Leak detection on Air reservoir via Acoustic Models with TensorFlow Based

Naparat Pairin and Ramil Kesvarakul

Abstract—**Fluid, both gas and liquid, is a widely used substance which can be used in pneumatic and hydraulic system. However, the pneumatic system with compressed air system integrated has a flaw that leakage air during power transmission cost a lot of loss both resources and performance. Leak detection is one of the main solution to plug the flaw. In this research, we use acoustic signal to detect the leakage by using it as an input for model. Artificial Neural Network (ANN) is used in our model to achieve deep learning property via Tensorflow. Acoustic signal is recorded in different situation and is used as a model input. So, our model can be trained with leak data and predict the leakage in pneumatic system. We evaluate model using test data and shows the leakage prediction in probability distribution.**

Index Terms—**Artificial neural network, leak detection, Tensorflow.**

I. Introduction

Most industries apply the compressed air uses in the pneumatic system for transmitting the power of fluid to mechanical energy form. This is widely used because air is green energy and the system is simple. However, there are huge amount of wasted energy since compressed air can be leaked during transmission. The fluid leakage can be found in several mechanical devices such as pipeline, value and air reservoir which usually leads to change some characteristic of acoustic waves, flow rates, etc. Therefore, it is possible to detect an air leakage using the ultrasonic leak detection method, the acoustic emission technique, the acoustic leak detection method [1]-[5], etc. The acoustic leak detection method has been proved to be high sensitivity, efficiency and accuracy [3], [6].

Acoustic leak detection method identifies the sound or vibration of fluid leak from escaping fluid caused by difference pressure between in-reservoir and out-reservoir. As fluid escapes from the reservoir, velocity of escaping fluid, diameter of leaky hole, air pressure and fluid flow are affect to sound of fluid leak. In terms of the mechanism of acoustic signal generation had related to the turbulent flow of fluid at the leaking area. Reference [3] use acoustic method to detect leak in gas pipelines. Acoustic signals collected by sensors had the ranges of 0-100 Hz and de-noised by wavelet transform. The result establishes de-noising system, leak detection and leak detect location which can be applied to other pipelines. Reference [4] use acoustic leak detection method to detect the leakage then figure out the leaky point in oil and natural gas pipelines. It locates leaky point based on acoustic velocity and time difference of acoustic signals between two adjacent acoustic sensors. As the result, leaky location between two sensors is calculated using two methods. The former is the different of pressure and distance while the latter is the different of velocity and time. Reference [5] use acoustic leak detection method to detect leak in gas pipelines based on wavelet transform and use Support Vector Machine as a classifier in laboratory scales. The results of leak and non-leak can be determined using discriminative features with 99.4% accuracy while the results of normal and several leak conditions can be classified using discriminative features with 95.6% accuracy. This can be used to develop a real-time monitoring system.

The original acoustic signal is recorded via microphone or sensor then is extracted by frequency range of each sound using mathematical process called Fast Fourier Transform (FFT) [7]-[9]. In terms of classification, data is classified using Decision tree and Neural network. Decision tree classifier is used for non-complicated data while complicated data such as acoustic signal uses the Neural network [10].

An artificial neural network (ANN) is the method of establishing the model for classified data to predict output from a group of the sample, called training data. Model with classified data can predict the result of unclassified data. ANN is available in many tools such as SOM toolbox [11] from MATHLAB or Tensorflow library which is machine-learning platform. Reference [12] is identify, characterize and locate leakage in gas pipelines using ANN via self organizing map (SOM). The result shows that leaky hole diameter and location can be distinguished. However, this work cannot identify and recognize pipelines with no leakage correctly. Reference [13] present the usage of TensorFlow for estimating Global Navigation Satellite System.

In this research, ANN is used for training acoustic signal data and classification trained data then prove that acoustic signal can be used to detect the fluid leakage of air reservoir via Tensorflow libraries. The experiments record the acoustic signal from air reservoir with different leaky hole at pressure higher than atmosphere. Then, acoustic method is used to classify acoustic signal and classified signal is used by ANN to establish training model. Finally, we evaluate model using unclassified data and measure probability of

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each situation.

