# Pipeline Monitoring System Based on Acoustic and Vibration

M Saravanabalaji, E Praveen, Samritha Sivakumar and S Shakthi Raagavi



November 3, 2022

# Pipeline Monitoring System Based on Acoustic and Vibration


Saravanabalaji.M
*Electronic and Instrumentation Engineering*
*Kumaraguru College of Technology*
Coimbatore
saravanabalaji.m.eie@kct.ac.in

Praveen.E
*Electronic and Instrumentation Engineering*
*Kumaraguru College of Technology*
Coimbatore
praveen.20ei@kct.ac.in

Samritha.S
*Electronic and Instrumentation Engineering*
*Kumaraguru College of Technology*
Coimbatore
samritha.20ei@kct.ac.in

Shakthi Raagavi.S
*Electronic and Instrumentation Engineering*
*Kumaraguru College of Technology*
Coimbatore
shakthiraagavi.20ei@kct.ac.in



***ABSTRACT*— MODERN PIPELINE NETWORK FACES A CRITICAL PROBLEM WITH LIQUID LEAKAGE THAT AFFECTS BOTH INDUSTRIAL PRODUCTION AND WORKER SAFETY. WE HAVE DEVELOPED A UNIQUE APPROACH THAT TAKES ADVANTAGE OF ACOUSTIC-INDUCED VIBRATION IN THE PIPELINE TO ADDRESS THIS IMPORTANT PROBLEM. WHEN THE CONDITION OF TURBULENT FLOW IS MET, DATA OF THE ACOUSTICALLY INDUCED VIBRATION OF THE PIPELINE HAVE BEEN EXTRACTED USING THE DYTRAN ACCELEROMETER 3055D2 AND CDAQ (NI 9174). IN LABVIEW, WE EXTRACT 100 SAMPLES OF DATA EVERY SECOND FOR A TOTAL OF 120 SECONDS. BY ASSESSING THE ACOUSTICALLY GENERATED VIBRATION AND PROJECTING THE LEAK BY POSITIONING THE ACCELEROMETER IN CERTAIN PLACES ON THE SURFACE OF THE PIPELINE, WE ARE PROGRAMMING THE LOGIC OF MACHINE LEARNING SOFTWARE. WE CAN FORECAST OR ASCERTAIN WHETHER THE PIPELINE IS LEAKING OR NOT THANKS TO THIS MACHINE LEARNING ALGORITHM. THEREFORE, THE SOLE GOAL OF OUR PROJECT IS TO REDUCE FLUID LEAKAGE AND SUBSEQUENCE**


## 1. INTRODUCTION

Water leakage is still a major concern around the world because it wastes the energy and resources used for extraction, transportation, and treatment causes more harm to the pipe network and poses a risk to public health.
Compared with underground pipelines, pipeline networks have a typical lifespan of 25 to 30 years. Existing pipelines are getting old and are quiet as a result of faulty construction of joints, fatigue, and material cracks[1].
Increased pipeline vibrations are typically a sign of risky situations, such as gas leaks, (ii) sloppy pipeline connections, and (iii) corrosion-caused structural damage. Numerous approaches and procedures were used in pipe stability and pipe leakage testing to find abnormal conditions in the pipeline system. The acoustic emission signals in this work were classified using binary classification. However, just the water leakage may be found with technique. This algorithm fails to identify the leakage pressure[2].The two potential techniques will be utilized either on the pipeline or inside the pipeline to maintain the conditions. The opposing approach is known as the Intouch measuring methodology for calculating the stability of the water pipeline's pipeline system.
An exceeding pipeline needs to be periodically analyzed to prevent failures. Both the noise and the vibrations caused by the liquid flowing through the pipeline were examined in this investigation. We developed a machine learning technique that can identify whether a pipeline has leaked by evaluating the digital signal of the acoustically induced vibration. A patented vibration acoustic device was created as part of a pursuing project for remote, real-time pipeline monitoring. The system comprises a relatively distance-installed discrete network of pressure and vibration sensors on a pipeline.

