# A LIVE TEST-BED FOR THE ADVANCEMENT OF CONDITION ASSESSMENT AND FAILURE PREDICTION RESEARCH ON CRITICAL PIPES

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**Abstract**
The prediction of a pipe's remaining life, especially for critical watermains, is important for developing effective renewals programs to manage pipe infrastructure and reducing the incidence of catastrophic failures, which impacts communities. A better understanding of the current condition and performance of buried water mains and sewer pressure mains is an important first step to help achieve improved understanding of remaining life. This has been identified by WSAA members as a high priority for research and collaboration. Despite this, one of the key factors impacting on condition assessment is the lack of data on large pipes. This is not only an issue for Sydney Water and other Australian water utilities, it is an international challenge. An experimental test-bed has been established as part of a larger collaborative research team of Australian and international researchers and a consortium of national and international agencies to improve the technological and financial management of buried water mains. To this end, the test-bed is being used for parallel research activities to deliver essential knowledge and guidance on the cause/effect of failure and for corrosion modelling. The test bed will address a number of knowledge gaps by generating data under controlled conditions. A verification method based on high-resolution geometric 3D laser scans of the exhumed and grit-blasted pipes together with algorithms to extract the pipe wall thickness out of the 3D geometric models, combined with lower-resolution ultrasonic measurements, is proposed to accurately determine the actual thickness of the pipes at a large scale. The set-up has allowed different condition assessment techniques to be applied to understand how their measurements relate to the pipe condition in terms of pitting, corrosion, structure etc., and to enhance their data interpretation with novel data mining techniques. The pipe used for the test-bed is a 1.5 km long section of 600mm cement lined cast iron pipe at Strathfield, Sydney, which was decommissioned due to poor condition. Examples from a number of large pipe segments from the test-bed will demonstrate the effectiveness of the proposed methodologies.

**Keywords**
Emerging trends, asset optimisation, intelligent networks

## INTRODUCTION

Sydney Water is the leading industry partner in a $16M international research project to examine when and why critical water pipes burst. The research is developing advanced condition assessment (CA) and failure prediction techniques that can evaluate remaining pipe life. This will be used to better target Sydney Water's and other utilities critical main renewal programs and reduce negative impacts on customers. As part of this project, current and emerging condition assessment tools are being evaluated in the world's first pipe research test-bed in Sydney, Australia. Research partners include the University of Technology Sydney (UTS), Monash University and the University of Newcastle.

This paper describes the research effort undertaken by UTS which aims to enhance knowledge in the area of direct methods for CA of buried large watermains using advanced data collection, analysis and interpretation techniques through machine learning algorithms. These techniques have been successfully used in other industries ranging from aerospace, cargo handling, undersea exploration, ecology, land vehicles and mining. To that end, Sydney Water has provided a 1.5 km long section of 600mm cast iron pipe laid in 1922 to research CA techniques. Collaborative agreements have been put in place with a number of industry partners that provide CA for water mains. Current and emerging CA technologies are part of the research program. Data collection and analysis is being carried out at a number of selected excavation sites and at pits constructed for local deployment of internal inspection tools. Data generated with the CA technologies from the test-bed is being used to design and implement software tools that in turn will provide an improved automatic interpretation of these data as an outcome of UTS's research. Improved data interpretation aims to accurately predict the pipe wall thickness and pitting defects from a set of the sensor readings for a given pipe.

The machine learning algorithms being developed by UTS rely on vast amount of data. The data required for these algorithms comprise sensor readings associated with what we call "ground truth", i.e., the real geometry of the pipe (remaining wall thicknesses and corrosion pitting defects). Obtaining this ground truth is a challenging engineering and civil works problem, where exhumation, grit-basting and 3D profiling need to addressed. Efforts from UTS and Sydney Water have been put together to produce a procedure that obtains an accurate ground truth of the assessed pipe section through high-resolution 3D laser imagery and ultrasonic sensors.

