CAAP Quarterly Report

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Project Title: Improved NDT Detection and Probabilistic Failure Prediction for Interacting Pipeline Anomalies

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Business and Activity Section

(a) Contract Activity

No modifications were made to the contract.

(b) Status Update of Past Quarter Activities

We have generated large datasets using our 2D finite element numerical simulations of ultrasonic testing of a steel (pipe) plate by varying multiple crack geometric parameters to be used with our neural network study. We have demonstrated success in prediction of crack length, location and orientation with reasonably good accuracy for the 2D case. Prediction for more than one crack parameter was achieved. We have been able to predict regression type continuous output using our machine learning method. We have also conducted literature review on probabilistic failure prediction of pipelines. Specifically, we have identified two established equations that model the burst pressure of defect-free and corroded pipes and have started to study their response using our probabilistic framework.

(c) Cost share activity

Partial support for the Ph.D. student tuition was provided by Brown University School of Engineering as per the cost share agreement.

1. Background and Objectives in the 2nd Quarter

1.1 Background

Application of popular ultrasonic non-destructive testing (NDT) technique remains challenging for crack characterization in pipelines as data interpretation is performed by people, which results in significant uncertainty in accurate crack feature predictions.[1][2] As hypothesized in our research, using a machine learning based automated solution to detect cracks has the potential to provide significantly more accurate results.[3][4][5] However, very limited publications report predictions over crack geometric properties such as size, location and orientation due to the lack of data, and they do not support continuous output (regression type).[6] These geometric parameters are of great importance since they determine the lifespan and failure conditions of pipelines.

Fracture mechanics is probabilistic in nature. Cylindrical pressurized vessels such as pipelines are prone to burst if cracks are present in the body. Many models already exist which try and predict the burst pressure of pipes using parameter-based criteria. However, these models are deterministic and rely heavily on the accuracy of inputs.[7][8] Given their exposure to the elements and the high internal pressure within these pipes, input measurements may not always be as accurate as what is needed for a deterministic model. Dealing with pipelines that may be transporting dangerous materials, there is no room for error. Thus, it is of importance that a probabilistic approach is developed which allows the model to take into account variability of input conditions and provides risk based failure predictions.

1.2 Objectives in the 3rd Quarter

During the second quarter, we successfully built an early dataset for the training and validation of the NN using 2D case. We performed a simple regression test regarding crack size and the results were very promising. In this quarter, we aimed to continue to use 2D numerical simulations to generate new datasets with sufficiently large data in each of these datasets. New datasets will have one or more crack geometric parameters for advance characterization of cracks, hence requiring a much larger volume of data. Also, we aimed to train a fully functional NN that is capable to predict multiple geometric parameters of cracks simultaneously with high confidence. Regarding the aim 2 in original proposal, we aim to conduct literature review on the current state-of-art failure prediction for pressurized cylindrical vessels. Lastly, we aimed to identify important deterministic bursting pressure equations and then study them to develop probabilistic failure assessment.

2. Experimental and Computational Program in the 3rd Quarter

2.1 Experimental design

Olympus EPOCH 650 Digital Ultrasonic Flaw Detector was acquired using Brown fund. Basic ultrasound test supplies were also acquired for future experimentation.

2.2 Computational setup

All computations were conducted on an existing workstation desktop (early computations are relatively smaller sized).

We studied finite element based numerical simulation requirements for sound wave propagation in steel pipelines. All of our numerical study used an ultrasound wave of 5 MHz frequency and wavelength of ~1.2 mm.

A steel plate geometry (which we will refer to as 'plate' later on) with width 60 mm and thickness 20 mm was used in our simulations. 50 elements in total on the bottom surfaces are assumed to be both the ultrasound signal exciter and receiver by monitoring the longitudinal wave (common in industry practice) for embedded cracks inside the plate. A short 5 mm long ultrasound signal exciter with 5 MHz raised-cosine type waveform was applied as boundary condition to one edge of the plate thickness. Profile for this waveform is shown in **Figure 1**. Step size is fixed at $\mathbf{2 \times 10^{-9}}$ s which corresponds to a 500 MHz sampling rate. Artificial anomalies in the form of elliptical cracks are placed in the plate. We conducted dynamic numerical simulations in Abaqus/Explicit and analyzed the displacement history profile at the selected point receiver locations on the plate surface.