## 2. ACOUSTIC-INDUCED VIBRATION

A piping system that has severe high-frequency vibration carrying gases or liquids is the Acoustic Induced Vibration. When there is a flow in the pipeline , a high-frequency sound wave in the range of 500–2,000 Hz is generated. Usually within minutes or hours , acoustic fatigue occurs when vibration and stresses cause the pipe wall to vibrate in the circumferential direction

In Acoustic Induced Vibration, elevated level of noise was given by the turbulent mixing, shockwaves downstream of the flow restriction and the high-velocity fluid impingement on the piping wall.
The pipe vibrates, creating work, heat loss to the surroundings, and noise transmission downstream of the flow limitation. When the circumferential vibration is no longer an issue, a noise or sound level of 155 dB is regarded as safe. Acoustic energy is attenuated by 3 dB for every 50 D of piping from the source, according to industry norms and experience. The first large vessel, such as the Separator, KO drum, etc., is affected by the response brought on by high-frequency acoustic excitation in the piping downstream of the source.

## 3. Proposed Methodology

To measure the acoustically induced vibration of the liquid flow in the pipeline in order to find the pipeline breach. With this solution, the controlled flow of water is used to prevent pipe bursts. The methods currently in use are ones that are primarily concerned with finding water leaks. The proposed approach operates by examining the data of the pipeline's acoustically induced vibration at the location of dimension change. As a result, the leakage might be anticipated. In this research, a method is planned to determine the acoustic resonance using a sensor on a pipeline for various dimensions and anticipate the leak's position using a machine learning algorithm.

### 3.1 EPANET Design

The software programme EPANET is used to simulate water distribution systems all over the world. It was created as a tool for analyzing how drinking water elements move through distribution networks and what happens to them after that. However, it may be applied to a wide range of distribution systems analysis tasks.

The Water Distribution Network (WDN) design in the EPANET software tool is displayed in **Fig. 4.4**. As seen in the dialogue box on the image's left side, it comprises of a main pipeline system and three sub-main pipeline networks, each with a different diameter. Each colour represents a particular diameter. Each sub-main pipeline network has three pressure regulator valves.

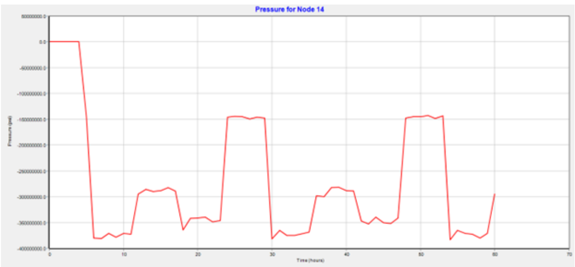



**Fig.1. Pressure Graph on Node 14**

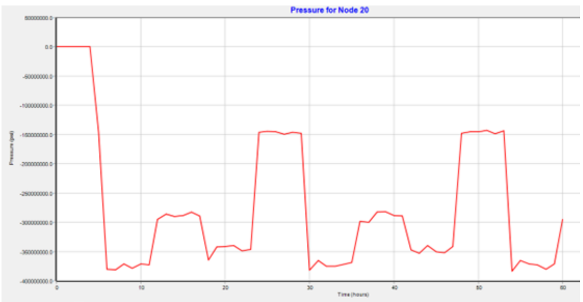



**Fig.2. Pressure Graph on Node 20**

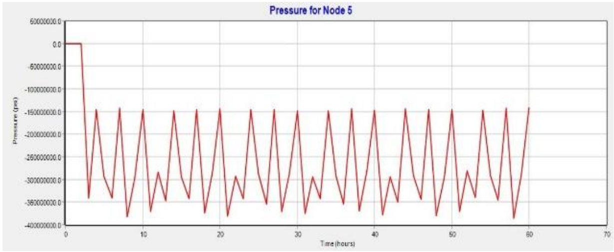



**Fig.3. Flow Graph on Link 6**

The pressure readings in each sub-main pipeline network are shown in **Figs. 4.5, 4.6, and 4.7.** The nature of the product being pumped, including its density, heat capacity, temperature, viscosity, and the speed at which it is traveling, causes the pressure changes in the pipe. Water is the system's primary output in our design.


