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CLASSIFICATION OF BLOCKAGE ACOUSTIC REFLECTOMETRY IN PIPELINE INSPECTION USING NEURAL NETWORK

RINGKASAN: Didalam aplikasi ujian tanpa kemusnahan, pantulan akustik membawa maklumat penting sepanjang laluan ujian. Maklumat paip tersumbat dan kebocoran paip seperti jarak dari lokasi ujian boleh diselesaikan dengan kajian tempoh masa. Walaubagaimanapun, maklumat tambahan seperti saiz sumbat hanya dapat dilakukan dengan penyelesaian analisa frekuensi-masa. Sering hilang dalam kebisingan data, proses penataan dimensi sumbat sering mengambil masa yang terlalu lama. Dengan kemajuan kaedah jaringan neural, penataan boleh dilakukan tanpa penyelesaian analitikal. Didalam kajian ini, kaedah jaringan neural telah digunakan untuk klasifikasi nisbah sumbat kepada luas dalaman paip dan panjang lateral. Keputusan klasifikasi telah dinilai melalui padanan keputusan eksperimen, dan menunjukkan potensi aplikasi yang baik.

ABSTRACT: In non-destructive testing, the acoustic reflectometry provides the relevant information along the propagation path. Blockages and leakages location can be determined by performing flight time calculation. However, greater classification to the type of disconformity can only be solved by time-frequency analysis. Often embedded in the noise, the interpretation of responses is a complicated process that requires time consuming procedures. With the available intelligent learning tools, the analytical stage of classification can be excluded in the procedure. In this work we have adopted a neural network technique to the classification of blockage severities in pipeline from acoustic pulse reflectometry. The experimental responses from open end excitation are used as the input to the classification of blockage size and trained using neural network. Results are validated using different geometry of blockage insertion. The paper presented the promising prediction performance that can be adapted to other machine learning procedures.

Keywords: Non-destructive methods, pipeline, pulse reflectometry, soundwave propagation

INTRODUCTION

In a typical Acoustic Pulse Reflectometry exercise (APR), the reflection from objects of inspection is obtained by studying the incident and the reflection of sound pressure using single and multiple sensor location(Sharp, 1996; Datta & Sarkar, 2016). Oil and gas pipeline integrity is very important to industry and maintaining a healthy pipeline reduced the risk of failure that can be expensive and fatal to organisation. Various modes of failures exist in a pipeline and blockage is one of the common situations that require fast and accurate classification using APR.

Researchers over the years work on the time and frequency domain analytical solution as a tool of classifying the type of blockage from pipeline APR responses (Vidal & Silva, 2014; Sharp, 2017). The sound wave propagation characteristic can be determined using both domain i.e. the solid and the liquid. Working in the solid domain however, can be complicated due to the dispersive nature of sound travelling in higher order mode compared to the easier plane wave understanding in the fluid domain.

The reconstruction of inner duct profile from the pulse response is often completed by analytical solution such as the profiles calculated using the Ware-Aki method (Duan *et al.*, 2012). The algorithm using input impulse response measurements were reasonably accurate with long source tube for the transceiver. However this method only offers information of the severity of blockage based on the intensity within time frequency analysis and inconclusive in the profile (Papadopoulou *et al.*, 2008).
A more recent work suggested the use of a layer-peeling algorithm which was modified to include the effect of losses. This work was later improved by Duan *et al.*, by introducing an analytical approach using the power reflection ratio of incident and reflected wave (Duan *et al.*, 2015). Coupled with the phase difference of the two wave forms, the reconstruction of blockage is solved by the ratio of cross sectional area of blockage to the healthy pipeline. This method however requires a rather complicated analytical process in both time and frequency domain that requires longer processing time.

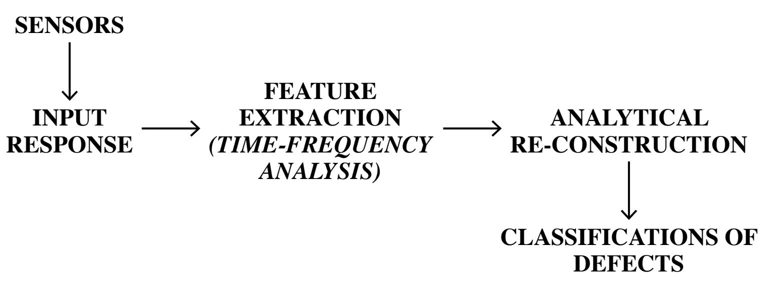

Figure 1. *Typical process flow for analytical classifications in Acoustic Pulse Reflectometry (APR)*

