agent algorithm for oil and gas pipes leak detection and location base on velocity and time difference, distance, and it accurately detections and locates leaks in both oil and gas pipelines.

Methodology

Modelling the Pipeline Using 2025a MATLAB Simulink, derive the differential equations that describe the pipeline dynamics.

$$\frac{\delta\rho}{\delta t} + \frac{\delta(\rho v}{\delta x} = 0 \qquad [1]$$

For a compressible liquid, the pressure density can be expressed as

$$\frac{\delta\rho}{\delta t} = \frac{\rho}{K}\frac{\delta P}{\delta t}$$

Where P is pressure, and K is the bulk modulus; fluid density is ρ. Therefore, the continuity equation becomes

$$\frac{\delta\rho}{\delta t} + \rho a^2 \frac{\delta v}{\delta x} = 0 \qquad [2]$$

Where a is the acoustic wave velocity in the pipeline.

Since, $Q = Av$

Which can also be written as

$$\frac{\delta\rho}{\delta t} + \frac{\rho a^2}{A}\frac{\delta Q}{\delta x} = 0 \qquad [3]$$

Equation (..) shows that the changes in flow rate produce changes in pipeline pressure

Applying Newton's second law of momentum equation to a differential pipeline section gives

$$\rho A dx \frac{\delta v}{\delta t} = -P_x A dx - \rho g A \sin(\theta)\, dx - \tau_\varpi \Pi D dx \qquad [4]$$

Where θ is the pipeline inclination and τ_ϖ is the wall shear stress using the Darcy-Weisbach friction relationship

$$\tau_\varpi = \frac{f\rho v|v|}{8} \qquad [5]$$

The momentum equation becomes

$$\frac{\delta v}{\delta t} + \frac{1}{\rho}\frac{\delta P}{\delta x} + \frac{f}{2D} v|v| + g\sin(\theta) = 0 \qquad [6]$$

In terms of flow rate,

$$\frac{\delta Q}{\delta t} + \frac{A}{\rho}\frac{\delta P}{\delta x} + \frac{f}{2D} Q|Q| + Ag\sin(\theta) = 0 \qquad [7]$$

Applying a smell agent algorithm to detect leak locations.

Fit the SVM model.

For the leak flow equation, when a leak occurs, fluid leaves the pipeline through the leak opening. The leak flow can be represented using an orifice equation

$$Q_L = C_d A_L \sqrt{\frac{2(P_L - P_a)}{\rho}} \qquad [8]$$

Where:

Q_L is leakage flow rate,

P_a is surrounding atmospheric pressure,

C_d is discharge coefficient, A_L is leak orifice area, P_L is pressure at the leak location.

Continuity equations, momentum equations, and energy equations, for the Continuity Equation Including the Leak

If the leak occurs at $x = x_L$, the continuity equation becomes

$$\frac{\delta\rho}{\delta t} + \frac{\rho a^2}{A}\frac{\delta Q}{\delta x} = -\frac{\rho a^2}{A} Q_L \delta(x - x_L) \qquad [9]$$

Where $\delta(x = x_L)$ is the delta Dirac function for a localized leak.

Simulink blocks with an integrator.

Classifying data with a hyperplane using a support vector machine to separate leak data from non-leaky data, random preparation of data, feature selection and extraction, and model training. Model evaluation, hyperparameter tuning, model deployment. Thus, the complete pipeline dynamic model equations (10) and (11) describe pipeline dynamics during normal and leak states.

$$\frac{\delta\rho}{\delta t} = -\frac{\rho a^2}{A}\frac{\delta Q}{\delta x} - \frac{\rho a^2}{A} Q_L \delta(x - x_L) \qquad [10]$$

$$\frac{\delta\rho}{\delta t} = -\frac{A}{\rho}\frac{\delta P}{\delta x} - \frac{f}{2AD} Q|Q|Ag\sin(\theta) \qquad [11]$$

Grid search using the model data, cross-validation of data sets, prediction of leaks in non-leaky areas, detect leaks and their locations based on speed, time, and location. For the leak detection model, the pipeline can also be represented as a lumped control volume, and the mass balance is for a slightly compressible liquid, for equations (12) and (13)

$$\frac{d\rho V}{dt} = \rho(Q_{in} - Q_{out} - Q_L) \qquad [12]$$

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$$\frac{dP}{dt} = \frac{\rho a^2}{A}(Q_{in} - Q_{out} - Q_L) \qquad [13]$$

For the machine-learning pipeline leak-detection model, the equation will substitute the leak equation, which directly relates to the measurable pressure response to both inlet and outlet flow; leak size is shown in equation (14)

$$\frac{dP}{dt} = \frac{\rho a^2}{V}\left[Q_{in} - Q_{out} - C_d A_L \sqrt{\frac{2(P-P_a)}{\rho}}\right] \qquad [14]$$