**Fig.4. Flow Graph on Link 27**

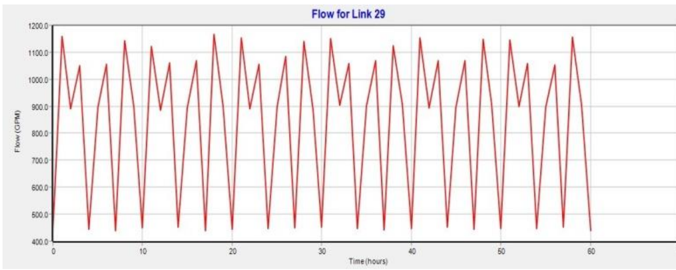
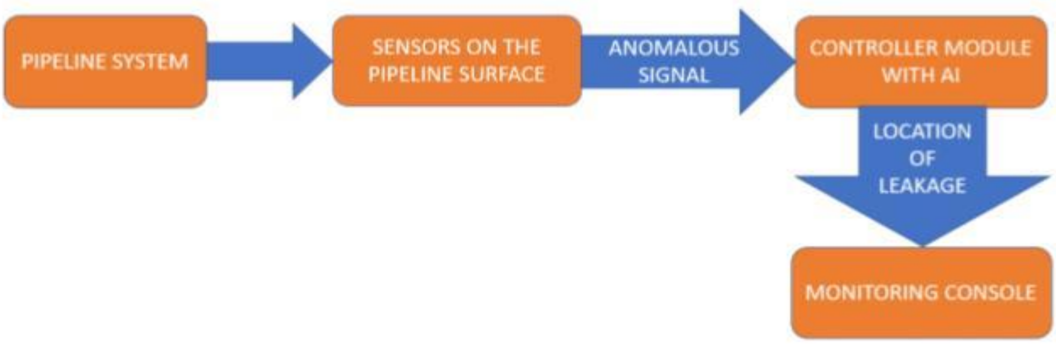



**Fig.5. Flow Graph on Link 29**

The flow rate at each of the sub-main pipeline systems is shown in **Figs. 4.8, 4.9, and 4.10.** It is evident that the system has changing flow rate due to pressure differences.

### 3.2 BLOCK DIAGRAM

**Sensors** – A microphone or acoustic emission sensor turns sound into an electrical signal. The vibration from the pipeline surface is picked up by discrete microphone placements, which characterize it as a disturbance or leakage if it exceeds a predetermined threshold. Here,



microphones are used to turn a sound wave's variations in air pressure into an electrical signal.

**Controller Module** – Integrated machine learning model in the controller can predict where a leak in the pipeline system is located. The input-process-output (IPO) model is the technique that is often used in the analysis of systems and software engineering so that the structure of an information processing program or another process can be described. In defining a process in introductory programming and systems analysis texts this presented as the most fundamental framework.

The system divides the work into three categories:

1. A requirement from the environment (input)
2. A computation based on the requirement (process)
3. A provision for the environment (output)

**Monitoring Console** – for using logical dashboards to present alerts and analyze critical metrics. The dashboards offer information on how well a deployment performs in terms of indexing, searching, and operating system resource utilization. They also offer a consolidated view of which analytical flows were executed and the assessments that were generated. To understand which analyses are running, use this dashboard.