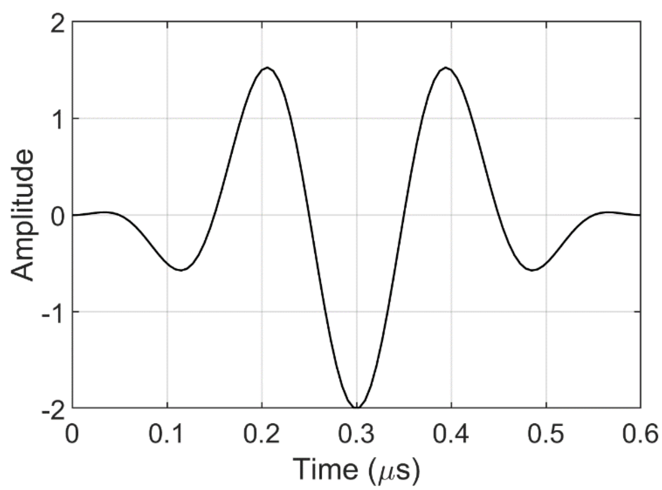

Figure 1. 5MHz, 3 period raised-cosine type pulse signal used in the simulations.

3. Results and Discussion

As described in the object section, we aimed to address four major problems in this quarter, namely

- To generate several large datasets using 2D UT numerical simulations where multiple geometric parameters of elliptical crack including size, location and orientation were systematically varied
- To build a fully functional NN for characterization of multiple crack properties
- To start literature review on failure prediction of pipelines
- To identify important deterministic equation for burst pressure and develop our early probabilistic prediction method

We will discuss all four problems in the following subsections.

3.1 Technical approach and result

In consistency with the previous quarter, our current focus is still elliptical embedded cracks. Five parameters were identified for an elliptical crack and illustrated in **Figure 2**.

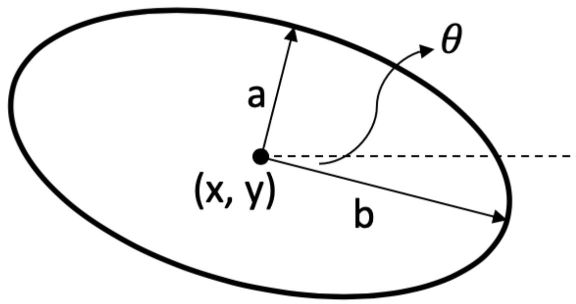

Figure 2. Five geometric parameters identified for an elliptical crack

To review the meaning of the five parameters, the location of the crack is characterized by a vector with two parameters $\boldsymbol{x}$ and $\boldsymbol{y}$, indicating the center of the ellipse. $\boldsymbol{a}$ is the short axis of the ellipse, $\boldsymbol{b}$ is the long axis of the ellipse and they both define the crack. size. $\boldsymbol{\theta}$ is the angle that long axis made with the horizontal direction, used to characterize the orientation.

Unlike the previous quarter, we have created several large datasets of 2D geometries that have more than one parameter varying. The information of the datasets is summarized in **Table 1**. Orientation is of particular interest to us because to our best knowledge, existing publications have not predicted such a feature as a continuous output. D*ataset 2* will be discussed firstly. In practice, crack size is most crucial parameter that affects the integrity of pipeline. Hence *dataset 5* is particularly interested to us and is generated for size and orientation combined prediction and will be studied thoroughly.