The remainder of this paper contains a detailed description of the test-bed, together with the protocols in place to obtain the ground-truth data used for both, algorithm development and validation. We will also describe the research runs carried out by UTS on the test-bed. Finally we will present some results of the algorithms developed by UTS in comparison with the ground truth.

## TEST-BED

The large collaborative research project has benefited from a test-bed of one and a half kilometres of pipeline that Sydney Water decommissioned in 2010 due to its poor condition. Table 1 shows the characteristic of this research test-bed. Figure 1 shows the map of the area in Strathfield, Sydney where test-bed lies. Figure 2 provides a longitudinal profile of the test-bed pipeline showing variations in elevation.

The main purpose of this test-bed is to be used for parallel research activities to deliver essential knowledge and guidance on the cause/effect of failure and for corrosion modelling. The test-bed will address a number of knowledge gaps by generating data under controlled conditions. UTS in particular is in charge of investigating methods to increase the confidence levels in CA technologies. Data from the inspected sections is transferred to UTS to be subsequently analysed.

**Table 1.** Sydney Water test-bed technical information.

| | |
|---|---|
| Location | Verona – Long Street, Strathfield, NSW |
| Year Installed | 1922 |
| Nominal Pipe Diameter | 600 mm |
| Internal Pipe Diameter | 579 mm to 590 mm (with cement lining) |
| External Pipe Diameter | 662 mm to 666 mm |
| Nominal Wall Thickness | 27 mm |
| Material | Pit cast iron |
| Internal Liner | Cement (installed in 1964) |
| Cement Lining Thickness | 9.5 mm to 16.5 mm |
| Pipe Lengths | 3.6 m |
| Jointing | Lead run joints (with tar soaked hemp sealants) |
| Total length in use for research | Approx. 1 km |

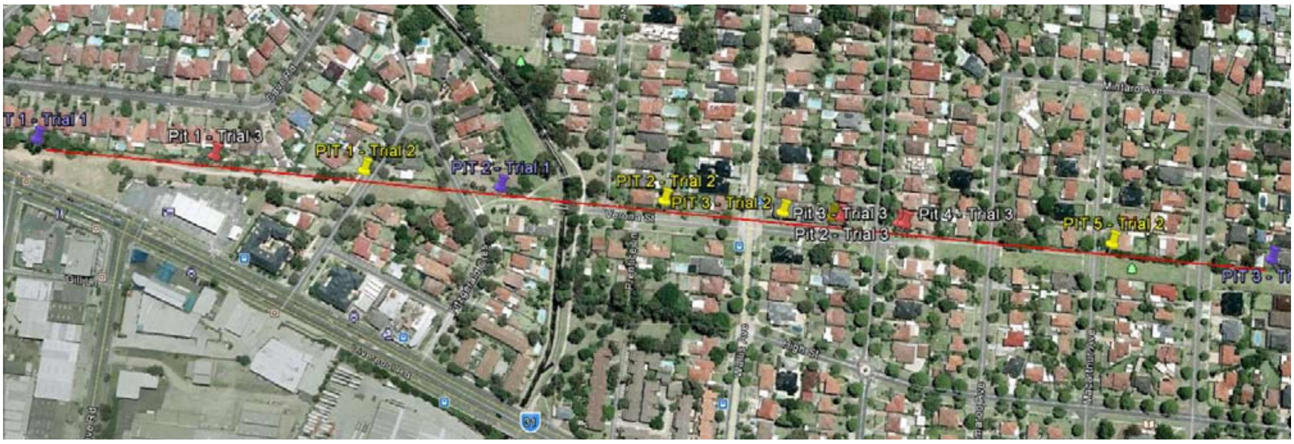



**Figure 1**. Google Earth (top-view) image of 1 km of Sydney Water's test-bed. Excavation pits for research run 1 are shown in purple, for research run 2 are shown in yellow and for research run 3 are shown in red.