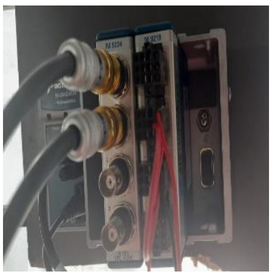
## 4. EXPERIMENTAL SETUP

### HARDWARE

- Microphone with 3.5mm jack (AUX).
- Audio Jack Female Socket
- Arduino (Microcontroller)
- Pump
- diaphragm

With the aid of an audio jack socket, a microphone with a 3.5mm jack and high sensitivity of -32dB senses changes in the acoustic signal flowing through a pipeline and is connected to a microcontroller (Arduino). The microcontroller then responds in accordance with the input signal.

**Fig.6. Complete Experimental setup**



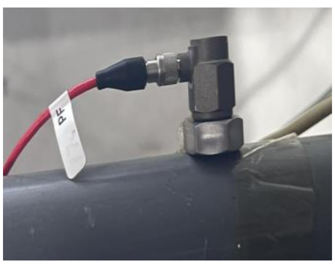


**Fig.9.**

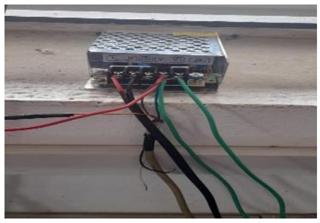


**Fig.10.**

## MACHINE LEARNING ALGORITHMS

### 4.1 NAIVE BAYES CLASSIFIER ALGORITHM

The Naive Bayes algorithm is a supervised learning method for classification issues that is based on the Bayes theorem. One of the most straightforward and efficient classification algorithms is the Naive Bayes Classifier, which aids in the development of quick machine learning models capable of making accurate predictions. Being a probabilistic classifier, it makes predictions based on the likelihood that an object will occur.
Bayes' theorem is also known as Bayes' Rule or Bayes' law, which is used to determine the probability of a hypothesis with prior knowledge. It depends on the conditional probability.
The formula for Bayes' theorem is given as:

Where,
P(A|B) is Posterior probability: Probability of hypothesis A on the observed event B.
P(B|A) is Likelihood probability: Probability of the evidence given that the probability of a hypothesis is true.
Working of Naïve Bayes' Classifier:
1. Convert the given dataset into frequency tables.
2. Generate a Likelihood table by finding the probabilities of given features.
3. Now, use the Bayes theorem to calculate the posterior probability

### 4.2 LINEAR REGRESSION

It uses a continuous variable(s) to estimate real values. By fitting the best line we can establish a relationship between dependent and independent variables. The regression line is referred to as the best fit line and can be represented by a linear equation Y= a *X + b.
In this equation:
· Y – Dependent Variable
· a – Slope
· X – Independent variable
· b – Intercept

a and b are the coefficients and are derived based on the sum of squared difference of distance between the regression line and data points minimization.
Simple linear regression and multiple linear regression are the two primary forms of linear regression. Linear regression can be defined by one independent variable. Additionally, many (more than one) independent variables are a feature of multiple linear regression, as the name suggests. A polynomial or curvilinear regression can be fitted while the best fit line is being determined. And these are referred to as curvilinear or polynomial regression.

### 4.3 SUPPORT VECTOR MACHINE ALGORITHM

One of the most well-liked supervised learning algorithms, Support Vector Machine, or SVM, is used to solve Regression and Classification problems. The objective of the SVM algorithm establishes the decision boundary best line that gives classes from n-dimensional space, so that fresh data points can be quickly classified in the future. The name given to this optimal decision boundary is the Hyperplane.

The extreme vectors and points that help create the hyper plane are chosen via SVM. The approach of SVM is based on support vectors, where extreme situations are represented by the utilization of these support vectors. The below diagram, uses a hyper plane or decision boundary for separating two different categories:

SVM can be of two types:

Linear SVM: The term "linearly separable data" refers to data that can be divided into two groups using only a single straight line. Linear SVM is used to classify such data, and the classifier utilised is known as the Linear SVM classifier.

Non-linear SVM: It is defined as non-linear, when straight line cannot be used to identify the dataset and the classification algorithm that was used is known as a non-linear SVM classifier.