Table 1. Summary of datasets with different parameters, bold numbers indicate a range in which the corresponding parameter varies

	$\boldsymbol{x}$ **(mm)**	$\boldsymbol{y}$ **(mm)**	$\boldsymbol{a}$ **(mm)**	$\boldsymbol{b}$ **(mm)**	θ	**Number of simulations**
Dataset 1	0	15	1	**[1, 3]**	0	479
Dataset 2	0	15	0.5	1.5	**[0, $\boldsymbol{\pi}$]**	957
Dataset 3	0	15	1	**[1, 3]**	$\pi/4$	446
Dataset 4	0	**[7, 16]**	1	**[1, 3]**	$\pi/4$	1878
Dataset 5	0	15	1	**[1, 3]**	**[0, $\boldsymbol{\pi}$]**	3728

We used MALTAB's deep learning toolbox to build our neural network. Feature selection was performed using WPT as was before. In addition, we applied signal filtering to the original signal using MATLAB's signal processing toolbox to acquire better signal quality. For a faster training process, we started with a simple three-layer structure: one input layer, one hidden layer and one output layer.

Here we demonstrate the orientation prediction for *dataset 2* for a typical run. The results are shown in **Figure 3**. The circles on the left panel represent individual test data (with different orientation) and the blue line represents the prediction value. All data have been normalized into the region (0, 1). The R value is very high (> 0.99), similar to the size prediction we reported in the previous quarter. Error histogram also follows closely to a Gaussian distribution with maximum relative error less than 8%.

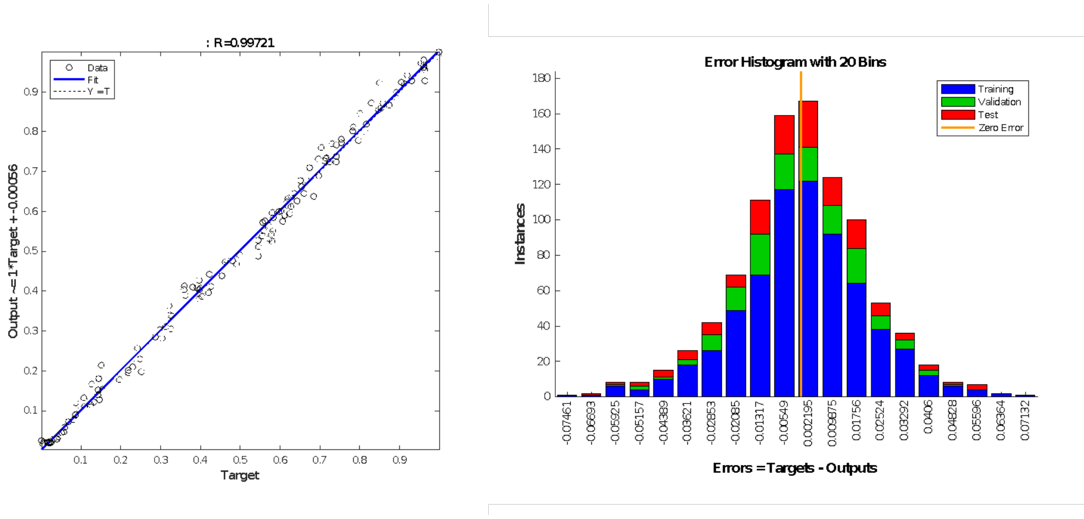

Figure 3. MATLAB NN regression plot (left) and error histogram (right) for predicting crack orientation

In **Figure 4** we show combined prediction for crack long axis and orientation simultaneously using *dataset 5*. By tuning the parameters for our NN, we can again achieve very high R value for crack long axis, which is over 0.99. For orientation, R value reached over 0.98. It is worth noting that there exist several data points whose orientations have been predicted poorly even for R value over 0.98. These off-points can be justified by the insufficient size of our dataset. As shown in **Figure 5**, with a 2-fold reduction in data numbers and leave all the NN parameters unchanged, the prediction is a lot worse than that of *dataset 5*. This highlights the importance of size of dataset for the accuracy of a NN.