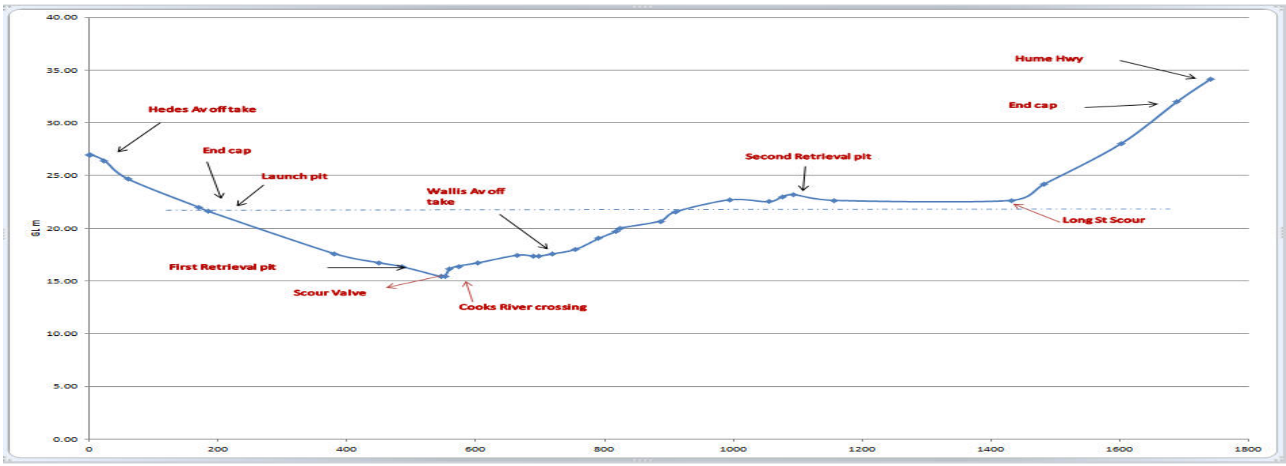



**Figure 2.** Sydney Water's test-bed pipeline profile.

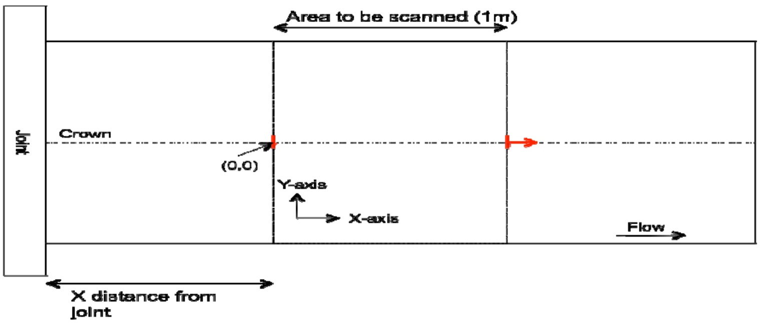
## GROUND TRUTH

Ground truth of the pipe sections that have been assessed by the CA technologies is paramount for UTS's learning algorithms. This ground truth is also being used for the verification of the analysis supplied by the CA providers and for the validation of the enhanced data interpretation.

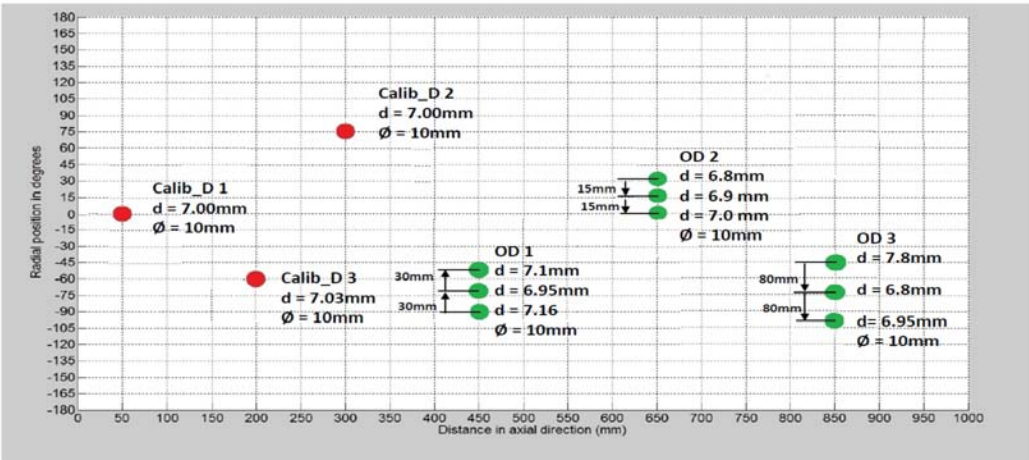
UTS together with Sydney Water have established a methodology to obtain the correct ground truth of the assessed pipe sections. There are three key steps to obtain the ground truth:

1. A protocol to exhume and grit-blast the assessed pipe section in a consistent manner. This protocol includes a) permanently mark a reference frame that can be correlated with the measurements taken by the providers, b) accurate positioning of the pipe section on the test bed, c) exhumation of section, d) cement lining removal, e) 3D scanning before and after grit blasting of both the internal and external surface of the pipe, and finally f) storage.
2. The use of a high-resolution 3D laser scanner to produce a profile of the pipe section before and after grit blasting. This step also includes the algorithm to recover the exact thickness (subject to resolution) of the 3D mesh produce by the laser scanner.
3. The use of an ultrasonic sensor to produce an accurate estimate of the thickness at discrete points, together with an improved algorithm to interpret this data.

The following sub-sections present the methodology in detail.




a) Cut marks and reference frame




b) Example of calibration defects

**Figure 3.** Data acquisition protocol scheme. Figure a) shows the marking scheme and reference frame. Figure b) shows an example of the calibration defects and some other artificial defects.

**Research data acquisition protocol**

As it is paramount throughout this project to reference the ground truth to the acquired data from various technologies, it is important to establish a protocol that will result in gathering data from each pipe section in a repeatable and reliable manner. Such a protocol should denote factors as:

- Coordinate frame; X-Y-axis and crown of the pipe.
- Physical marks on the pipe sections for future reference.
- Position of calibration defects.
- Referencing any natural defects visible in the coordinate frame.
- Location of the area to be scanned by various technologies, with regards to the joints of the specific pipe section.

Figure 3a) shows a drawing of a pipe section, where the factors described in the data acquisition protocol are explained in a graphical manner. In this figure, the red markings are physical cuts in the pipe intended to remain visible after grit blasting. It also shows the coordinate system used for the data acquisition and ground truth.

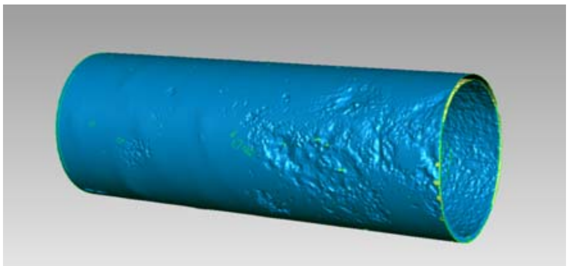
Figure 3b) shows an example of a possible defect map. The red markings denote the “calibration” defects, which will be exactly the same in each pipe section, whereas the green markings denote individual defects, which are chosen based on expected outcomes for the various technologies. The green markings will differ in shape, size and location for each individual pipe section. Once the defects are machined in the given pipe section, the defect map is updated with actual sizes, as it is very difficult to achieve a high accuracy for the depth and size of defects while on site.

