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Pipeline Leakage Detection and Monitoring Model using Enhanced Multiple Signal Classification Algorithm and Hybrid Acoustic Emission Techniques

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Abstract
The consequences of pipeline leakages pose great multifaceted hazards, including carcinogenicity and cytotoxicity in humans exposed to leaked toxic substance from pipelines. Pipeline leak also causes environmental contamination of soil resulting to environmental pollution, fire disaster and even loss of life. Therefore, pipeline leakage detection monitoring is a crucial concern in pipeline industry for ensuring the safe and efficient operations. Background noise and detection of single leak are significant limitations of the existing pipeline monitoring and leakage detection techniques. These undesired noises can arise from multiple sources, including environmental, proximity industries, pipe vibration, and electronic interferences. This study therefore optimizes the conventional Multiple Signal Classification (MUSIC) algorithm and Acoustic Emission (AE) technique with the aim to develop a novel technique to address the effect of the background noise. The proposed method combines the advantages of the MUSIC algorithm and AE techniques with real-time monitoring to promptly and accurately detect leakages in pipeline systems. The model achieved Accuracy of 95.5%, Sensitivity of 75%, Mean Detection Time of 1.02 seconds and Response Time of 1.06 seconds. These quantitative results demonstrate the effectiveness of our proposed Enhanced MUSIC algorithm and Hybrid AE technique (Enhanced-MUSICHAE) to detect and monitor pipeline leakage. This has the potential to improve pipeline safety, reduce economic losses, and minimize environmental damages.

Keywords: Multiple Signal Classification (MUSIC), Acoustic Emission (AE), Pipeline Monitoring, Pipeline Leakage Detection

1. Introduction

Detection and monitoring of leakages is a critical aspect of ensuring the safe and efficient operation of pipeline systems. Leaks can result in significant economic losses, environmental damage, and even risk to human life. Traditional leak detection methods often rely on visual inspections, pressure testing, and other techniques that can be time-consuming, costly, and potentially unreliable [14]. Pipeline leakage is the unintended escape of liquid from a pipeline due to an opening caused by crack, gap, vandalism and deterioration of pipeline [7] Often, vandalism leads to Pipeline leakages and product's adulteration [1]. Pipeline leakages also invoke a lot of havoc to our environmental, economic and even loss of human life; the effects of leakage and vandalism go beyond cost of transporting oil and gas or repair expenses but also significantly affect environment and human lives [6]. Pipeline leakage does not just cause wastage of oil and gas but social, economic and environmental degradation.

Background noise is one of the significant limitations of the AE techniques as examined in Wang et al., [13]; and Ullah et al., [12]. To overcome the weakness of background noise of the AE technique, this study proposed to incorporate background noise cancellation technique to the AE technique to hybridize the traditional AE technique. Another limitation to existing principles and approaches of pipeline leakage detection include detection of single leak as examined by Nawal *et. al.* [15] and Ahmad *et. al.* [4]. However, multiple leak

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sources in pipeline network are common especially if the pipeline becomes corrosive when used over a long period of time [2]. This study therefore leverages on the strengths of Multiple Signal Classification (MUSIC) algorithm and Hybrid Acoustic Emissions (AE) techniques.

Advancement & recent innovation in Signal Processing especially Sensor Technology (ST) have led to the development of more sophisticated leakages detection methods [3]. An enhanced multiple signal classification (MUSIC) algorithm can accurately detect and localize leaks by analyzing acoustic emissions signals [5]. This approach can provide a powerful tool for pipeline leakage detection and monitoring when it is combined with acoustic emissions (AE) techniques.

This research proposed a monitoring and detection of leakages model with an enhanced MUSIC algorithm and hybrid AE techniques. The proposed method is designed to improve the accuracy and reliability of leak detection, while also reducing the computational complexity and cost associated with traditional methods.

2. Related Works

AE techniques can analyze the high-frequency acoustic signals emitted by the fluid flow in a pipeline. However, AE techniques is being affected by noise and interference, reducing their accuracy and reliability. Existing literatures have explored pipeline leakage detection and monitoring using principle and working approaches of AE techniques but there are still major drawbacks in these methods.