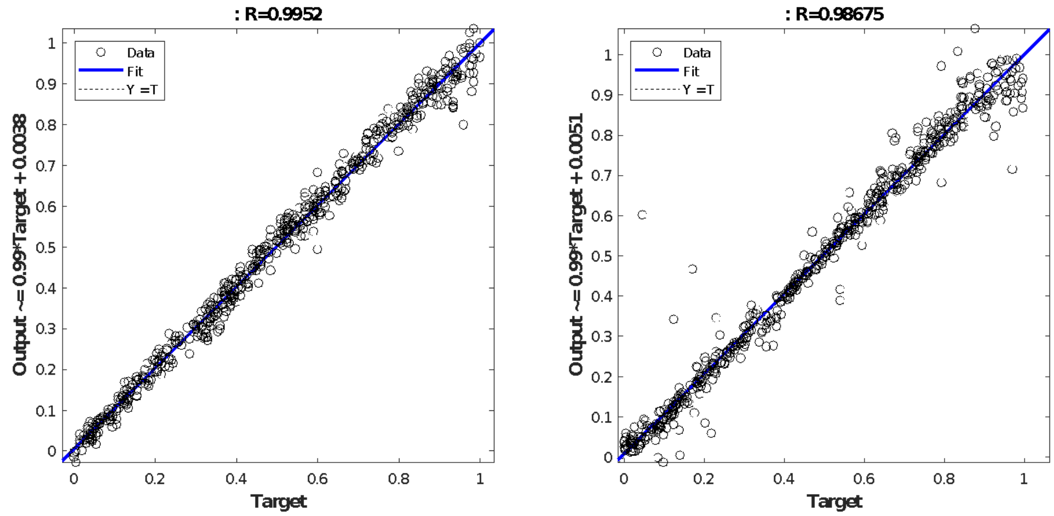

Figure 4. MATLAB NN regression plot of crack long axis (left) and of orientation (right) simultaneously for combined parameter (*dataset 5*)

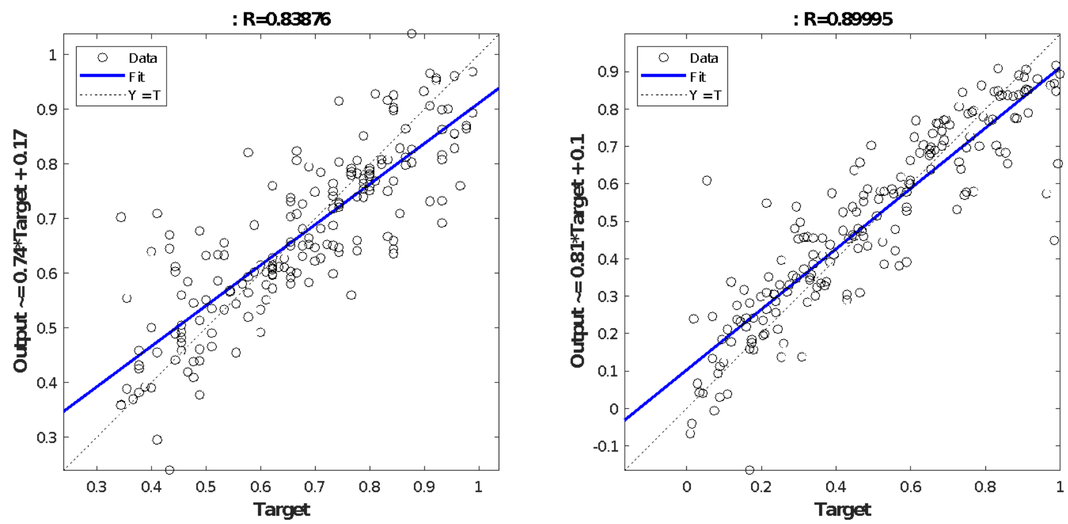

Figure 5. MATLAB NN regression plot of crack long axis (left) and of depth (right) simultaneously for combined parameter (*dataset 4*)

Research work regarding probabilistic failure prediction of pipelines has been initiated in this quarter. We conducted literature review of models predicting burst pressure of thin-walled, defect-free pipelines subjected to internal pressure as a starting point. In the paper by Zhu and Leis [7], 20 models are summarized and presented. Among the models, the ASTM boiler code was considered one of the most accurate models. This model has three input parameters in total, namely the ultimate stress $\boldsymbol{\sigma_{uts}}$, inner diameter of the pipe $\boldsymbol{D_i}$, and the outer diameter $\boldsymbol{D_o}$. The burst pressure is then given by the deterministic equation

$$\boldsymbol{P_b = \sigma_{uts}\left(\frac{\frac{D_o}{D_i}-1}{\frac{0.6D_o}{D_i}+0.4}\right)} \tag{1}$$