**3D Scanner profiling**

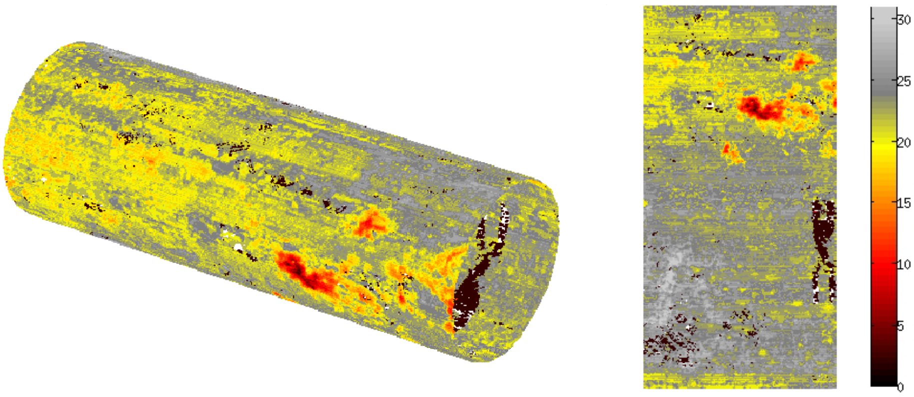
In order to get an accurate ground truth of the pipes, a high–resolution 3D laser scanner was selected for measuring the geometry of the pipe sections. As this particular pipeline consists of cast iron pipe sections, each individual pipe section will have different dimensions. Thicknesses differ up to 30% between sections. For this reason it is important that the thickness of the pipe is measured at a high resolution, also to capture small anomalies in the pipe.

In order to produce an accurate thickness (our ground truth), the ability to scan the surface of the pipe, both externally and internally, is fundamental. The EXAscan® scanner from Creaform was selected as the preferred scanner to produce the desired profile. This sensor suite is a 3D laser scanner capable of scanning up to 0.05mm resolution and, as it is a relatively small hand held device, it is also capable of scanning the inside of pipe sections removed from the test bed. Note laser scanners are not be able to “see through” graphitization, and therefore the pipe sections need to be grit blasted both externally and internally in order to acquire an accurate ground truth. The output of the scanner consists of a 3D mesh, or model, of the scanned pipe section, which can be manipulated by software.

UTS has developed a software algorithm that uses the 3D model obtained by the 3D scanner and extracts the thickness of each point in the pipe. The algorithm is based on the ray tracing algorithm with octrees developed in (Revelles et al. 2000) implemented in the Point Cloud Library (Rusu & Cousins 2011). Both the spatial and the thickness resolution are set to 2mm. An example of the output of the 3D laser scanner together with the thickness plot produced by UTS algorithm is presented in Figure 4.



a) 3D laser scanner profile




b) Thickness plots obtained through the UTS algorithm

**Figure 4.** Example of 3D profiling and software analysis for Pit 3, research run 2.

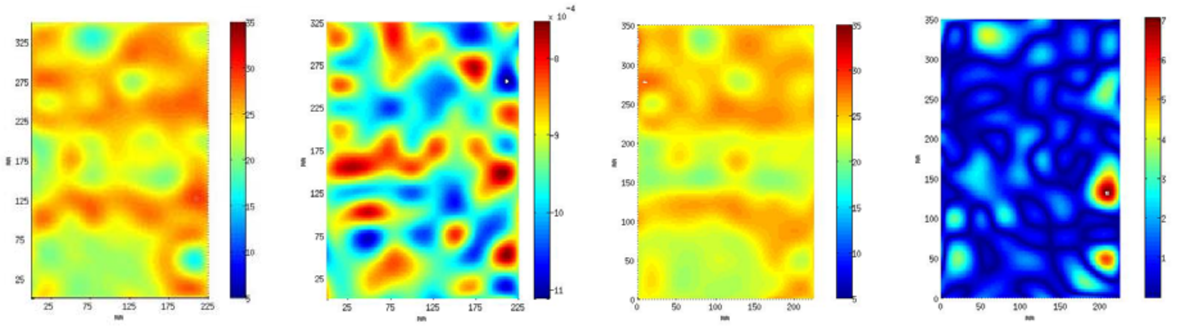
**Ultrasounds**

Ultrasound thickness (UT) measurements are widely used in the field of non-destructive pipe testing (for the technical details refer to (Pagodinas 2003)). With ground-truth collection in mind, UTS has developed an automatic ultrasonic scanner that will be used to complement the data from the 3D laser scanner. The automatic scanner is capable of scanning a 1m section of a 600mm cast iron pipe. Figure 5 shows a rendered image of the designed scanner when set-up around a pipe section. It can be seen that the ultrasonic probe moves by controlling a linear actuator. The linear actuator in turn can be moved over the curved tracks around the pipe circumference (although this rotational movement is yet to be automated). The UT signal is captured using an ultrasonic flaw detector (the Krautkramer USN 60). The linear position resolution of the system is about 0.1mm.

