A Case Study to Fuse MFL-A and MFL-C Inspections for 3D Metal Loss Depth Map Reconstruction

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Abstract

The inspection capability of magnetic flux leakage (MFL) is subject to the angle between its magnetic field and the anomaly. To get a comprehensive assessment on corrosion anomalies, more and more pipelines are inspected with two MFL techniques with perpendicular magnetic fields, i.e., axial MFL (MFL-A) and circumferential MFL (MFL-C). Currently, inspection data from each MFL tool are analyzed separately, and two inspection reports are generated respectively. In this paper, we propose a model which aligns the data from two magnetic field orientations and fuses the respective signals a single inspection result to achieve a 3D metal loss depth map with laser-like precision. The alignment of the signals is achieved through conversion into the same modality i.e., MFL-A converted to MFL-C and vice versa. The fusion model is a neural network trained on historical MFL and laser scan data. It takes the aligned MFL-A and MFL-C signal data as the input and produces 3D metal loss depth maps with high resolution. In this case study with Enbridge Liquid Pipelines, the proposed model is validated on the field data from an operational pipeline. The depth comparison of the derived 3D metal loss depth maps versus 3D laser scans has very promising results. The 3D metal loss depth maps are also used for deriving 2D profiles as inputs to RSTRENG and P² methodologies. The fusion derived results, compared to the box geometry, allow for more accurate estimation of pipeline burst pressure.

Introduction

Magnetic flux leakage (MFL) inline inspection tools remain one the most utilized inspection methods to detect and size corrosion on a pipeline. The MFL technologies can be run with magnetic field aligned axially (MFL-A) or circumferentially (MFL-C) in the pipeline. MFL-A tools are typically used for circumferential, pinhole, pitting and general corrosion features whereas the MFL-C focus more on the axial oriented corrosion anomalies. These tools are complementary and therefore are often run together to provide improved confidence in detection and sizing of a wide range of corrosion morphologies on the pipeline.

To gain the most benefit of running the tools concurrently, they may be evaluated together by a highly experienced evaluation expert. With deep knowledge of both tools, an evaluator may use the signals to infer the best length, width, and depth sizing of the corrosion anomalies. This specialized evaluation is extremely labour intensive, and the sizing process is subjective.

Evaluation of MFL technologies, whether individually or together, is always presented as a resulting box around the corrosion area. This cuboid box of length, width and depth is a simplified way of describing the corrosion anomalies, and although it is a convenient way to receive corrosion details in a tabular report, much of the information is lost about the corrosion shape and conservatism is inherently introduced around the failure pressure calculations.

ROSEN has previously presented results of direct field analysis (DFA) which showed the benefits of moving away from calculation of failure pressures based on clustering of boxed anomalies to calculations on the actual metal loss depth maps [1] [2]. The results of DFA are a step change in presenting data from the two MFL tools as one combined 3D depth map as opposed to an evaluated

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box based on expert evaluation. The computation of the 3D shape allows one to directly leverage the strength of both MFL tools for accurately evaluating a wide range of morphologies on the pipeline as well as a more accurate calculation of failure pressure.

In this paper, ROSEN will show the continuing evolution of combining of signals of the two MFL tools into one 3D depth map using a Machine Learning Data Fusion Model. The advantage of this methodology is that once the tools have been adequately aligned the pre-trained Convolutional Neural Network (CNN) can be applied effectively to all the corrosion anomalies on a pipeline. The improvements of computational speed allow the evaluation of every corrosion feature on a pipeline with a full high resolution 3D depth map; like that of an in-ditch laser scan. The advantages in morphology, depth and failure pressure calculations will be presented here through a case study with Enbridge Liquid Pipelines on one of their more challenging tape coated lines.

Technology Outline

As described above the combining of two signals is typically manual process. It requires a very experienced analyst (or team) with expertise in both MFL-A and MFL-C technologies. They must understand the both the strengths and the limitations of each tool to glean the most pertinent information from the tools to properly characterize the feature. This analysis at best however will only ever result in a cuboid representation of the feature itself. The method of data fusion on MFL-A and MFL-C outlined in this paper, is the fusion of two input magnet signals into a CNN and outputting one depth map. This image-to-image translation negates the need for experts to attempt to combine individual MFL signals, and it fully describes the feature not only in depth but also its entire 3D morphology.