### 4.4 DATA ACQUISITION

The required data must be in decibels, so we use the formula to convert voltage to decibels after collecting the sensor output voltage with Arduino and storing it into a file with the aid of Python language.

DECIBEL is equal to (Voltage + 83.2073)/11.003;

=AVERAGE (INDEX (B: B,2+100*(ROW()-ROW($F$2))): INDEX (B: B,100*(ROW()-ROW($F$2)+1)))

Here is the voltage and decibel data for the first 39 seconds after executing this code:

| T IN SECONDS | Converted voltage | Converted decibel |
|---|---|---|
| 0 | -1.9E-05 | 7.562236 |
| 1 | 0.000984 | 7.562327 |
| 2 | 0.001134 | 7.562341 |
| 3 | 0.000272 | 7.562262 |
| 4 | -0.00025 | 7.562215 |
| 5 | 8.31E-05 | 7.562245 |
| 6 | -9.8E-06 | 7.562237 |
| 7 | 4.62E-05 | 7.562242 |
| 8 | -0.00083 | 7.562163 |
| 9 | -5.8E-05 | 7.562232 |
| 10 | 0.000719 | 7.562303 |
| 11 | 0.000117 | 7.562248 |
| 12 | 0.00068 | 7.562299 |
| 13 | 0.000181 | 7.562254 |
| 14 | 0.000353 | 7.56227 |
| 15 | 0.000978 | 7.562326 |
| 16 | 0.000315 | 7.562266 |
| 17 | -4.6E-05 | 7.562233 |
| 18 | 0.00034 | 7.562269 |
| 19 | 0.000459 | 7.562279 |
| 20 | 0.001562 | 7.56238 |
| 21 | 0.000272 | 7.562262 |
| 22 | 0.000818 | 7.562312 |
| 23 | 0.00096 | 7.562325 |
| 24 | 0.000652 | 7.562297 |
| 25 | 0.000851 | 7.562315 |
| 26 | 0.000275 | 7.562263 |
| 27 | 0.000109 | 7.562247 |
| 28 | 0.001033 | 7.562331 |
| 29 | 0.00017 | 7.562253 |
| 30 | -0.00051 | 7.562191 |
| 31 | -0.00074 | 7.56217 |
| 32 | 0.00019 | 7.562255 |
| 33 | 0.000287 | 7.562264 |
| 34 | -0.00016 | 7.562223 |
| 35 | -0.00085 | 7.562161 |
| 36 | 0.000176 | 7.562254 |
| 37 | 4.35E-05 | 7.562242 |
| 38 | -0.00021 | 7.562219 |
| 39 | -0.00052 | 7.562191 |

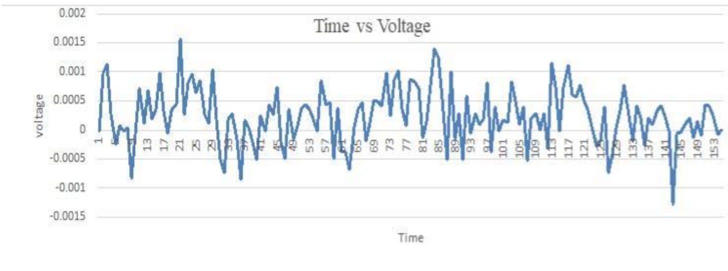



**Fig.11. Graph – Time Vs Voltage**

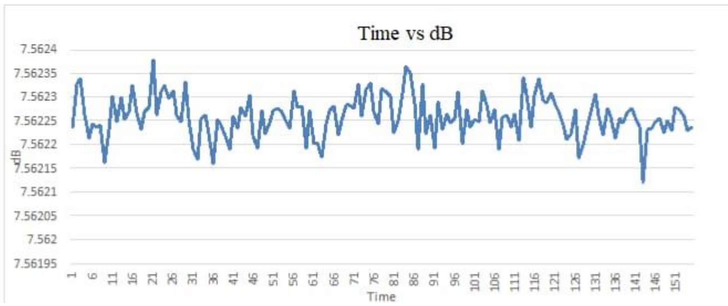



**Fig.12. Graph – Time Vs dB**

The program's threshold value is derived from the graph, and we arrived at the conclusion that it is 0.0003 for the time vs. voltage chart.