The AE technique in pipeline leakage detection, localization and monitoring have been reported in several literatures such as Li *et. al.* [10] who proposed an experimental investigation for pipeline leakage detection and monitoring which was subject to socket joint failure using pattern recognition and AE technology to investigate pipeline leakage experimentally. The study found that dominant frequency of environmental acoustic signal is concentrated at 0-10kHz in range and dominant frequency of environmental noise is less than 2khz. A set of agent were trained with Artificial Neural Network (ANN) and obtained good estimation accuracy of 96.9% which indicates that an AE based technique can exhibit high sensitivity over long distance. However, additional sensitivity such as pressure amplification is required to increase the leak noise. Zhang *et. al.* [18] devised combination of Hidden Markov Model (HMM) and Linear Prediction Cepstrum Coefficient (LPCC) to examine damaged acoustic signals. The LPCC represents short-time acoustic signals and was adopted for the parameter of the characteristic signal while the HMM was adopted for identification of corrupted signals. The results obtained revealed significant improved of the acoustic signal with a value rate of up to 97%.

Also, Jia *et. al.* [8] carried out pipeline leakage detection experiment with sensors positioned at different locations along a gas pipeline of 3.13km in length. The experiment was conducted by measuring acoustic waves with the sensors positioned along the gas pipeline and it was observed that acoustic wave generated as a result of leakages from the damaged points to different part of the pipeline at the rate of gas velocity, as a result of this, the high frequency components of the acoustic decayed much faster than the low frequency did and the authors therefore concluded that it is sufficient to detect leakage in gas pipeline using low-frequency signals. The effect of background noise was noted as it easily mask the sound of the leak.

Ozevin and Yalcinkaya [16] developed gas leakage detection and monitoring system in a gas pipeline using acoustic emission technique to detect and monitor leak as the system works perfectly provided the escape liquid passes through the defect part of the pipeline and the acoustic signal propagates along the pipeline which in turn is picked up by the acoustic emission sensor installed along the pipeline. This technique has the advantage of detecting leak accurately in real time but external sources such as background noise affect the signal and cannot be applicable to network of pipeline covering long distance.

Scott and Barrufet [17] applied acoustic emission technique for detection and localization of leakage in gas pipeline network.

The system detects early leaks, estimates leak size and localization. However, the effect of the background noise was noted as it easily masks the actual sound of the leakage.

Among the predictive methodologies, Robles-Velasco *et. al.* [11] employed Logistic regression and Support Vetor Machine stand out in prediction of pipe failures in water supply networks because they presents failure probability the demands of pipeline industry, have ability to work with unbalanced data due to leakages, making the predictive system more realistic and can work efficiently with small and medium size database, which is the case of many companies whose records are not too extensive. Ullah *et. al.* [12] developed pipeline leakage detection and monitoring using acoustic emission and machine learning algorithm. The study was carried out by extracting certain statistical measures such as skewness, kurtosis, mean square, root mean square, standard deviation, peak value, frequency spectrum features and entropy were extracted from acoustic emission signals as features sets in training machine learning model. The authors further utilizes adaptive threshold sliding window to retain the properties of continuous emission and burst signal. Three acoustic emission sensor datasets were collected for the experiments; the authors also extracted 14 frequency domain and 11 time domain features for each of the sensor category which were further transform into features vectors for the training and evaluation of the supervised machine learning model for detection and localization of leakages of various pin size hole

The use of Multiple Signal Classification (MUSIC) and Acoustic Emission (AE) technique for pipeline leakage detection and monitoring have been proposed in few studies.

Wang *et. al.* [13] developed a spectral-based system for identification of leakage based on one dimensional search. It was found that two or more close leakages on pipeline surfaces cannot be separately detected and can only detect single leak at a time. Li *et. al.*[9] developed a transient-based leakage detection system to overcome the drawback of Wang *et. al.* [13] that developed a spectral-based system that could only detect single leak at a time. The authors proposed a transient model using matrix analysis to detect two separate leakages at a time. Though the model developed by Li *et. al.* [9] could overcome the limitation of Wang *et. al.* [13] a spectral-based system, it is only applicable to short length of pipeline under laboratory condition.

3. Methodology

3.1 Theoretical Analysis

This study combines Multiple Signal Classification (MUSIC) algorithm with AE techniques to form an enhanced model. The MUSIC algorithm is a subspace-based method that can accurately estimate the frequency components of a signal. The Enhanced-MUSICHAE technique combines the advantages of the MUSIC algorithm with the Hybrid AE technique to accurately detect and localize leaks.