Fusion Process

The process itself is comprised of several steps outlined in Figure 1 and starts with both MFL-A and MFL-C tools being run in a pipeline segment. The tools are run as in any traditional service, and no special coordination of the tools is required. The necessity for the tools to be run at the same (or nearly same) date is not a strict requirement of the process, however the further apart the inspection dates of the two tools the more one should consider the effects of corrosion growth in the results. This paper does not specifically address corrosion growth rate and is a topic for future investigation. Next is a pre-processing step for each tool individually to remove background magnetization and noise in the signal. Then a standard pipeline alignment is performed to ensure each joint of pipeline is matched between the two runs. A fine alignment is then done on each individual joint to ensure a high alignment of the anomalies from the two tools. The aligned anomalies are then processed by the data fusion model producing a highly detailed 3D metal loss depth map.

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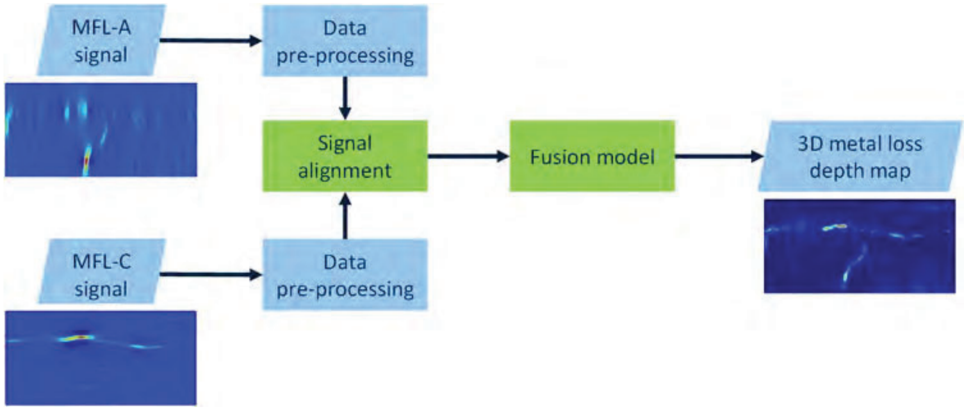

Figure 1. Fusion process

Data Pre-Processing

Two pre-processing steps are required on the raw signal data. Step one is magnetic normalization to compensate for individual tool effects on background magnetization, and the next step is to remove individual artefacts in the signal data. The aim is to have robust quality input data for the data fusion model without compromising the signal of the anomalies themselves.

Alignment

The initial pipeline alignment is performed by a standard pipeline process, done routinely within the inspection analysis process. It is an important step, however it is a standard process so is not discussed further here. Following the general alignment of the features detected by both MFL runs in a pipe is a detailed alignment of the signals.

The signal alignment of the two tools is a vital step in the process of data fusion. If the signals are not accurately aligned, then fusion of the two signals will be adversely affected. The method used for alignment of the two MFL signals was a manual process described in Figure 2. First, 1) using neural networks, measured MFL-A signals were converted into MFL-C signals, and measured MFL-C signals were converted into MFL-A signals. Then, 2) the newly converted signals were matched to the respective measured signals. Finally, 3) a two-channel template matching was used to align the two matched signals sets together. To ensure a high quality of matching every matched set was reviewed manually and adjusted as needed.