a) Solid Works 3D render　　　　　　　　b) Actual installation

**Figure 5.** CAD model (left) and real system picture (right) of automatic UT scanner on a pipe.

The ultrasonic measurements are known to be very coarse and inaccurate for non-homogeneous materials, like cast iron, due to the carbon particles present in this material. This is evident when looking at an UT signal, which will mostly consist of noise due to the high sound wave attenuation nature of cast iron. Although this is true, we found that in cases, when the signal is noise free, the accuracy of the thickness measurement is high. In order to distinguish between high and low accuracy readings, UTS has developed an algorithm that produces an uncertainty measure associated with the interpreted thickness (related to the quality of the UT signal). Results of interpreting UT signals on a grid of 22 x 10 cm (each cell being 2.5 x 2.5 cm) are shown in Figure 6. A comparison with the 3D laser scanner results (Figure 6(c)) show that areas where the thickness derived from the ultrasonic signal (Figure 6(a)) with high uncertainty (Figure 6(b)) correlate well with areas of high errors (Figure 6(d)). Therefore, discrete UT measurements that produce certain thickness provide really useful information for the ground-truth thickness.



a) UT prediction　　b) UT uncertainty　　c) 3D laser plot　　d) Error (laser – UT)

**Figure 6.** Comparison of the ultrasonic testing results with the 3D laser scanner.

As the resolution of the 3D laser scanner, albeit due to time constraints, is normally set to around 2mm, it results in a ± 2 mm thickness. We believe that the UT results can be combined with the laser scanner results to increase the thickness resolution.

## RESEARCH RUNS

As mentioned previously, UTS has signed research agreements with five different industrial partners. To date, four research runs have been conducted with three of the industrial partners' technologies. The CA technologies that have been involved in the four runs are:

- Magnetic Flux Leakage (MFL) provided by AIA/AESL[1] using the SMART-CAT tool,
- Broadband Electromagnetics (BEM) provided by RSG[2], and
- Remote Field Testing (RFT) provided by Russell NDE Systems Inc using the See Snake tool.

Figure 1 shows the location of the pits for three of the research runs carried out by UTS.

### Research Run 1

**Figure 7.** MFL tool in Pit 1 (left) and BEM grid (right).

In February 2012 the first of the research runs on the test-bed took place. MFL and BEM technologies were used to assess five pipe sections at three excavations. MFL is based on magnetic flux leakage being useful to detect pitting areas, while BEM is based on pulse eddy currents, which estimates general changes in thickness. In all the research runs, only one metre of pipe at each selected location is scanned with these CA tools.

Research run 1 location pits are shown in Figure 1 in purple. Figure 7 shows a picture of Pit 1 being scanned by MFL and BEM. The data from this CA tools was transferred to UTS and it was used to validate simulation models and to develop the data acquisition protocol implemented in the following research runs.

### RFT Run

After research run 1 in May 2012, the See Snake tool owned by Russell NDE Systems was brought to the test-bed to generate research data. This is an inline tool that produces results over relatively long sections of pipe, in this case a 1km length. Pits 1 and 3 of research run 1 were used for insertion and retrieval respectively. The See Snake technology employs remote field technology (RFT) for measuring pipe wall thickness. RFT technology works by generating an alternating current electromagnetic field in the wall of a pipe and detecting its changes caused by metal loss.

A comprehensive report from this research run detailed the condition of the full kilometre including the location of the three worst defects for each pipe and the location of all construction elements such as the joints, off-takes and elbows. From this report, Figure 8 shows the average remaining wall for each pipe of the inspected section.

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[1] Asset Integrity Australasia Pty Ltd (AIA) is a joint venture with Advanced Engineering Solutions Limited (AESL).
[2] Rock Solid Group (RSG).