The Multiple Signal Classification (MUSIC) algorithm collect data from sensor array over a period of time and compute the variance of the collected data (received data) using:

$$R = \frac{1}{M}\sum_{m=1}^{m} x(t_m).x^H(t_m) \qquad (1)$$

Where:

R denotes the covariance matrix of the received data,

M is the number of snapshots,

$x(t_m)$ is the received vector at time ttt, and

H represents the conjugate transpose.

The covariance matrix can further be decomposed into its eigenvectors and eigenvalues

$$P(\theta) = \frac{1}{a_H(\theta)V_N(\theta)} \qquad (2)$$

Where:

$a_H(\theta)$ denotes the array response vector

$V_N(\theta)$ is denotes noise subspace

Thus, the peak in the spatial spectrum is used to estimate the Direction of Arrival (DOA) of the signal.

To suppress background noise in the MUSIC algorithm, as expressed in Equation (2), an adaptive noise cancellation algorithm is incorporated. This enhancement improves the traditional MUSIC algorithm by subtracting the unwanted noise from the source signal, thereby generating the desired signal, as expressed in equation (3).

$$R_{Enhanced} = R - \alpha . R_n \quad (3)$$

Where:

$R_{Enhanced}$ denotes the enhanced MUSIC covariance matrix that emphasizes the desired signal component

R represents the original source signal consisting of both the desired signal and unwanted noise, and

α denotes an adaptive control parameter that regulates the extent of noise suppression, thereby facilitating the extraction of the desired signal.

In order to adapt to fluctuations in the source signal, α is reformulated as α *(n+1)*

Where:

α *(n+1)* is denotes the estimate of noise *n* which can be expressed as:

$$\alpha(n+1) = \alpha(n) + \mu . e(n) \quad (4)$$

Where:

μ denotes the learning rate

$e(n)$ is the difference between the source signal *R* and the unwanted noise *Rn.*

By substituting the corresponding parameters $\alpha(n) + \mu . e(n)$ in α of equation (4):

$$R_{Enhanced} = R - (\alpha(n) + \mu . e(n)) . R_n \quad (5)$$

Assuming a leakage occurs in the pipeline from a source, the Acoustic Emission (AE) signal generated by the rapid release of energy due to cracking or other structural damage can be detected by:

$$R(t) = A.W(t).F(t) + N(t) \quad (6)$$

Where:

$R(t)$ represents the received AE signal from the source at time *t*

$A.W(t)$ denotes the waveform function or characteristic pattern of the AE signal at time, *t*

$F(t)$ is the frequency of the AE signal that changes over time *t*

$N(t)$ represents the background noise.

Hybridizing the traditional AE technique involves removing the background noise as expressed in Equation (6). To suppress the background noise in Equation (6), a filtering mechanism is integrated to minimize its impact while preserving the desired signal. This process is achieved by cancelling the noise, as formulated in Equation (7):

$$R_{ANCFilter}(t) = Filter(R(t) - NoiseFilter) \quad (7)$$

Where:

$R_{ANCFilter}(t)$ denotes the desired signal

R(t) represents the AE source signal, which consists of both the desired signal and the unwanted background noise. Equation (7) can therefore be further expanded as:

$$R_{ANCFilter}(t) = R(t) - \hat{N}(t) \quad (8)$$

Where:

$R_{ANCFilter}(t)$ denotes the desired signal obtained after adaptive noise cancellation.

R(t) represents the AE source signal, which contains both the desired signal and the unwanted background noise.

$\hat{N}(t)$ denotes the noise component

The estimated noise component $\hat{N}(t)$ is continuously updated in response to variations in the AE source signal *R(t).* The adaptive noise cancellation algorithm adapts to these changes in *R(t)* through a feedback loop, which is integrated into Equation (8) and can be further expressed as:

$$R_{ANCFilter}(t) = R(t) - \hat{N}(t+1) \quad (9)$$

Where:

$\hat{N}(t+1)$ denotes the refined estimate of the noise component at a given time t+1 which can further be expressed as:

$$\hat{N}(t+1) = \hat{N}(t) + \mu . X(t) . e(t) \quad (10)$$

Where:

$\hat{N}(t+1)$ denotes the refined estimate of the noise at a given time t+1 μ denotes the adaptive parameter that adjusts in response to variations in the background noise signal.