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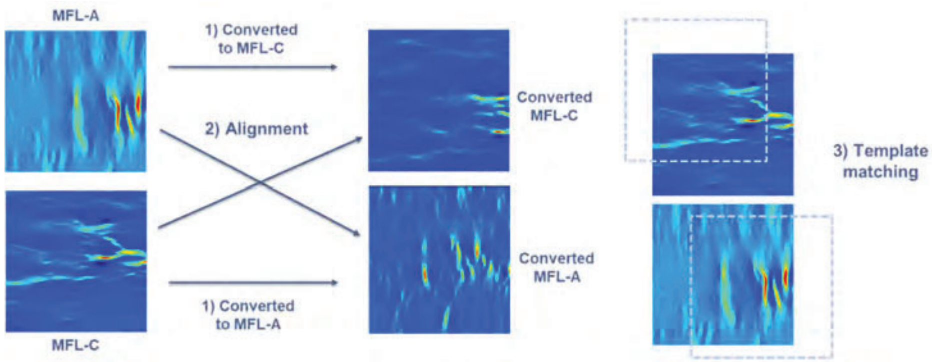

Figure 2. Signal alignment procedure

Training of the Data Fusion Model

The data fusion model has a U-Net architecture. U-Nets are fully convolutional neural networks that use skip-connections in addition to a simple encoder-decoder structure [3]. The training of the network uses a supervised learning method in which paired input data and desired output data are used. The training data consisted of laser scans and simulations of those laser scans as shown in Figure 3. One training pair consists of the MFL-A and the MFL-C signal stacked on together forming the input and one laser scan patch as the desired output.

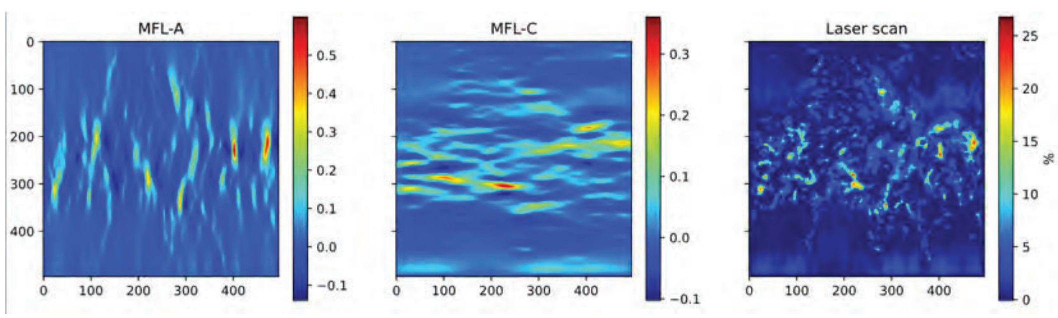

Figure 3. Training data set example – MFL-A and MFL-C signals are simulated from the laser scan

Fine-Tuning Option

If an operator has historical laser scans on a pipeline, it is possible to carry out a fine-tuning of the data fusion model. The initial or pre-trained model is trained with original entire training set. A fine-tuning of the model starts with the pre-trained model and further trains using the just historical laser scans. This extra training tailors the model to the corrosion on the specific pipeline of interest.

Validation of the Training

To validate the training of the model, the magnetic responses of MFL-A and MFL-C are simulated on additional laser scans (not used in the training) and processed with the data fusion model. A data fusion example is given in Figure 4, it shows the high accuracy of image reconstruction. A pixel-by-pixel comparison on depth was then carried out between the original laser scan patch and the resultant 3D prediction image. A unity plot comparison is shown in Figure 5, in which the mean absolute error (MAE) is 0.26% in depth. It's demonstrated that the model is adequately trained. It

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does not show the accuracy of the data fusion on real pipeline data, for this a case study was conducted.