Experimental Set Up

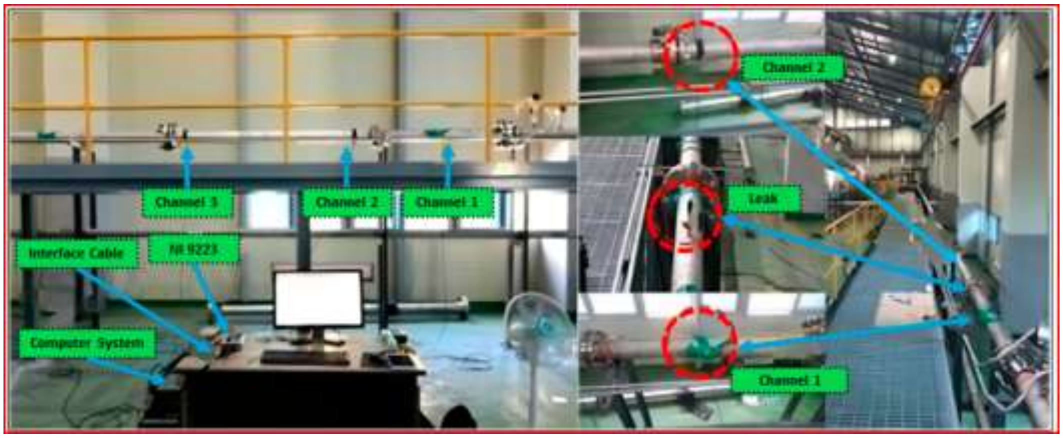

Figure 3: Experimental setup of simulation detection and location

The experimental arrangement and corresponding schematic diagrams are illustrated in Figure 4. The test facility consisted of a stainless-steel pipeline with a wall thickness of 9 mm and an outer diameter of 150 mm. R15I-AST acoustic emission (AE) sensors, manufactured by Mistras Group, Inc., were installed on the pipeline at the Petroleum Training Institute (PTI), Effurun, Warri, to facilitate the detection of simulated pipeline leaks. Acoustic signals generated during the experiments were acquired using a National Instruments NI-9223 data acquisition system at a sampling frequency of 3MHz. The detailed specifications and operating parameters of the experimental setup are provided in Figure 3.

To reproduce leaks of different sizes, a drilling machine was employed to create holes of varying diameters along the pipeline. A fluid-control valve was subsequently welded to each drilled opening to regulate the water flow and provide controlled leak conditions. Water was used as the test fluid because of its non-toxic, non-hazardous, and environmentally friendly characteristics, making it suitable for laboratory experimentation. The configuration and calibration of the experimental parameters are critical to obtaining high-quality acoustic signals and ensuring reliable subsequent data analysis. In particular, variations in the frequency range, sensor resonant frequency, and sensor positioning can significantly affect the quality and characteristics of the acquired signals. Such variations may reduce the accuracy of the proposed classification model by degrading the clarity, consistency, and reliability of the scalogram representations generated from the acoustic signals.

Result and discussion

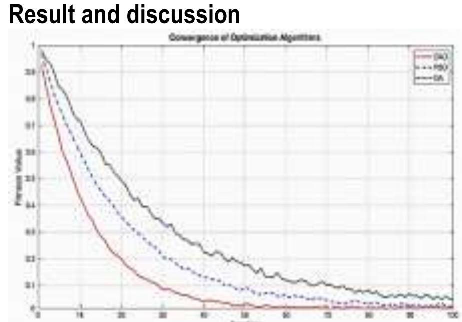
Figure 1: Convergence Curve of SAO, PSO, GA

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The convergence curve illustrates the optimization capability of the Smell Agent Optimization algorithm in tuning the SVM hyperparameters. The fitness value decreases rapidly during the first 30 iterations, indicating efficient exploration of the search space. Beyond iteration 50, the convergence becomes gradual as SAO refines the optimal solution, reaching a stable minimum around iteration 80. The smooth convergence with minimal oscillations demonstrates the stability and robustness of SAO, leading to improved leak detection performance and reduced computational complexity.