X(t) denotes the vector

$e(t)$ denotes the rate of error

To suppress the unwanted noise in order to generate clean signal, $\hat{N}(t+1)$ is replaced with $\hat{N}(t)+\mu.X(t).e(t)$ since $\hat{N}(t+1)=\hat{N}(t)+\mu.X(t).e(t)$, hence equation (10) expands to:

$$R_{ANCFilter}(t)=R(t)-(\hat{N}(t)+\mu.X(t).e(t)) \quad (11)$$

3.2 Experiment

The architecture of the Pipeline Leakage Detection and Monitoring Model consists of a host computer system, Acoustic Emission (AE) sensors installed along the pipeline, a Data Acquisition Centre (DAC), a memory card, and connecting wires. The experimental setup employed a pipeline of 3 m length with a diameter of 1.5 inches. Artificial leaks of 0.5 mm, 1 mm, and 2 mm were introduced into the pipeline. A data cable was used to transmit signals from the AE sensors to the DAC. The pipeline was instrumented with AE sensors at two distinct locations, separated by a distance

regulates the rate at which the filter

of 1 m, and labelled S1 and S2. To evaluate both leakage and no-leak conditions, gas was released at high pressure from a 3 kg gas cylinder.

3.3 Prototype Model

A total of 1,000 datasets were pre-processed and divided into two subsets: 70% for training and 30% for testing. These datasets were specifically utilized for training and predicting pipeline leakage and non-leakage states.

To emulate real-world pipeline leakage detection and monitoring scenarios, Gaussian noise was incorporated into the existing MUSIC algorithm to simulate the effect of background noise. This approach enabled an evaluation of the algorithm's robustness and performance under noisy conditions.

Signals were generated from the artificial leaks induced in the pipeline, as illustrated in Figure 1. These signals were recorded using the DAC and subsequently simulated with the hybridized mathematical model. The optimized MUSIC algorithm was then employed to localize the Direction of Arrival (DOA) of the signals and to detect the leakages.

Figure 1: Prototype of the Proposed Model

3.4 Development of Pipeline Leakage Detection and Monitoring Model

The development of the pipeline leakage detection and monitoring system depends on a synergistic combination of hardware and software components. Section 3.41 itemize the specific software Utilized.

3.4.1 Software Requirements and Tools

The following software were utilized for data augmentation, processing, model formulation, evaluation and deployment:

i. Python 3.13 Version
ii. Read Eval Print Loop (Replit) Platform.
iii. Windows 11 “Second Half of 2024” (24H2) Version.
iv. GitHub Database
v. Kaggle Database

3.4.2 Data Collection

Data were collected from Github, Kaggle and Nigeria National Petroleum Company Limited (NNPCL) through Nigerian Midstream and Downstream Petroleum Regulatory Authority (NMDPRA) respectively with break down and detail in Table 1.

Table 1 depicts the datasets collected from GitHub Kaggle and Nigeria National Petroleum Company Limited (NNPCL) respectively; a total 6000 datasets were collected from GitHub and Kaggle online database sources respectively, other data were collected from NNPCL. The data were processed using specific steps stated in Section 3.4.3.

3.4.3 Data Pre-processing

Data preprocessing is an indispensable and critical component in the development of machine learning model. Within the domain of pipeline monitoring and leakage detection, the quality and integrity of the input data directly impact the interpretability, generalization and classification accuracy. This section outlines not merely the step but methodological imperative for efficient accurate pipeline monitoring and leak detection. The following steps were taken on the preprocessed 6250 datasets collected from GitHub, Kaggle and NNPCL:

i. **Data Conversion:** The Datasets collected from open source databases and NNPCL were converted and stored from .xlsx to .csv format.
ii. **Data Merging and Consolidation:** This involves the integration of the 5000, 1000 and 250 datasets collected from GitHub, Kaggle and NNPCL respectively into a coherent, and single datasets of 6250 with the aim of aligning the records based on shared indices, input features and instances The data consolidation was initially carried out to integrate the collected datasets from online database sources, the next step involved merging the data collected from NNPCL the consolidated online database datasets. This step is necessary to ensure structural consistent and normalizations across all features before augmenting the datasets.

(iii) **Data Transformation**: To mitigate the ramification of redundancy and optimize the computational efficiency, the merged 6250 datasets was transformed into 2500 samples through instance selection and stratified filtering with the aim of preserving informative and representative pattern crucial to accurate pipeline monitoring and leak detection.