With the availability of machine learning tools, the classification can be improved by reducing the needs to perform analytical procedure to the response obtained in time domain. Raj *et al.*, presented a neural network prediction of failure type using Support Vector Machine for corrosion in pipeline detection(Lee *et al.*, 2013). Working at ultrasonic frequency within the solid domain, this method reduced the processing time over time as the classification is automatically done by the artificial intelligence tool. By adopting the same framework in an acoustic frequency APR (Figure 1), the length of pipeline under investigation can be increased accordingly hence the inspection time can be reduced.

Blockage impedance

Profiling of defect of discontinuity in pipeline can be determined analytically by its input impulse response. Discontinuity of propagating, results into the reflection of transmitted sound by the source. As the acoustic pressure waves propagate in the air-filled pipe and encounter changes in the cross-sectional area, the associated impedance change will generate transmitted and reflected waves (Rienstra & Hirschberg, 2015). Ratios of the pressure amplitudes for the reflected and transmitted waves to the pressure amplitude of the initial incident wave depend only on the change in impedance which, in turn, depends only on the change in the area (Gray, 2005). As acoustic pulse travel along the longitudinal length of the pipe, the sound energy will encounter losses due to viscosity, heat conduction, internal molecular processes and wall friction at boundary layer. Adding to these losses is the impedance due to cross sectional area changes of the pipe. Assuming a straight pipe with uniform internal cross sectional area and zero losses due to internal molecular processes and the decay to peak values along the longitudinal length of the pipe is negligible, the propagation can be solved by understanding the impedance coming from changes of cross sectional area.

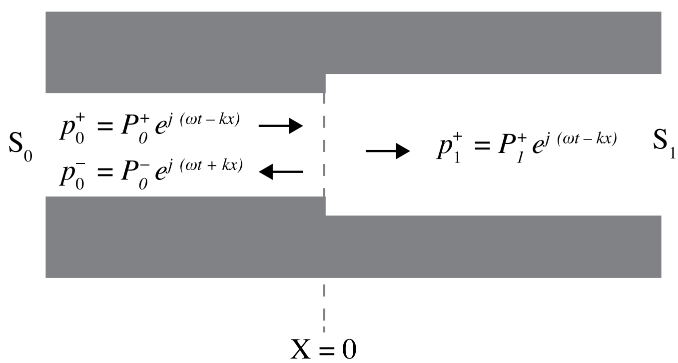

Figure 2. *Cross sectional reduction of inner pipe and the propagating sound pressure*

Figure 2 shows a semi-infinite pipe (Figure 2) with a cross-sectional area S_0 discontinuously joined to a second semi-infinite cylinder of cross-sectional area S_1. If a pressure wave of frequency ω with normal incident to the boundary between the two cross-sectional area within the pipe is defined by the function,

$$p_0^+ = P_0^+ e^{j(\omega t - kx)} \tag{1}$$

as the impulse struck the boundary, it will generate a reflected wave,

$$p_0^- = P_0^- e^{j(\omega t - kx)} \tag{2}$$

and a transmitted wave that continues to propagate,

$$p_0^+ = P_1^+ e^{j(\omega t - kx)} \tag{3}$$

(where $p_0^{\pm}$ indicates that the pressure wave propagates in the positive/negative χ direction). The power reflection ratio of the reflection and the incoming input pulse is therefore can be obtained and used in the prediction of blockage ratio.