II. Acoustic Signal

A. Waveform

Acoustic signal is recorded in analog signal with amplitude-time domain. Digital signal processing is used to convert analog signal into digital signal while $x(t)$ is the amplitude of the analog sample and t is time. As shown in Fig. 1, analog signal (a) is a continuous graph which cannot used in FFT, so discretization is used to acquire discrete in time (b) with period n. Then, quantization is applied to graph to get average amplitude of each n. Amplitude of digital signal is represent in N-bit resolution form.

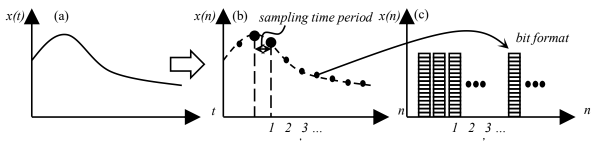


Fig. 1. Step of digital signal processing (a) analog signal (b) discrete time signal (c) digital format.

B. Fast Fourier Transform

Fast Fourier Transform (FFT) is an algorithm which computes the Discrete Fourier Transform (DFT) of a sequence. Fourier analysis converts a signal from the amplitude-time domain to the frequency-time domain. According to Fourier theorem, a signal is a composition of a number of sinusoidal functions with given amplitude, frequency, and phase. Cooley and Tukey presents the calculation of the DFT as define in equation (1).

$$X(m) = \sum_{n=0}^{N-1} x(n) W_N^{mn} \tag{1}$$

where $x(n)$ is complex numbers or sequence number of real number N, $X(m)$ is DFT of $x(n)$ at m-point, $m = 0, 1, 2, \ldots, N-1$, $j = \sqrt{-1}$ and W_N is a primitive N^{th}-root of unity as in (2)

$$W_N = e^{\frac{-j2\pi}{N}} \tag{2}$$

In equation (1), input is divided into two groups odd number and even number then they are calculated separately as in equation (3).

$$X(m) = \sum_{n=0}^{\frac{N}{2}-1} x(2n) W_N^{(2n)m} + \sum_{n=0}^{\frac{N}{2}-1} x(2n+1) W_N^{(2n+1)m} \tag{3}$$

$$= \sum_{n=0}^{\frac{N}{2}-1} x(2n)(W_N^2)^{mn} + \sum_{n=0}^{\frac{N}{2}-1} x(2n+1) W_N^m (W_N^2)^{mn}$$

Then, equation (2) is applied to W_N and we get following formula.

$$W_N^2 = (W_N)^2 = e^{2\left(\frac{-j2\pi}{N}\right)}$$

$$= e^{\frac{-j2\pi}{N/2}} = W_{N/2}$$

When W_N is a primitive $(N/2)^{\text{th}}$-root of unity then $X(m)$ equation is reformed into equation (4)

$$X(m) = \sum_{n=0}^{\frac{N}{2}-1} x(2n) W_{N/2}^{mn} + W_N^m \sum_{n=0}^{\frac{N}{2}-1} x(2n+1) W_{N/2}^{mn} \tag{4}$$

However, m can be reassigned into 2 parts. The former is $m = 0, 1, 2, \ldots, \frac{N}{2}-1$ and the latter is $m = \frac{N}{2}, \ldots, N-1$. Then, we consider $m + \frac{N}{2}$ instead of m as in equation (5).

$$X\left(m+\frac{N}{2}\right) = \sum_{n=0}^{\frac{N}{2}-1} x(2n) W_{N/2}^{\left(m+\frac{N}{2}\right)n} + W_N^{m+\frac{N}{2}} \sum_{n=0}^{\frac{N}{2}-1} x(2n+1) W_{N/2}^{\left(m+\frac{N}{2}\right)n} \tag{5}$$

$$= \sum_{n=0}^{\frac{N}{2}-1} x(2n) W_{N/2}^{mn} \left(W_{N/2}^{N/2}\right)^n + W_N^m W_N^{N/2} \sum_{n=0}^{\frac{N}{2}-1} x(2n+1)\, W_{N/2}^{mn} \left(W_{N/2}^{N/2}\right)^n$$