Table 1: Sources of Data Collection

GitHub	Kaggle	NNPCL	Total No. of Datasets	Total No. of Datasets Processed
5000	1000	250	6250	2500

iv. **Data Acquisition and Initial Inspection**: The transformed raw datasets stored in .csv format were imported using “import pandas as pd df=pd.read csv (‘pmlddataset.csv’)”.

v. **Data Cleaning**: This step involves identifying, correcting and transforming inconsistent or inaccurate data in the datasets to improve its reliability and quality with the aim of ensuring the processed data is consistent, reliable, accurate and usable for the HAEMUSIC modeling, analysis and evaluation. This can be achieved by removing duplicate, incomplete text-based and irrelevant data. Furthermore, this step is fundamental to prevent the proposed Enhanced-MUSICHAE model from leaning spurious pattern in the data, which could lead to misleading or inaccurate predictions. At this stage, this study removes the “*S”* prefix from all the feature set in the Sensor_ID column, along with other non-informative or irrelevant data.

vi. **Data Splitting:** The 2500 cleaned datasets were partitioned into two distinct subsets; 70% of the datasets for training and 30% for testing the model with the aim of preventing overfitting and to ensure impartial and valid assessments of the performance evaluation of the Enhanced-MUSICHAE model.

3.4.4. Model Formulation

The Enhanced-MUSICHAE model was formulated using Logistic Regression Algorithms. 2500 transformed datasets with features sets; Pressure, Flow Rate, Temperature and Sensor_ID. Leak Status were label with 0 for normal state and 1 for leak state.

3.4.5. Model Simulation (Experimental Procedure)

The 2500 datasets were pre-processed and spilt into two; 70% for training and 30% for testing. These were specifically utilized for training and prediction of the leak and no leak status. The Logistic Regression (LR) model was adopted and utilize due to the number of datasets available at the time of carrying out this research. The model was trained using Scikit-learn.

To simulate real-world pipeline leakage detection and monitoring scenarios, Gaussian noise was added to the existing MUSIC algorithm to impacts the effect of the background noise, which helps assess the algorithm's performance in the presence of background noise. Signals were generated from the artificial leaks induced in pipeline in Figure 2.

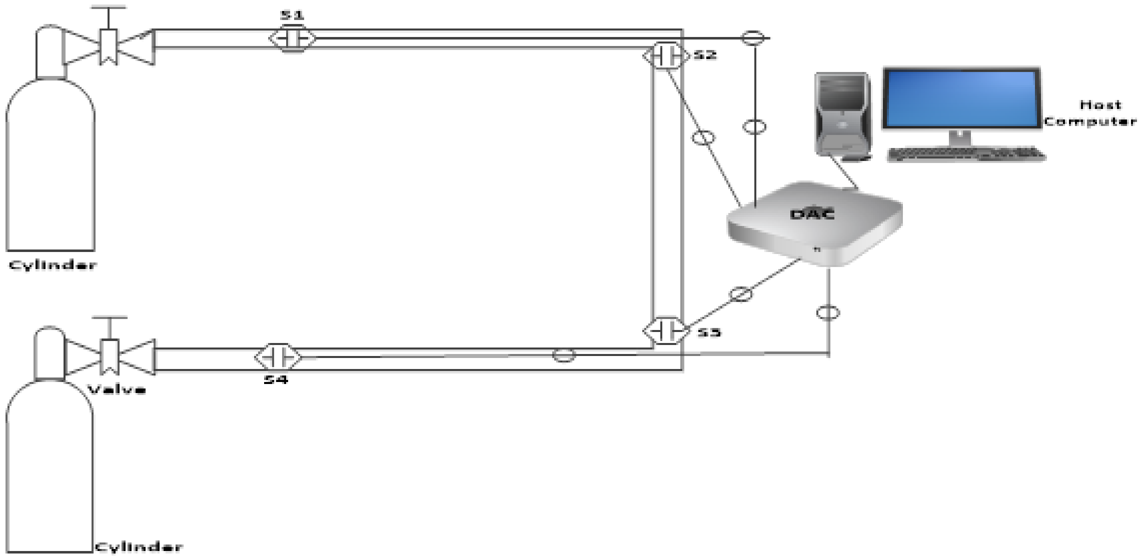

Figure 2: Architecture of Proposed System

4. Results and Discussion

4.1 Results

The quantitative results demonstrate the effectiveness of the proposed hybridized Enhanced-MUSICHAE algorithm with AE technique for real-time monitoring and rapid detection of leakages, achieving an accuracy of 95.5%, an average sensitivity of 75%, and a response time of 1.06 seconds. The proposed MUSIC algorithm is enhanced by addressing the limitations of noise interference and single-leakage detection inherent in traditional MUSIC algorithms. Conventional MUSIC algorithms are highly sensitive to noise, which often results in inaccurate detection and localization of pipeline leaks. To overcome this drawback, the enhanced MUSIC algorithm integrates advanced signal processing techniques such as wavelet denoising and independent component analysis (ICA) to effectively suppress noise and improve the accuracy of leakage detection.