Neural Network

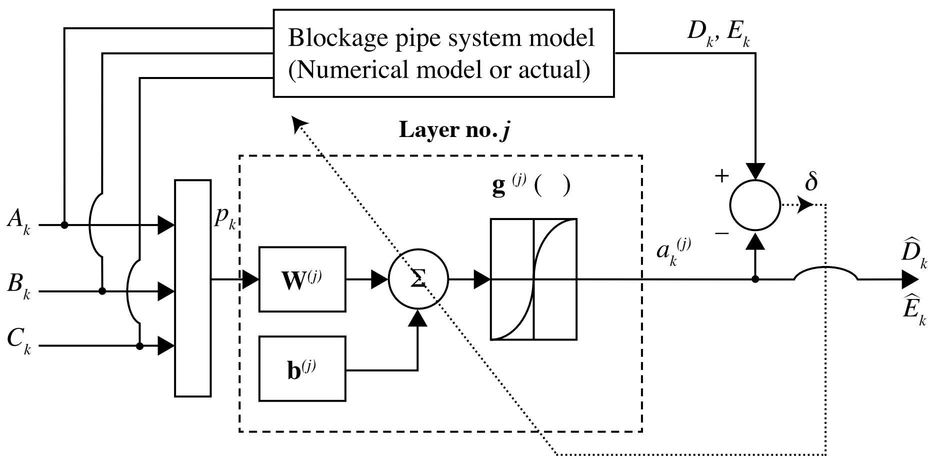

Figure 3. *The schematic of the data acquisition system*

The identification (training) procedure is illustrated in Figure 3. Parameters of a given assumed network architecture are optimized to minimise the difference (error) δ between the true (target) output D_k, E_k and the network output $\hat{D}_k$, $\hat{E}_k$ when the NN is presented with experimentally-obtained input/output training data.

Assume $S^{(j)}$ is the number of neurons in the j^{th} layer and let p_k be the signal inputs to layer no. j:

$$p_k = [\,A_k \quad B_k \quad C_k\,]^{\mathrm{T}} \tag{4}$$

If a_k^((j)) is the S^((j))×1 vector comprising the signal outputs of the jth layer, the:

$$a_k^{(j)} = g^{(j)}\,(w^{(j)} a_k^{(j-1)} + b^{(j)}),\ j = 1, 2, \ldots j \tag{5}$$

where $\boldsymbol{W}^{(j)}$ and $\boldsymbol{b}^{(j)}$ are respectively the matrix of weights and vector of biases of the j^{th} layer and $\boldsymbol{g}^{(j)}$ is a vector operator comprising the transfer functions of the neurons of the j^{th} layer. The network output, $a_k^{(j)} = \widehat{D}_k, \widehat{E}_k$.

MATERIALS AND METHOD

In determining the responses from blockages as the input to the neural network training, an experimental set-up is completed using APR assembly for a short range pipe. The APR (Figure 4) assembly consists of a speaker (Visaton) acting as the sound transmitter and a B&K microphone as the sound pressure sensor (installed in source tube). The length of the test pipe is 12 meter made of PVC with 2 inch internal diameter and 6 mm thickness. Various blockages (Figure 5) are used to obtain the signature for data training with the dimension shown in Table 1.

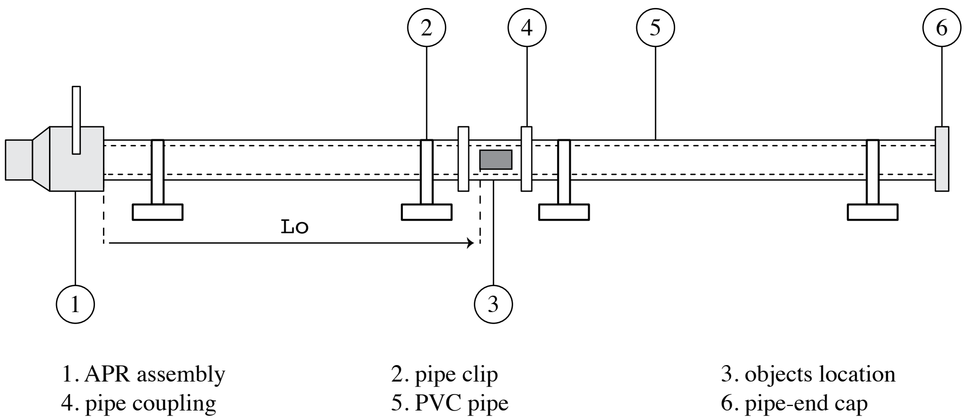

Figure 4. *Schematic of mechanical set-up of test pipe: 1-Visaton speaker, 2- B&K microphone and 3 - Pipe end Cap*