Because of

$$W_{N/2}^{N/2} = e^{N/2\left(\frac{-j2\pi}{N/2}\right)} = e^{-j2\pi} = 1$$

And

$$W_N^{N/2} = e^{N/2\left(\frac{-j2\pi}{N}\right)} = e^{-j\pi} = -1$$

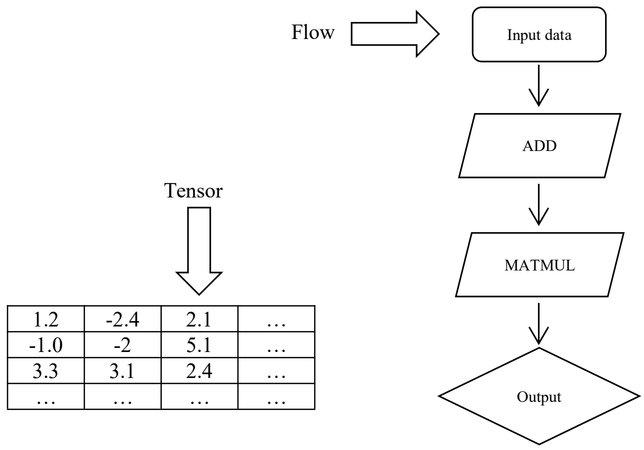
We then get equation (6).

$$X\left(m+\frac{N}{2}\right) = \sum_{n=0}^{\frac{N}{2}-1} x(2n) W_{N/2}^{mn} - W_N^m \sum_{n=0}^{\frac{N}{2}-1} x(2n+1)\, W_{N/2}^{mn} \tag{6}$$

III. TensorFlow

A. TensorFlow

TensorFlow is an open-source library widely used for machine learning (ML) which is developed by the Google Brain team. It is a symbolic math library such as neural networks. Tensors are just multidimensional arrays, an extension of 2-dimensional tables to data with a higher dimension arrange the sequence of executing as a flowchart (or graph). The data has been input, flowed to the result, output shown in Fig. 2.



1.2	-2.4	2.1	…
-1.0	-2	5.1	…
3.3	3.1	2.4	…
…	…	…	…

Fig. 2. Tensor and flow.

Tensor is consists of node and edge. Node is represent operation defined while edge is link output from node to another node as an input. The architecture of TensorFlow is consists of three part which is preparing data, constructing model and training and testing model. The neural network in TensorFlow is executed via Keras() function.

B. Artificial Neural Network

Artificial neural network is an interconnected group of nodes, inspired by a simple of neurons in a brain. The neural network components have three main parts, there are input layer, hidden layer, and output layer as shown in Fig. 3.

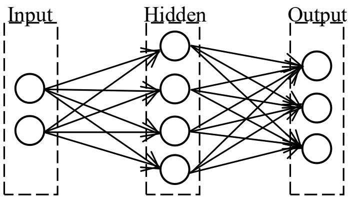


Fig. 3. The components of neural network.

The input layer had been put in the AE hits. The number of neuron node (○) in this layer represent number of initial input for further calculation. Hidden Layer is located between input and output layer is used to compute input and return output as a result, this layer represents efficiency of learning model. Hidden layer with one level is called single-layer perceptron, for two or more levels are called multilayer perceptron. The number of neuron nodes of the hidden layer is unlimited. The output layer provides result of data calculation while the number of neuron nodes is equal to number of expected output. Result of output layer can be represented as in (7).

$$y_i = f\left(\sum_{i=1}^{n} x_i w_{ij} + \theta_j\right) \tag{7}$$

where y_i is the output of the neuron, f is the activation function, w_{ij} is the weight of the neuron; x_i is the vector input value of the neuron and θ_j is a bias term. Activation function from Sigmoid Function shown as in (8)

$$f(u) = \frac{1}{1 + e^{-u}} \tag{8}$$

IV. Experimental Setup

This paper methodology contains 3 parts: audio signal record, audio training model and audio test model as shown in Fig. 4. For acoustic signal record part, we record the acoustics signal using condenser microphone. The, use recorded signal as an input for Audio training model to establish the learning model. Finally, audio test model is used to predict the acoustic signal from test signal.