### 4.5 DATA PROCESSING

In order to train an AI model, the sensor data must be processed. Here are a few of the model's outcomes.

**The distribution of leak data:**

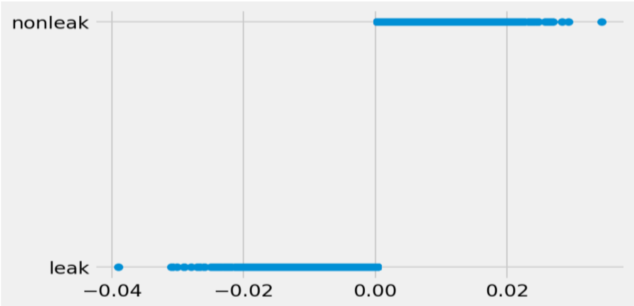



**Fig.13. Distribution of leak data**

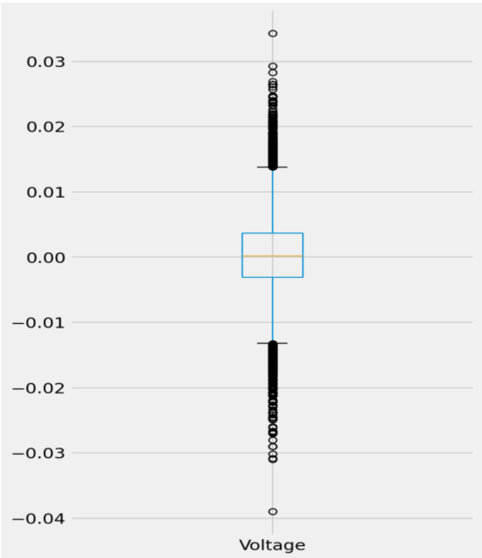



**Fig.14.**

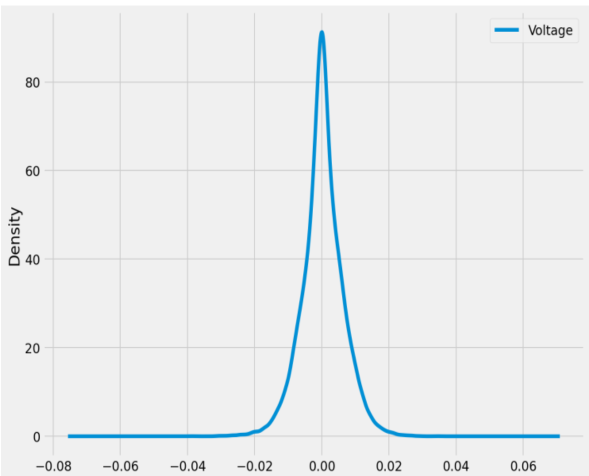



**Fig.15.**

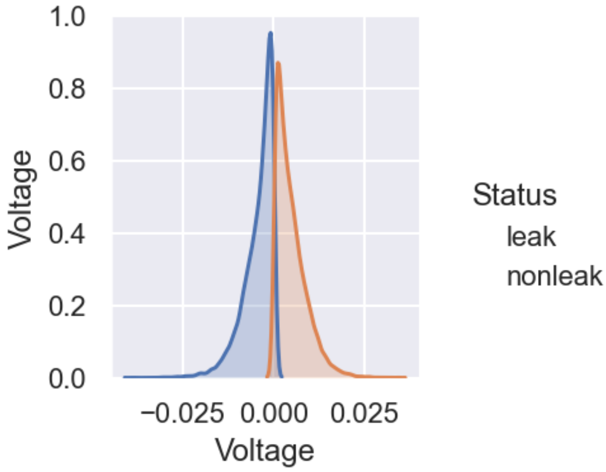



**Fig.16.**

**Final prediction model:**

The below image is the final predictions using the the test data. Predicting the area of leak and non-leak