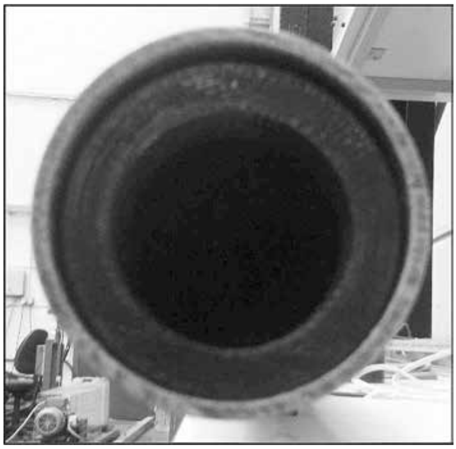

Figure 5. *The cross sectional view of artificial blockage*

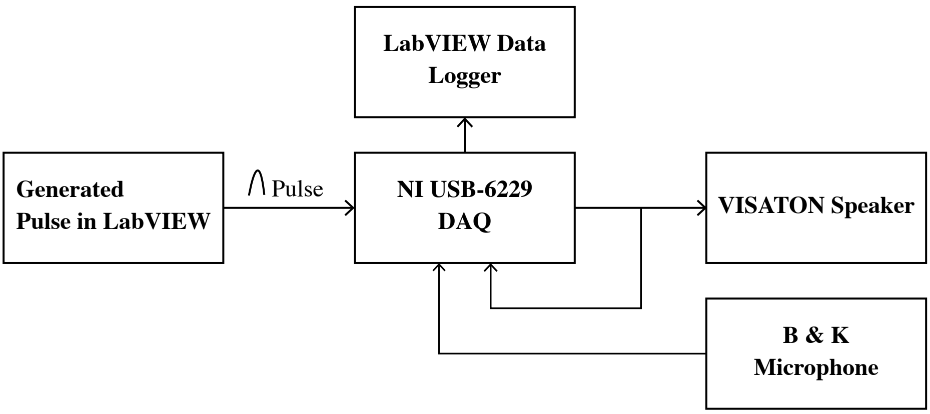

Figure 6. *The schematic of the data acquisition system*

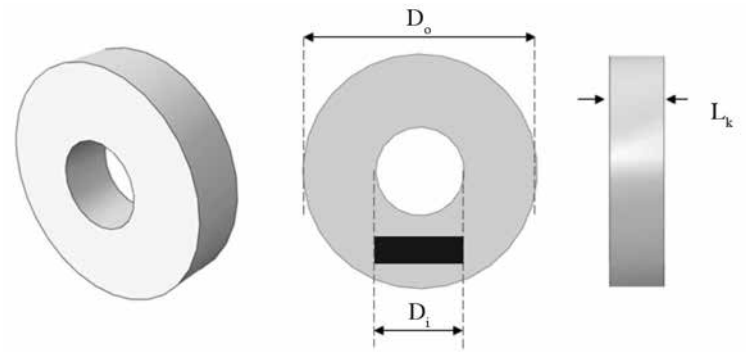

Table 1. Artificial blockages dimension

Percentage of Blockage	D_i (mm)	L_n (mm)			
		Test 1	Test 2	Test 3	Test 4
10%	50.3	10	25	50	75
30%	29.0	10	25	50	75
50%	37.5	10	25	50	75
70%	29.0	10	25	50	75
90%	16.8	10	25	50	75

Data acquisition of the propagating wave is designed using LabView data logger. Digital output of sound pulse is translated to sound pressure using loudspeaker (Figure 6). The propagating sound wave is recorded on the microphone and translated to digital output by a digital output converter (NI USB 6229 DAQ) and recorded in data logger. The response signal is validated using cross correlation to the speed of sound of 340 m/s with the density of air at 1.225 kg/m^3, temperature of 208.15 K and at atmospheric pressure. Pulse is truncated and undergone Fourier transforms to determine the effective central frequency. The amplitude of reflected signal and incident wave is recorded and the phase angle is determined for every reflection. Power reflection ratio of the responses from various blockages is recorded for every related frequency of excitation. Attenuation factor is introduced to the experiment to account the attenuation of propagating sound along the pipe by introducing losses due to heat and surface friction. The excitation frequency is limited to plane wave propagation by observing the cut off frequency of first higher order mode for the pipe.

RESULTS AND DISCUSSION

Time Domain Response

For empty pipe APR, the responses in Figure 7 shows two peaks in time domain i.e. the incident wave and the reflections from pipe end cap. The amplitude of reflection from the pipe end is lower than the incident due to the attenuation effect. After truncating the signal and further analyses in frequency domain, it is evident that the single digital frequency excitation is however translated into hybrid frequency sound pressure by the loudspeaker. However, the effective frequency interest can be analyzed independently in frequency domain analysis.