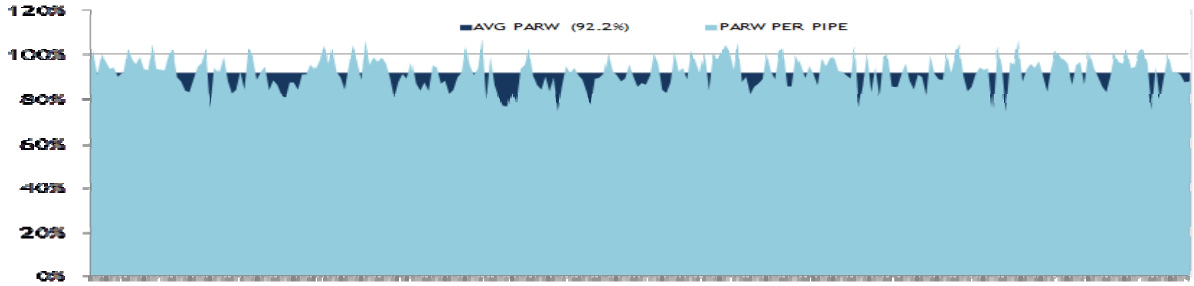


**Figure 8.** Results from Russell run: Average remaining pipe wall

**Research Run 2**
From research run 1 several lessons were learnt; 1) the need for a fixed permanently marked reference frame, 2) a more controlled experimental data acquisition and 3) the exact location of each pipe to correlate with RFT report. The research data acquisition protocol detailed in a previous section was put into place for this second run. Five different locations, based on RFT report, were chosen and analysed in this research run.

MFL and BEM inspected one metre long segments of these five locations in February 2013. Following the data acquisition protocol, the pipe segments were inspected, marked, exhumed, scanned and passed through our thickness recovery algorithm. Results from this run will be presented in the results section.

**Research Run 3**
In May 2013, UTS proceeded with research run 3. As briefly explained in the introduction of this paper, UTS aims at enhancing the data interpretation for selected technologies. For this purpose, we are using machine learning algorithms that require a vast amount of data. Research runs 2, 3 and further planned research runs will allow us to acquire the necessary amount of data for the development of enhanced data interpretation. This data is also being used to evaluate our algorithms and demonstrate the improved results to utilities and technology providers.

For this research run four locations were chosen again using Russell NDE's report. The pipe segments were scanned by MFL and BEM technologies and exhumed; they are currently being scanned. An extra meter segment from a large pipe already exhumed form run 2 was also scanned by these technologies.

**RESULTS**
In this section, we will present some results about the improvements made by UTS machine learning algorithms in comparison with the ground-truth. In particular, the results presented here are from Pit 3 of research run 2. The machine learning approach followed by UTS is shown in Figure 12. This algorithm requires a data set of sensor measurements associated with the respective ground-truth (thickness) at each point. Gaussian Process (GP) models (Rasmussen & Williams 2006) are used to learn a non-parametric model out of the dataset that is subsequently used to predict the thickness from new sensor measurements. The advantage of this method it that a measurement of uncertainty associated with the predicted thickness is also produced. We have learnt non-parametric for MFL and BEM readings.