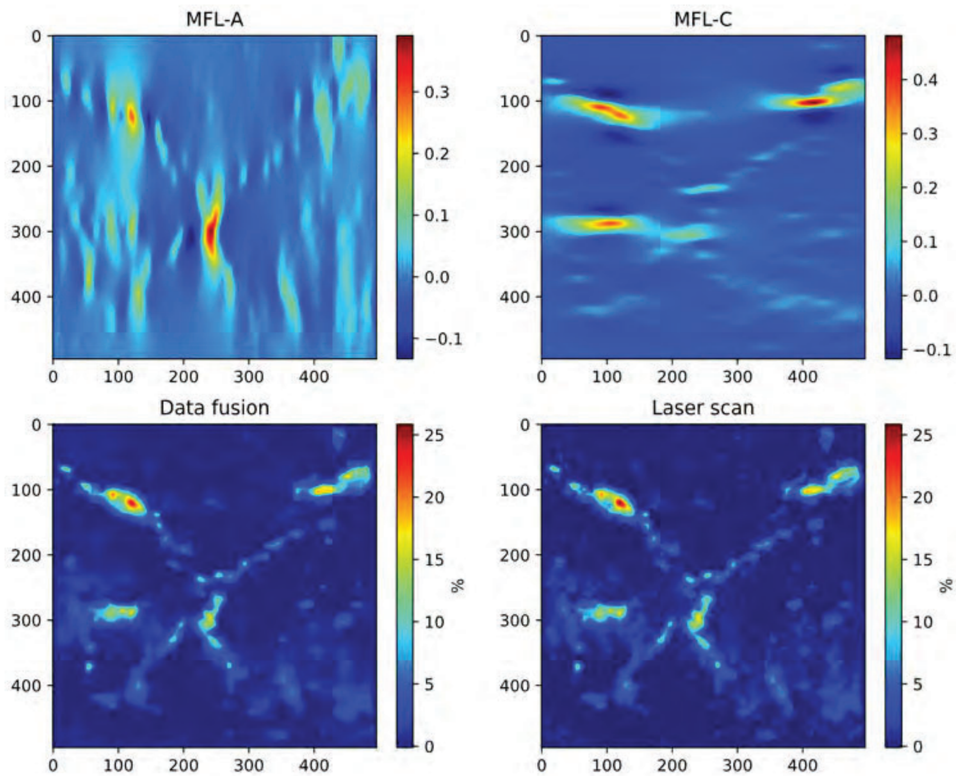

Figure 4. Example of data fusion on simulated data

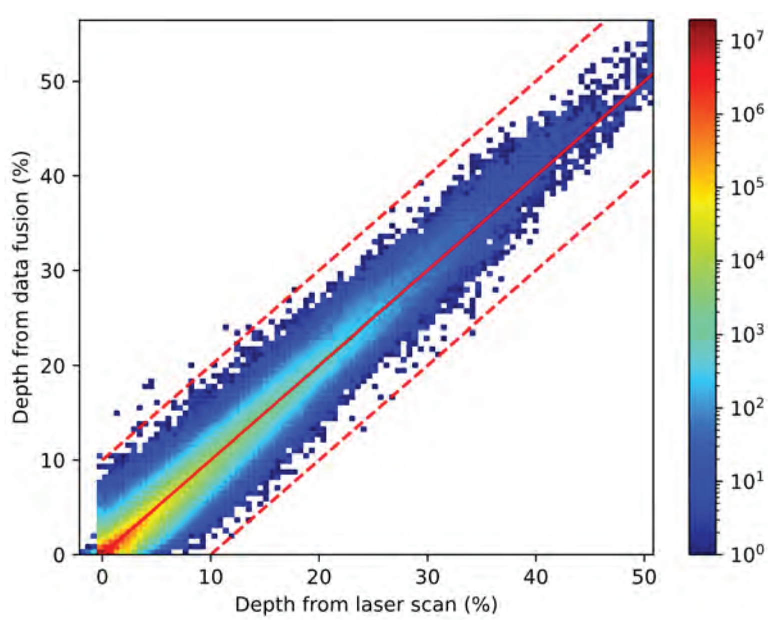

Figure 5. Depth (%) comparison on simulated data

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Case Study

To demonstrate the effectiveness of the data fusion technique, a real pipeline validation was carried out by ROSEN and Enbridge Liquid Pipelines. Enbridge ran two inspections in a tape coated segment of pipeline: an MFL-A Ultra (high resolution MFL-A) in 2019 and an MFL-C in 2021. Enbridge provided 20 laser scans for depth and failure pressure validation of the data fusion model and an additional 19 laser scans were provided for fine tuning of the model. Depth and failure pressure validation of the model was carried out for both the pre-trained model and the fine-tuned model.