A. Audio Signal Record Method

The acoustic signal was recorded in the Pneumatic and Hydraulic Laboratory at Production Engineering, King Mongkut's University of Technology North Bangkok. We used three 550 ml capacity air reservoir with 0, 0.5 and 1.0 mm diameter leaky hole respectively as shown in Fig. 5. We then set air pressures for experiment to 0.5 and 1.5 bar at room temperature.

For audio recording system, Audio Interface Model Audient iD4, Condenser Microphone model CM-90 (Frequency response is 40-16000Hz) were used with Cubase Elements 10 as recording application. Acoustic signal was recorded in 96 kHz, 96 sampling rates and 24-bit rate.

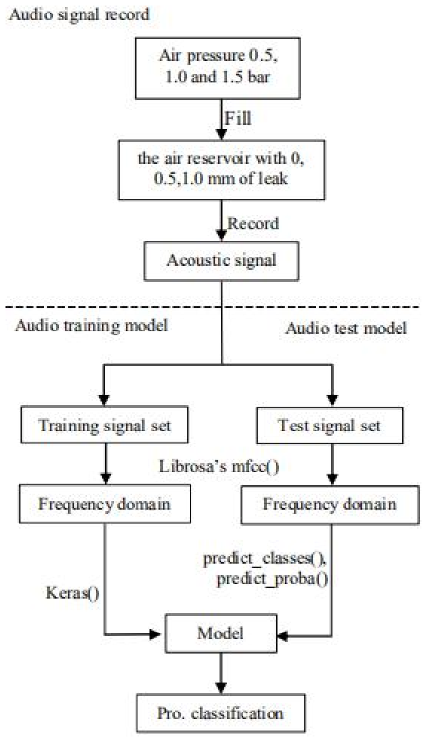


Fig. 4. Process diagram.

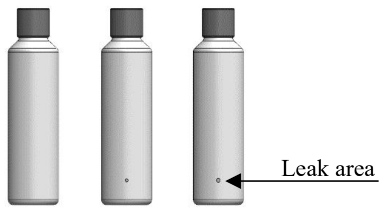


Fig. 5. The air reservoir.

Fig. 6 showed the leak system set up, then we filled air into each air reservoir and recorded the audio within stabilize air pressure at 0.5 and 1.5 bar.

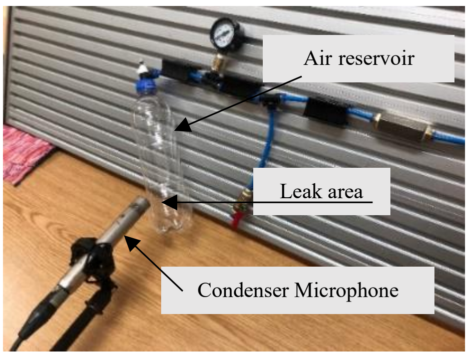


Fig. 6. Leaks system setup with condenser microphones installation.

B. Audio Training Model Method

The research had the computer with following specification: 14-bp104tx, Intel® Core™ i5-8250U, 8 GB DDR4 of RAM, 256 GB and M.2 SSD of Hard drive.

Leak acoustic signal had constant leakage rate while non-leak acoustic signal never leaked. Each acoustic signal was recorded into one minute length file. Then each file was split into sub-files with two seconds each. Each sub-filed was counted as a training data and test data.

As for model training's parameter, we used 72 epochs with 256 batch sizes. Spyder (Anaconda) and Tensorflow library to were used to create python 3 file for training data.

and Tensorflow libraries was used as an ANN platform in this research.

Recorded acoustic signal's time domain had been converted to frequency domain using FFT with Librosa's mfcc() function. Then, the frequency of acoustic signal group had been trained using Tensorflow's Keras() function. Finally, trained data was saved in the learning method model as classification characteristics of data types. Table I showed the number of data trained by our model in various group type.