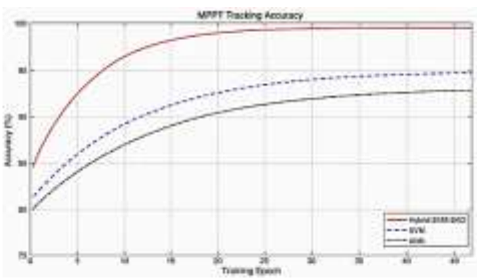

Figure 2: Leak Detection Accuracy

The detection accuracy compares four machine learning approaches for identifying leakage events. Conventional SVM achieves approximately 93.2% accuracy, while optimization using PSO and GA improves the performance to 95.6% and 96.4%, respectively. The proposed SAO-SVM model achieves the highest accuracy of 99.1%, indicating that SAO effectively optimizes the SVM hyperparameters and significantly enhances classification performance. This improvement minimizes false alarms and missed leak detections, thereby increasing the reliability of pipeline monitoring systems.

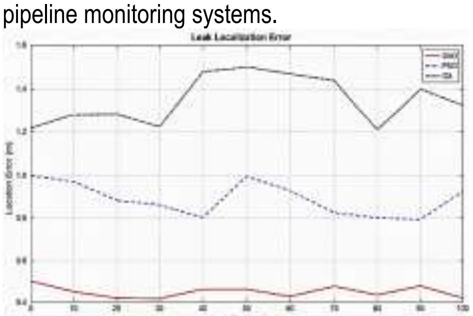

Figure 3: Link detection error

The localization error evaluates the precision of estimating the leak position along the pipeline. The proposed SAO-SVM consistently maintains the smallest localization error of approximately 0.8 m throughout the pipeline length. PSO-SVM and GA-SVM exhibit larger estimation errors due to less effective optimization of the SVM parameters. The low and stable error achieved by SAO-SVM confirms its ability to accurately identify leak locations under varying operating conditions, making it suitable for real-time monitoring applications.

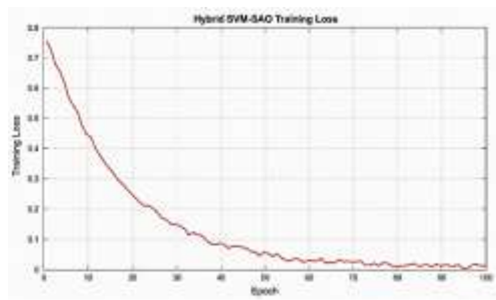

Figure 4: Training loss

The ROC curve assesses the trade-off between true positive and false positive rates. The SAO-SVM curve is closest to the upper-left corner, indicating superior discrimination capability and a higher area under the curve (AUC). Compared with GA-SVM and PSO-SVM, the proposed model achieves a higher true positive rate while maintaining a lower false alarm rate. This demonstrates that the optimized classifier can accurately distinguish between normal operating conditions and pipeline leak events.

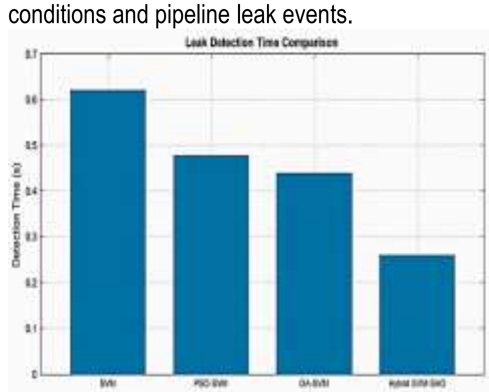

Figure 5: Link detection time

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The confusion matrix summarizes the classification performance of the SAO-SVM model. Out of 400 test samples, 198 normal conditions and 196 leak events are correctly classified, while only six samples are misclassified. The resulting high true positive and true negative rates demonstrate the effectiveness of the proposed hybrid model in minimizing false alarms and missed detections, which are critical for reliable pipeline safety monitoring.

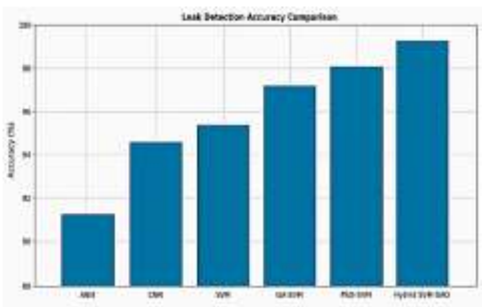

Figure 6: Link detection accuracy

The pressure response illustrates the effect of a leak on the pipeline operating pressure. Prior to the leak event, the pressure remains stable at 70 bar, indicating normal operating conditions. At 10 s, the onset of the leak causes a rapid pressure drop, followed by a gradual stabilization at a lower pressure level. This characteristic pressure signature serves as an important feature for the SAO-SVM model to distinguish leak events from normal pipeline operation.