Pre-trained Depth Validation

As outlined above, the pre-trained data fusion model was trained on laser scans and simulations from 50 different pipeline segments. This model was used to fuse the MFL-A Ultra and MFL-C signals into 3D metal loss depth maps. Figure 6 shows an example of the data used for the fusion (top left MFL-A signal, and top right MFL-C signal), the resultant data fusion 3D depth map (bottom left) and the corresponding validation laser scan (bottom right). The similarity of the morphology is immediately apparent in a visual comparison of the data fusion 3D depth map and the laser scan. Data fusion is effective at reproducing all the fine details of the corrosion structure.

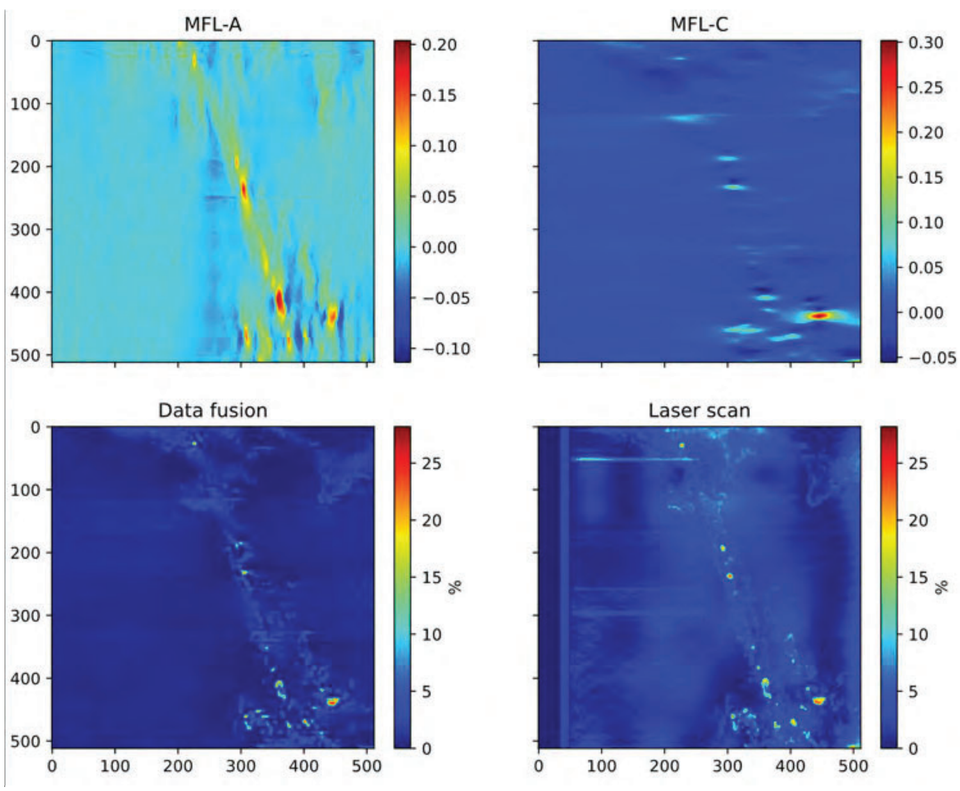

Figure 6. Example of data fusion on measured data

The comparison of the depth was performed by boxing the validation laser scan data with an in-house boxing routine. These boxes were projected onto the data fusion 3D depth map in the same region and the deepest points of each boxed anomaly was compared. Boxing of anomalies on the 20-validation laser scan provided 5570 individual boxed anomalies for feature validation. A comparison of the deepest point in the laser scan anomalies and the data fusion anomalies are given in Figure 7.