TABLE I: TYPE OF CLASSIFICATION

Group type	Number of data set 1 (file)	Number of data set 2 (file)
Non-leaks 0.5 bar	20	40
Non-leaks 1.5 bar	20	40
Leaks 0.5mm, 0.5bar	20	40
Leaks 0.5mm, 1.5bar	20	40
Leaks 1.0mm, 0.5bar	20	40
Leaks 1.0mm, 1.5bar	20	40

C. Audio Test Model Method

The method of sample test had a separated audio recorded set, which was not the trained set. The frequency of acoustic signal test sample was test via TensorFlow's predict_classes() and predict_proba() function. The result reported the probability and classification of the fluid leakage.

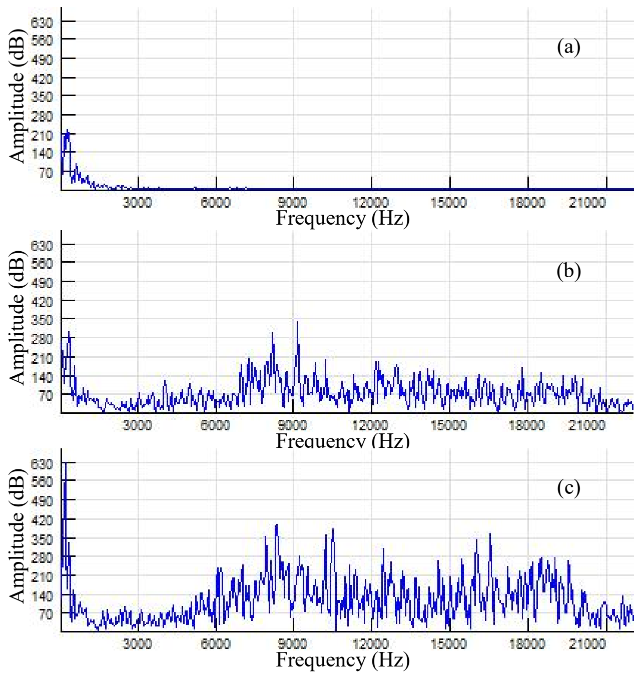


Fig. 7. Frequency domain of acoustic signal at 0.5 bar.

V. RESULTS AND DISCUSSION

A. Result of Frequency

The result of converting acoustic signal from amplitude-time domain to amplitude-frequency domain at 0.5 and 1.5 bar was shown in Fig. 7 and Fig. 8 respectively. Both figs contained subplot of non-leak at (a), 0.5 mm diameter leakage hole (b) and 1.0 mm diameter leakage hole (c).

Graphs represented that the amplitude of acoustic signal at 0.5 and 1.5 bar were null at high frequency while acoustic signals with leaky hole were not null. The leaky hole with smaller diameter cause to have more frequency, while amplitude at the same frequency has increased at higher air pressure, this is because of Flow Rate Formula as in (9)

$$Q = Av \tag{9}$$

When the flow rate (Q) is stable, the speed (v) of fluid inverses to cross-section area (A). Wavelength Formula is shown in equation (10)

$$\lambda = \frac{v}{f} \tag{10}$$

When the flow rate (λ) is stable, the speed (v) of fluid relate to frequency (f). The relation of f and A is shown in equation (11)

$$A = \frac{Q}{f\lambda} \tag{11}$$

When cross-section area increase, the velocity of fluid decrease and with Sound Intensity Formula (12)

$$I = \frac{P}{A} \tag{12}$$

The constant of cross-section (A) make Amplitude (I) relate to air pressure (P).