Figure 3 illustrates the signal-to-noise ratio (SNR), where the background noise signal exhibits frequencies below 50 Hz, while the cleaned signal is concentrated at frequencies above 50 Hz.

The cancellation of the noise signal is illustrated in Figure 3, which depicts the signal-to-noise ratio (SNR) after background noise suppression. This visualization explicitly highlights the relationship between the noise and the desired signal, thereby indicating the calculated SNR. The results provide a clearer understanding of the effectiveness of the Enhanced-MUSICHAE algorithm in mitigating background noise and demonstrate its robustness in enhancing signal clarity.

As illustrated in Figure 4, the frequency of the noise lies within the ranges of 0.0 to –1.4 Hz and 0 to 203 Hz, whereas the hybridized signal occupies the range of 204 to 1000 Hz. Consequently, any signal within 0.0 to –1.4 Hz and 0 to 203 Hz is suppressed by the background noise cancellation algorithm incorporated into the hybridized AE and MUSIC framework, thereby generating a clean signal. This ensures efficient and reliable leakage detection in pipeline systems.

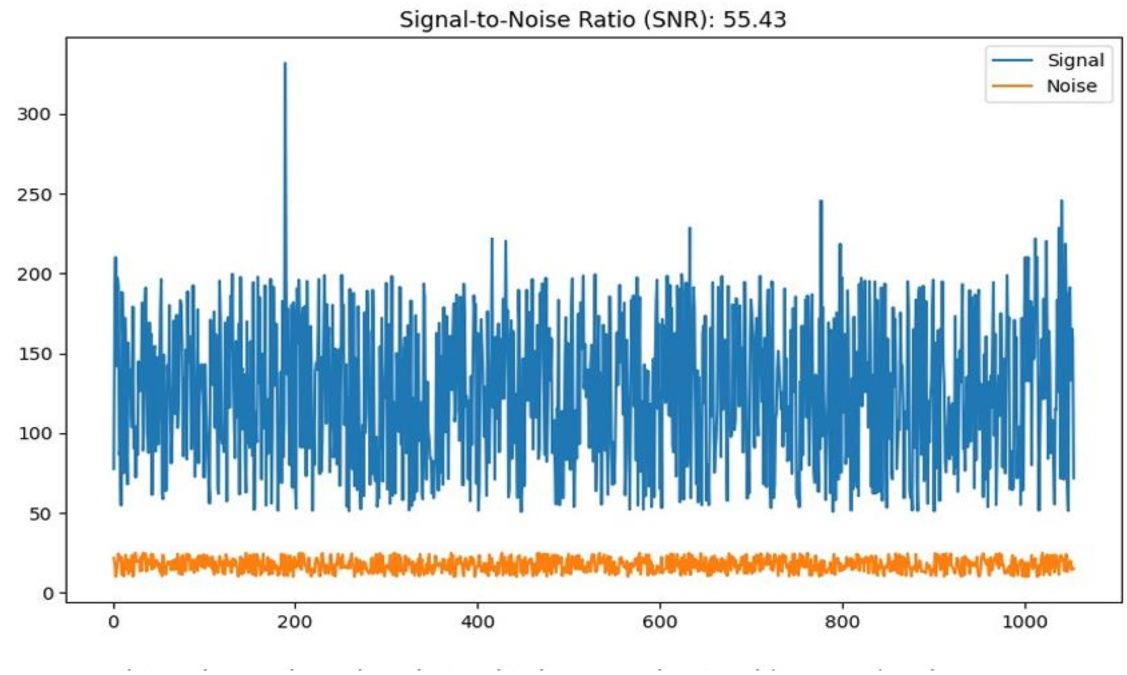

Figure 3: Signal to Noise Ratio

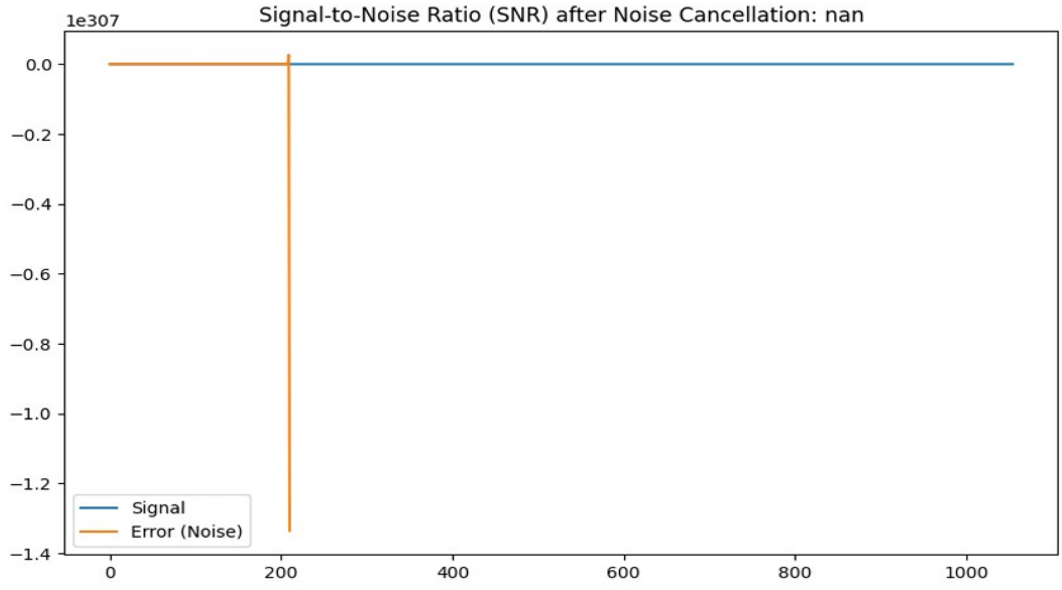

Figure 4: Background Noise Cancelation

4.2 Performance Evaluation

The Logistic Regression (LR) model of the MUSIC and AE technique for PLDM was developed and tested using dataset comprising 1000 labeled observations, each characterized by multiple parameters including timestamp, pressure, flow rate, temperature and leak status. (with 1 indicating leak state and 0 normal state). The LR model was evaluated using standard performance metrics; Detection Accuracy (DA), Mean Detection Time (MDT) and Sensitivity. The key outcomes are as follows:

- **Detection Accuracy:** 95.5%, this indicates that the model correctly classified 95.5% of the instances in the dataset, demonstrating a high overall reliability in predicting leakage events under the given conditions.

Mean Detection Time: 1.02 seconds which reflects the average time it takes the model to detect a leak event after its occurrence.