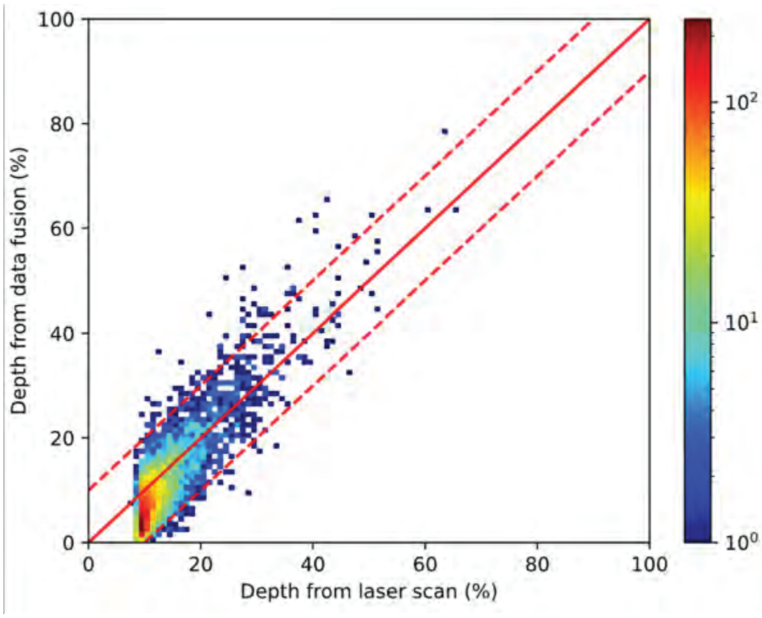

Figure 7. Depth (%) comparison of pre-trained model

The comparison of the deepest point shows 97.5% of anomalies within the ±10% depth band of the unity plot with an associated 4.42% MAE. Qualitatively, the results of the validation show a slight under-call in the depth of anomalies under 20%wt and a tendency of slight overcalling of some anomalies above about 40%wt.

Investigating these cases, it was observed that many of the laser scan results had areas of data quality inconsistencies. This is thought to be due to the stitching together of the images in the software for the handheld laser scanners. This may have in part contributed to some of the under-calling of anomalies under 20% depth.

Some of the deeper anomalies appear to have a prediction which are slightly narrower than actual anomalies which is likely due to training on feature types that are different from the ones seen in this segment. It may also be due to relative fewer training anomalies greater than 40%wt. To address this issue a fine-tuning of the model was performed to tailor the model to the specific of this segment.

Fine-Tuned Depth Validation

The pre-trained fusion model was fine-tuned using an additional 19 laser scans that were not included in the original training. The validation of depth was carried out on the same set of 20 laser scans given in Figure 8.

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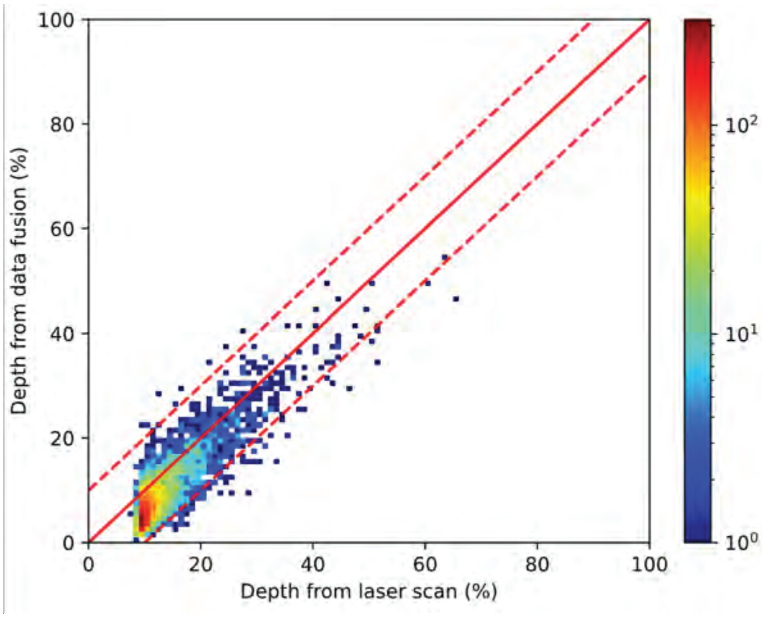

Figure 8. Depth (%) comparison of fine-tuned model

The results of the fine-tuning increased the number of anomalies in the ±10% depth band to 98.3% with an MAE of 3.32%. The comparison of depth shows a tightening of the distribution around the unity line. The previously observed over calls have been reduced, however there are a few minor under calls. In general, the results improved with the fine-tuning which demonstrates it is beneficial to integrate previous knowledge of the pipeline feature characteristics into the data fusion model.