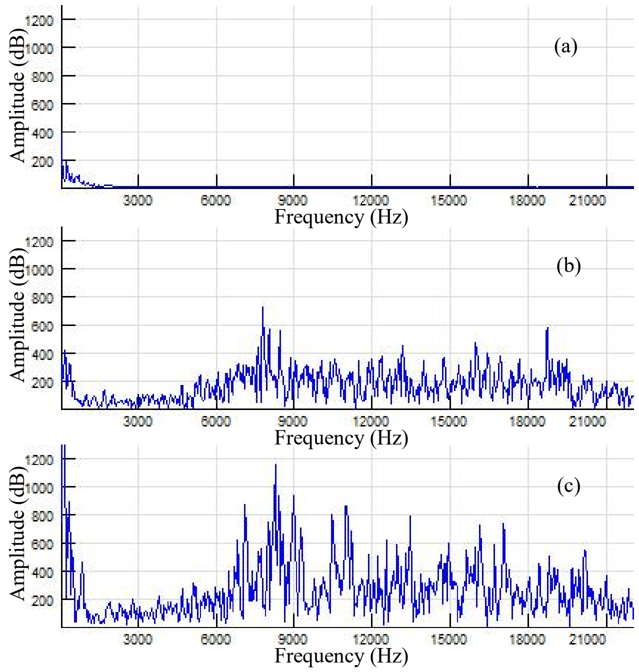


Fig. 8. Frequency domain of acoustic signal at 1.5 bar.

B. Result of Classification

Training time for dataset training was shown in Table II which represented that the number of data in dataset significantly relate with training time. The higher amount of data in dataset lead model to train data with longer time.

TABLE II: TRAINING TIME FOR THE TRAINING

	Amount of data (file)	Time (s)
Training data set 1	120	14
Training data set 2	240	32

Probability of leakage from dataset 1 and 2 as trained model are shown in Table III and Table IV respectively.

With acoustic signal method, we could detect that the signal was leak or not. As for non-leak situation, we could not predict air pressure inside air reservoir. The result of classification prediction showed that leak prediction at 0.5 bar had less average accuracy than 1.5 bar which were 65.20% and 84.95%. This is because signal at higher air pressure had more intensity than lower air pressure. Moreover, if we doubled amount of file trained, the average accuracy was increased from 75.08% to 83.93%.

TABLE III: RESULT OF CLASSIFICATION BY TRAINING DATA SET 1

File test \ Class		Leak dia. with 0.5 bar			Leak dia. with 1.5 bar		
		0mm	0.5mm	1.0mm	0mm	0.5mm	1.0mm
0.5 bar	0 mm	0.682	0.017	0.001	0.300	0.000	0.000
	0.5mm	0.042	0.713	0.081	0.067	0.097	0.001
	1.0mm	0.005	0.034	0.591	0.008	0.324	0.039
1.5 bar	0 mm	0.459	0.007	0.000	0.534	0.000	0.000
	0.5mm	0.006	0.054	0.044	0.005	0.854	0.038
	1.0mm	0.001	0.007	0.078	0.001	0.068	0.845

TABLE IV: RESULT OF CLASSIFICATION BY TRAINING DATA SET 2

File test \ Class		Leak dia. with 0.5 bar			Leak dia. with 1.5 bar		
		0mm	0.5mm	1.0mm	0mm	0.5mm	1.0mm
0.5 bar	0 mm	0.786	0.004	0.003	0.207	0.000	0.000
	0.5mm	0.018	0.833	0.086	0.003	0.059	0.000
	1.0mm	0.002	0.002	0.635	0.009	0.237	0.114
1.5 bar	0 mm	0.302	0.002	0.000	0.696	0.000	0.000
	0.5mm	0.003	0.004	0.058	0.000	0.918	0.016
	1.0mm	0.000	0.000	0.008	0.000	0.020	0.971

VI. CONCLUSION

Air compression has leakage that cost huge amount of energy. For detecting leakage, acoustic model is used by converting analog signal into digital signal then use it as an input for model training. We collect analog signal with different leaky hole and air pressures at room temperature. The frequency of leakage inversely relates to hole diameter and air pressure relates to amplitude. Then, we process analog signal to digital signal using discretization and quantization and then apply FFT to convert domain of digital signal from the amplitude-time domain to the frequency-time domain. After that, we build up a prediction model integrated with ANN using python 3 and Tensorflow. This model is used for separate and predict the classification of the test input. Then, we experiment model with different leaky hole in air reservoir and air pressure. The result of this experiment is that our model can predict the test input with 75.08% accuracy and 83.93% accuracy with higher number of trained data. Air pressure is a significant variable since higher air pressure produces signal with higher intensity. For future work, we will add real-time monitoring feature to make our model available on real world. Noise cancelling is one of the main feature with which we improve signal quality.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

All authors carried out the experiment. N. Pairin wrote the paper and R. Kesvarakul had approved the final version.

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