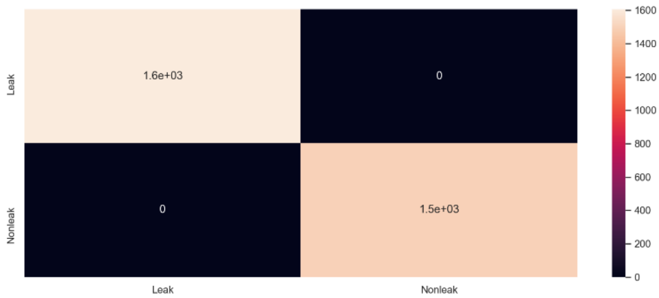



**Fig.17.**

## 5.WORKING MODEL(OPERATION)

The system with the acoustic sensors is modelled using Ansys simulation software. Ansys is a general purpose simulation software which can be used to model, simulate and solve the problems regarding various mechanical systems. The images below (Fig.18. and Fig.19.) are the models developed using Ansys which depicts the Acoustic Power level at various points in the pipeline.

**Fig.18. Isometric view**

**Fig.19. Side View**

## 6. RESULTS AND DISCUSSIONS

This experiment uses acoustic sensor that senses the vibration from the pipeline surface and converts it into an equivalent analog voltage. The voltage value is converted to its corresponding decibel value and is recorded in an excel sheet. By analyzing the graph of Time versus Voltage for every second, we were able to find the threshold voltage to be 0.0003 V. We developed a machine learning model using Decision tree and Support Vector Machine(SVM) algorithms that detects the water leakage using the data from the acoustic sensor.

## 7. CONCLUSION

Acoustic based water leak detection proves to be a very effective technique in detecting the damage in the water pipelines because these sensors are very sensitive and can detect even a small range of acoustic signal. SVM algorithm works well in classifying the data from the acoustic sensor as ‘Fine’ and ‘Leakage’ based on the threshold value. By further processing the data from the acoustic sensor, it is also possible to detect the location of water leakage in the pipeline system.

## 8. REFERENCES


❖ [1] Giunta, G., Dionigi, F., Bernasconi, G., Del Giudice, S., Rovetta, D., 2011a, “Vibroacoustic Monitoring of Pigging Operations in Subsea Gas Transportation Pipelines,” ASNT Fall Conference, Palms Spring, USA.

❖ [2] Banjara, N. K., Sasmal, S., &Voggu, S. (2020). Machine learning supported acoustic emission technique for leakage detection in pipelines.

❖ [3] P. Karkulali, H. Mishra, A. Ukil and J. Dauwels, "Leak detection in gas distribution pipelines using acoustic impact monitoring," IECON 2016 - 42nd Annual Conference of the IEEE Industrial Electronics Society, 2016

❖ [4] A. Mostafapour, S. Davoudi, (2013) Analysis of leakage in high pressure pipe using acoustic emission method, Applied Acoustics, Volume 74, Issue 3

❖ [5] Shuaiyong Li, Yumei Wen, Ping Li, Jin Yang, Xiaoxuan Dong, Yanhua Mu (2014) Leak location in gas pipelines using cross-time–frequency spectrum of leakage-induced acoustic vibrations, Journal of Sound and Vibration, Volume 333, Issue 17

❖ [6] F. Wei Liang, Laibin Zhang, Qingqing Xu, Chunying Yan (2013) Gas pipeline leakage detection based on acoustic technology, Engineering Failure Analysis, Volume 31

❖ [7]https://www.analyticsvidhya.com/blog/2017/09/common-machine-learning-algorithms/

❖ [8] M. Saravanabalaji, N. Sivakumaran, S. Sankarnaraynan (9 April 2019) “Dynamic Compensation of Acoustic Resonance for Water Flow System” – A journal published at Springer