Failure Pressure Validation

In the pipeline industry two failure pressure calculation methods commonly used are Remaining Strength (RSTRENG) and increasing Plausible Profiles (P^2), both of which rely on 2D river bottom profiles in their calculations. MFL technologies traditionally only provide boxed data sets in the reports. Therefore, generated river bottom profiles used for RSTRENG and P^2 calculations are derived from box data by the projection of a path through the box pseudo 3D landscape. Using boxed anomalies for river bottom profiles has an inherent conservatism because the boxed anomalies are represented by the max depth of the corrosion anomaly. The volume loss of feature or cluster is overestimated and results in a conservative failure pressure calculation [4].

To demonstrate rigorously the conservatism of the boxed data sets vs the detailed 3D depth maps the validation laser scans were sectioned into 180 patches of corrosion and boxed. RSTRENG and P^2 were calculated on each of these patches, for 2D profiles derived from the boxed data sets and the actual laser scans. The result of the comparison is given in Figure 9.

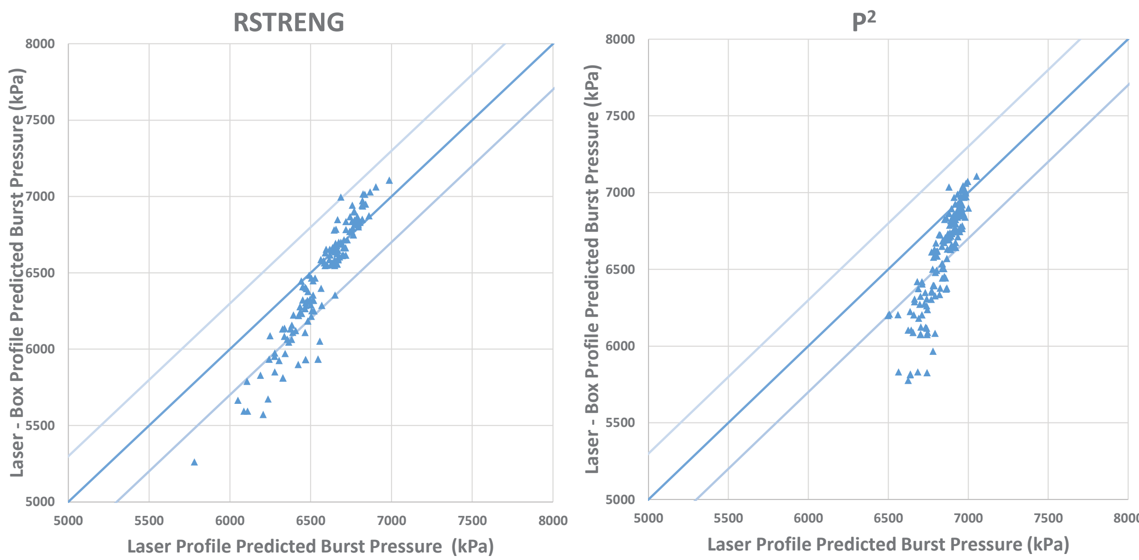

Figure 9. RSTRENG and P^2 for box data vs laser scans

It is evident that for anomalies with a lower failure pressure there is a conservatism that results from boxing the data. This is consistent for both RSTRENG and P^2 calculations. Therefore, it is expected that 3D depth maps derived from the fusion will also eliminate this element of conservatism and would yield more accurate results. The results of both RSTRENG and P^2 calculation of the data fusion versus the laser scan are given in Figure 10.