For X80 ex-mill pipes (selected as a trial example), the experiments showed that the bursting pressure of such pipe is 27.44 MPa, given the inner and outer diameters and the ultimate stress of 343 mm, 359.9 mm and 677 MPa, respectively. However, these parameters are not error-free and there exist distribution ranges around the mean values that they fall in. To show this, we used a probabilistic approach in which each parameter follows a normal distribution with the mean value given above and a variance to be fine-tuned. We found that our model prediction follows a normal distribution with a peak around 26.83 MPa as shown in **Figure 6**, which is more accurate than the deterministic prediction of 26.78 MPa from equation (1) when comparing to the experimental value. Also, it provides a range of possible bursting pressures, from 26.7 MPa to 26.95 MPa, which could serve as a guiding principle for practical use.

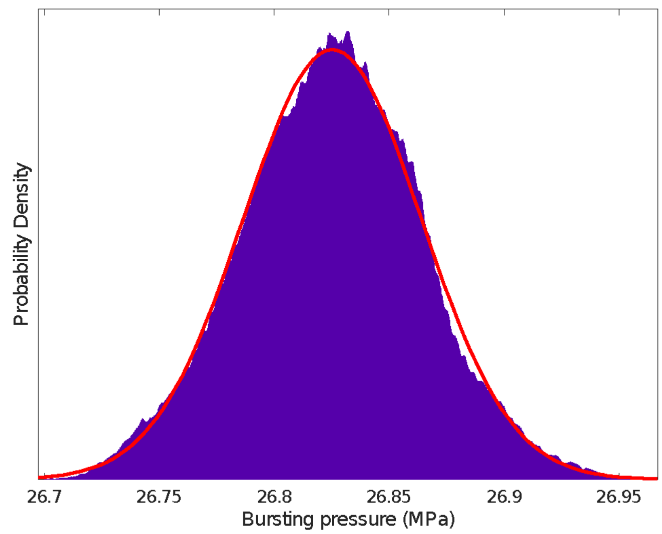

Figure 6. Probabilistic bursting pressure prediction of an end-capped, thin-walled, defect-free pipe using ASTM boiler code. Purple shaded area is the probability density and the red curve represents the fitted normal distribution of the outcome.

3.2 Discussion

In the recent quarter, we successfully accomplished the aims that are discussed above. Using the 2D case, we have demonstrated that orientation and length predictions for cracks can be accurately obtained using our methodology. We showed that we can achieve relatively high accuracy for more than one parameter and also demonstrated that errors increase when insufficient size of dataset is used for NN training. Next step is to apply our methodology for more challenging but more important and practical 3D geometries.

We identified several important mathematical models that are currently used to predict pipe bursting pressure in a deterministic fashion. We conducted studies to assess application of existing established models for risk based failure prediction. Our preliminary studies show we can determine probabilistic burst pressure prediction with a Gaussian-like distribution.

4. Future Research

We have demonstrated a fully functional NN that can predict multiple crack geometry parameters with relatively high confidence when aided by large datasets. However, the current simulation setup is limited to a two-dimensional plane strain condition which does not fully represent the real cracks in pipelines. Following our success with our 2D simulation based NN predictive results, we aim to develop a 3D numerical simulation methodology and develop full three-dimensional simulation datasets which mimics the real world. Once our NN has been trained by the new datasets, we aim to conduct validation experiments using the Olympus Ultrasound test equipment that we currently have in the lab.

Further work on probabilistic modeling of burst pressure of pipelines will be conducted including risk based burst pressure prediction for corroded pipelines [8]. We will study mathematical models for pipes with embedded cracks, and pipes with corrosion wall loss, besides the case of macroscopic defect-free pipe. In addition to mathematical phenomenological models, we will also study a more physical model for pipeline failure assessment.

References

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