- **Sensitivity (True Positive Rate)**: 75%; this measures the model's ability to correctly identify actual leakages.
- **Respond Time**: 1.06 seconds, the respond time defined the time it takes to responds to leak.

4.3 Performance Comparison with Baseline works

As stated earlier the background noise is one of the significant limitations of the AE techniques as examined in Wang *et a*l, [13]; and Ullah *et al*, [12]. This research overcomes the drawbacks of previous studies by incorporating background noise cancellation technique to the AE technique to hybridize the traditional AE technique. This study also gave solutions to the other limitation to existing principles and approaches of pipeline leakage detection which is detection of single leak as examined in Nawal, *et al.* [15]; and Ahmad *et al*, [4].

5. Conclusion

This study proposes a novel approach for monitoring and detecting pipeline leakages by Enhancing Multiple Signal Classification (MUSIC) algorithm in conjunction with Hybrid Acoustic Emission (AE) techniques. The primary Enhancement lies in the hybridization of AE by incorporating a noise reduction mechanism to pre-process AE signals. The proposed method capitalizes on the strengths of both algorithms while addressing their limitations, enabling accurate detection of multiple leakages and effective suppression of background noise in pipeline systems. The quantitative results demonstrate the effectiveness of the proposed Enhanced-MUSICHAE technique for real-time monitoring and rapid leakage detection, achieving an accuracy of 95.5%, an average sensitivity of 75%, and a response time of 1.06 seconds. In addition, the Logistic Regression (LR) model exhibited promising performance in terms of detection accuracy, response time, and reliability in minimizing false positives.

Nonetheless, improving sensitivity remains an important area for further enhancement.

Future work will focus on expanding the dataset, applying class-balancing strategies, and exploring non-linear models to complement the logistic regression approach, with the aim of further enhancing detection performance and robustness.

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