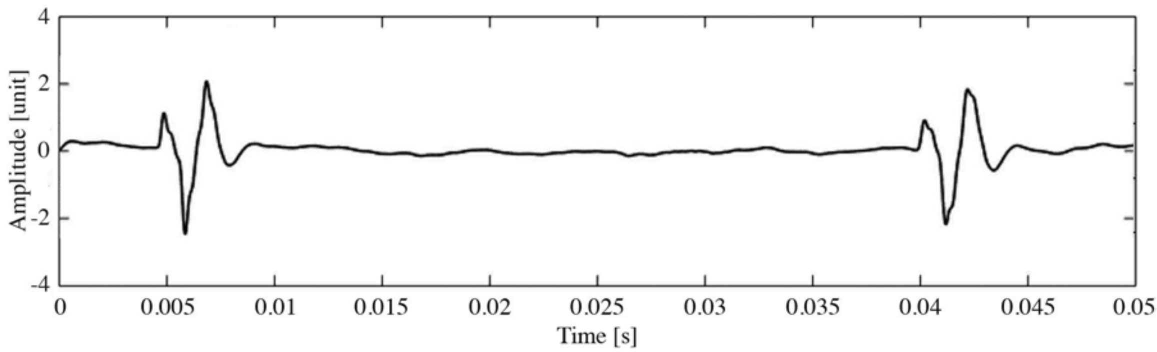

Figure 7. *Typical time domain response for empty pipe*

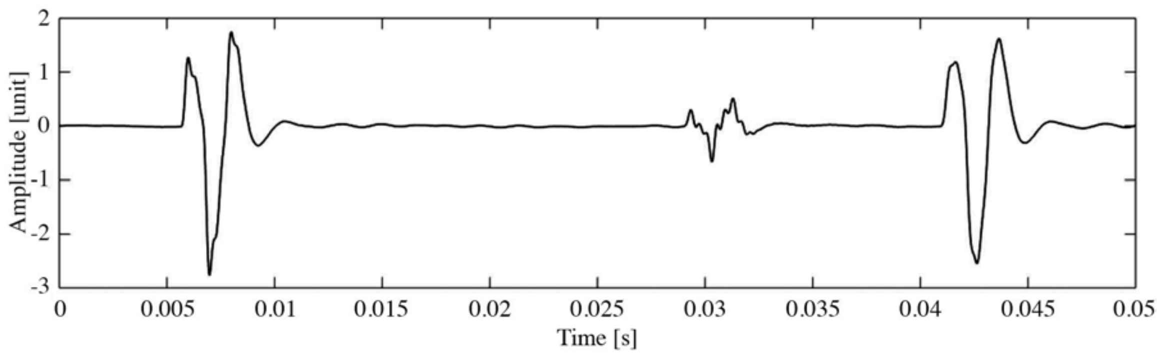

Figure 8. *Typical time domain response for blocked pipe*

Further analysis of the response for blocked pipe can best be observed in Figure 8. The time domain response shows the existence of reflection coming from the blockage which arrived earlier than the reflection of pipe end. To understand the frequency response of both set-ups, the acquired signal can be represented in Short Time Fourier Transform (STFT) which can be observed in Figure 9.