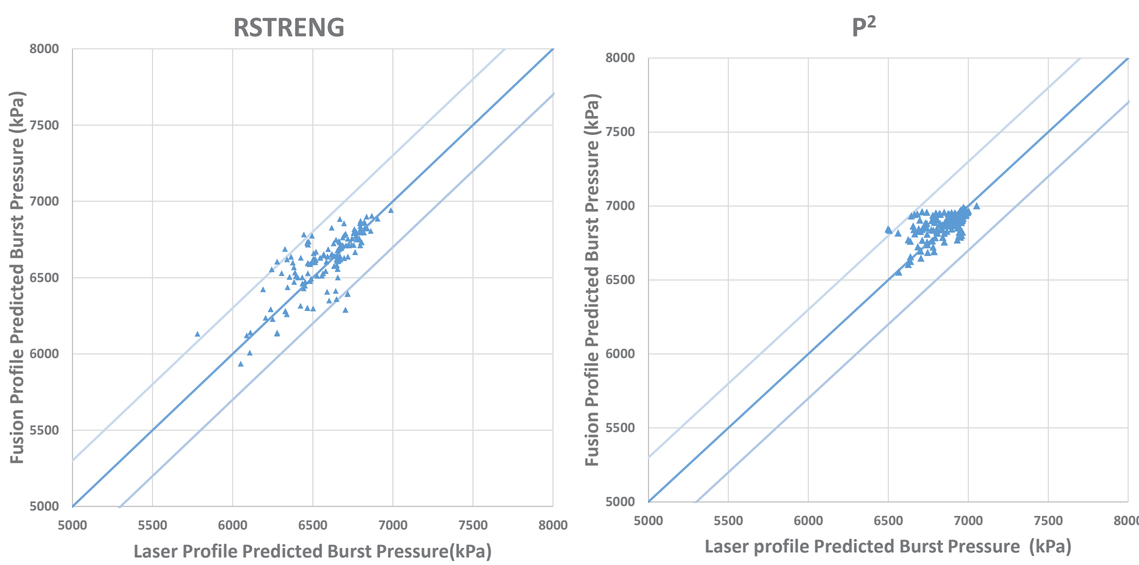

Figure 10. RSTRENG and P^2 for 3D depth maps vs laser scans

Figure 10 shows 2 important results. First, failure pressure calculations of the fusion results correlate strongly to the failure pressure calculations of the lasers scan in both RSTRENG and P^2. Second, MFL technologies can provide an accurate 3D metal loss depth map using data fusion which can

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eliminate the conservatism traditionally inherent in the failure pressure calculations of MFL technologies.

It should be noted that there was no noticeable difference between the failure pressure results of the pre-trained model and fine-tuned model and as such only the pre-trained results are presented here.

Conclusions

- It has been shown that the data fusion technology can accurately predict the corrosion depth maps using MFL-A and MFL-C technologies together.
- The depth profiling from data fusion shows accurate morphologies of the corrosion anomalies as well as a strong correlation in the max depth of the anomalies.
- The ability to eliminate the principal conservatism in failure pressure calculations by eliminating the need to box anomalies allows for much more accurate failure pressure calculations with MFL.
- The fine-tuning with laser scans can slightly improve maximum depth values but has lower influence on pressure predictions.

Future Development

Future work in the data fusion technology includes:

- Data pre-processing: Further techniques in data refinement to eliminate background noise and improve data quality can further increase the quality of the data fusion depth maps.
- Alignment: More robust automatic alignment of MFL-A and MFL-C
- Augmentation of training data: Continuous augmentation of training data particularly in areas with deep anomalies.
- Validate Data fusion model on additional line segments of varying diameter and wall thickness.

Abbreviations

CNN	Convolutional Neural Network
DFA	Deep Field Analysis
MAE	Mean Absolute Error
MFL	Magnetic Flux Leakage
MFL-A	Axially orientated magnetic flux leakage technology
MFL-C	Circumferentially orientated magnetic flux leakage technology
P^2	Plausible Profiles
RSTRENG	Remaining Strength

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