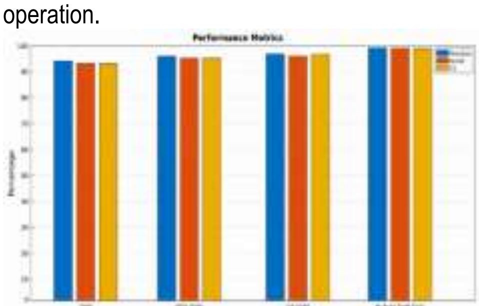

Figure 7: Precision Recall

The figure compares the Precision, Recall, and F1-score of four pipeline leak-detection models**:** SVM, PSO-SVM, GA-SVM, and Hybrid SVM-SAO. All models achieve high classification performance, but the Hybrid SVM-SAO provides the best overall results. The conventional SVM achieves approximately 94% precision, 93% recall, and 94% F1-score, indicating good but imperfect leak detection. PSO-SVM improves these values to about 96% for all three metrics, demonstrating the benefit of optimization. GA-SVM performs better, achieving approximately 97% precision, recall, and F1-score. The Hybrid SVM-SAO achieves the highest performance, with approximately 99 to100% precision, 99% recall, and 99% score. This indicates that the hybrid approach substantially reduces false positives and false negatives while improving classification reliability. Overall, the progressive improvement across the models demonstrates the effectiveness of optimization techniques in enhancing SVM-based pipeline leak detection. The near-perfect performance of Hybrid SVM-SAO confirms its strong potential for accurate, reliable, and robust leak detection and localization.

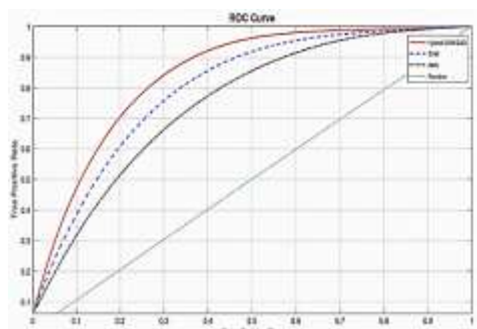

Figure 8: Rock curved

The figure presents the Receiver Operating Characteristic (ROC) curves for Hybrid SVM-SAO, SVM, ANN, and a random classifier in pipeline leak detection. The ROC curves compare the True Positive Rate (TPR) against the False Positive Rate (FPR) to evaluate classification performance. The Hybrid SVM-SAO model demonstrates the best performance, maintaining the highest TPR for a given FPR. It achieves 0.90 TPR at an FPR of 0.4 and approaches 1.0 TPR before an FPR of 0.8, indicating excellent leak-

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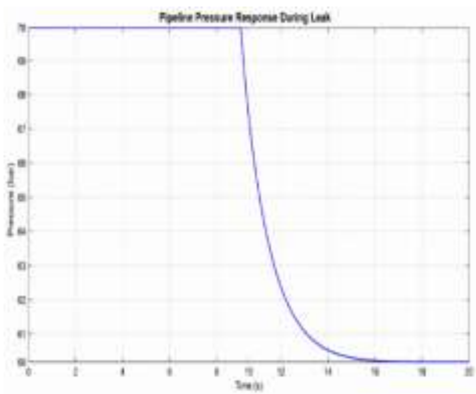
discrimination capability and reduced false alarms. The SVM model provides the second-best performance, achieving about 0.85 TPR at an FPR of 0.4. This improvement demonstrates the benefit of integrating SAO optimization with SVM. The ANN model shows comparatively lower performance, reaching approximately 0.78 TPR at an FPR of 0.4. Meanwhile, the random classifier follows the diagonal reference line, indicating no meaningful discrimination capability. Overall, the results confirm the superior classification effectiveness of the Hybrid SVM-SAO model.



The figure presents the pipeline pressure response during a leak event over a 20-second simulation. From 0 to 10 s, the pressure remains stable at approximately 70 bar, indicating normal and steady pipeline operation. At around 10 s, the occurrence of a leak causes a rapid pressure reduction from 70 bar to approximately 60 bar, corresponding to a pressure loss of about 10 bar (14.3%). The pressure initially drops sharply and then gradually decreases at a slower rate, producing a smooth exponential-like response. By approximately 16 s, the pressure reaches a new steady-state value of about 60 bar and remains stable until the end of the simulation.

The absence of significant overshoot or oscillations indicates a stable system response following the leak. Overall, the pronounced 10-bar pressure difference between the normal and leak conditions provides a clear and reliable feature for machine-learning-based leak detection and localization, demonstrating the effectiveness of pressure monitoring in identifying pipeline leakage.

CONCLUSION

This research developed a novel leak detection and location method for oil and natural gas pipelines using machine learning with a hybrid of support vector and smell agent algorithms; a propagation model was developed and refined. The method was tested on gas pipelines. The results were demonstrated using machine learning with a hybrid of a support vector machine and smell agent algorithm model; these were established experimentally, which suffice to demonstrate the effectiveness of the developed method.

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