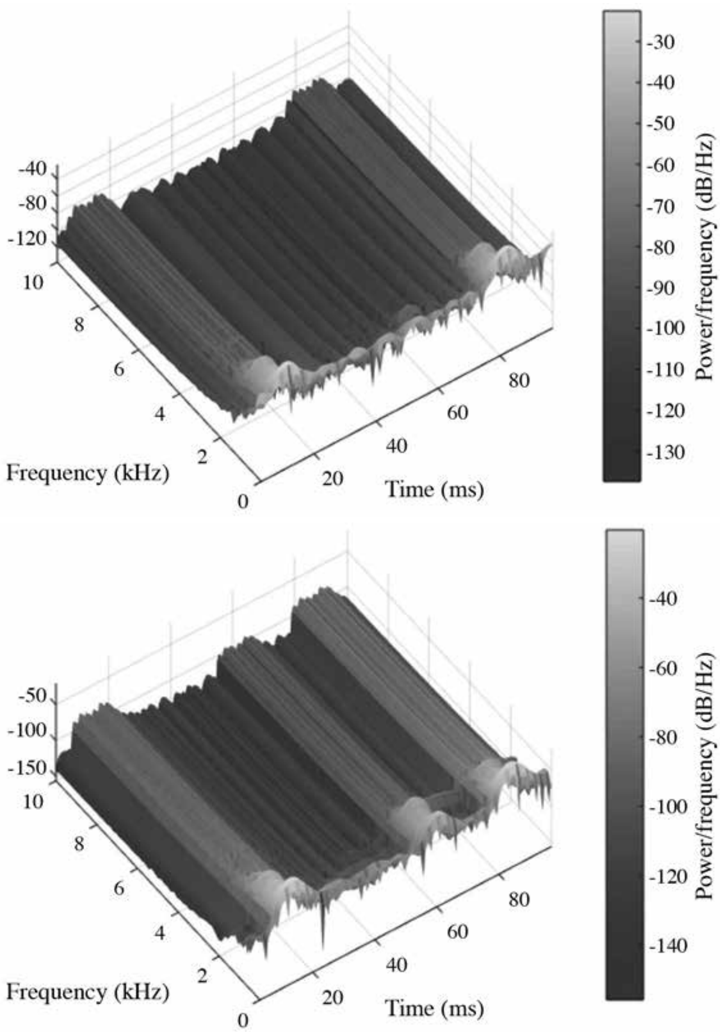

Figure 9. *Short Time Fourier Transform of (top) empty pipe, and (bottom) blocked pipe*

Prediction of Failure Using Neural Network

As the existence of non-conformity can be observed in time domain, the next stage is to look at the response signature. A black box is designed in the Matlab with three inputs and two outputs. Three parameters used as the inputs during the training are the maximum power reflection ratio, the frequency of excitation for at which the reflection is at the highest and the tangent of phase angle differences between the incident and the reflections. To validate the prediction potential, the experiment was repeated with different combination of blockages and the responses were used as the inputs to the established black box from earlier training. It can be seen from Figure 10 that the percentage of error in predicting the blockage ratio ranges from 1% to 12 %, which bigger errors occurred mainly for longer blockage.

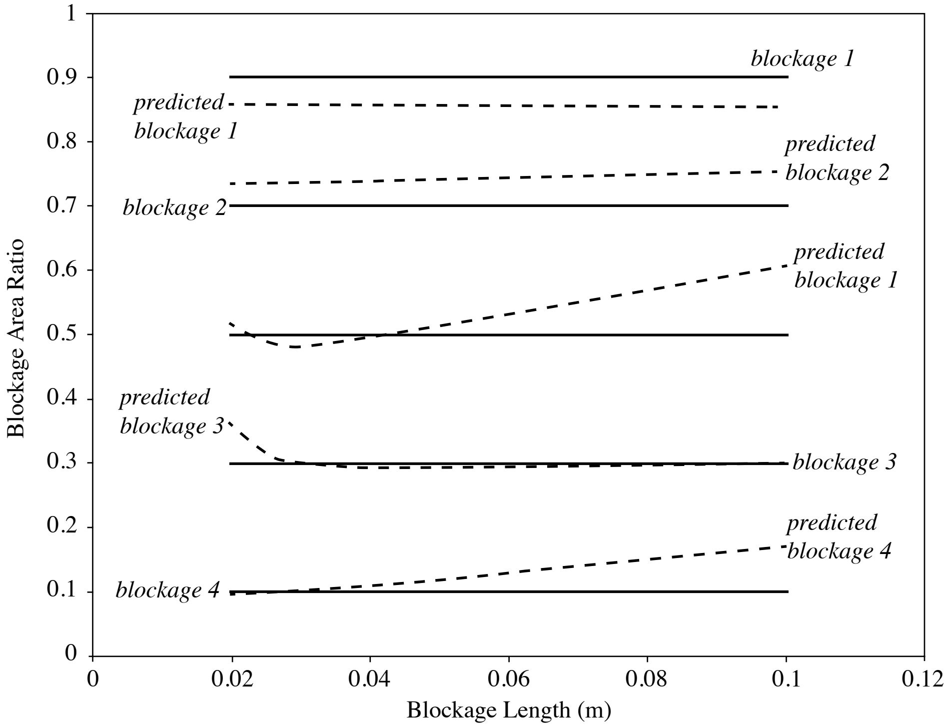

Figure 10. *Classification of blockage ratio and length prediction performance*

CONCLUSION

It is evident that the introduction of neural network to classifying method for pipeline NDT can eliminate the needs to run complicated analytical procedures. Although the performance of prediction in this works shows inconsistent errors, this can simply be improved by increasing the training data. Designing experimental procedures as a method obtaining training data can be costly and challenging; therefore, there is a great need to look at modelling the propagation of sound wave within the finite element method. With available commercial driven 3 dimensional simulations, researcher will be able to model a rather complicated structure and use the responses signature as an input to neural network for wider classifying models.

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