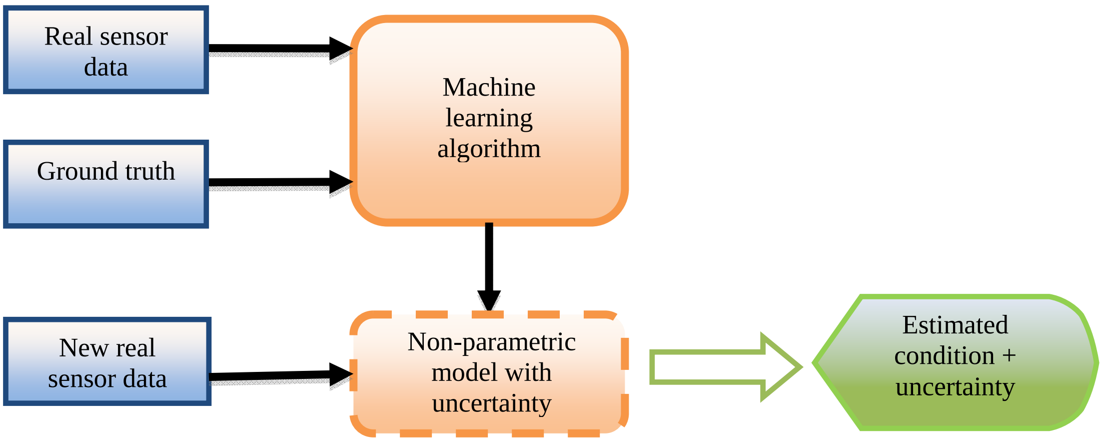
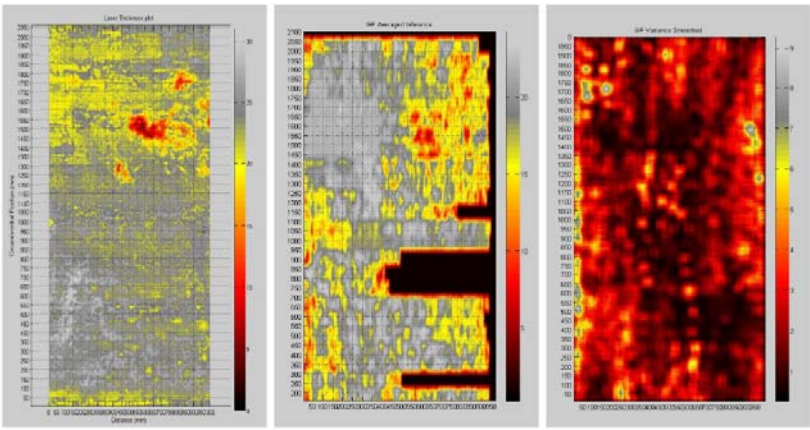



**Figure 9.** Diagram of the machine learning approach using Gaussian process regression.

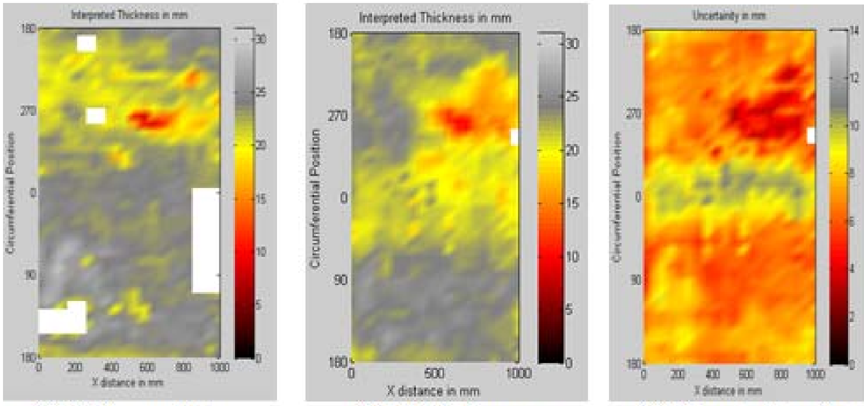
In MFL technology a test substance is magnetically saturated and in the presence of anomalies, a leakage flux is developed. Suitable sensors are used to read these leakage fields. A GP model learnt off-line is used to infer the thickness (please refer to (Wijerathna et al 2013) for further details). Figure 10 shows the inference results for Pit 3 of research run 2. The results show that the model captured the worst deterioration of the pipe. The model predicted the remaining wall thickness as 5.94mm with a deviation of ± 1.27mm where the ground-truth is 6mm. By combining the predictions for each acquisition point, the full plot of the depth profile of the scan area is generated along with the uncertainly. Figure 10(b) shows the overall condition of the scan area while the uncertainty associated with the interpretation in presented in Figure 10Figure (c).



(a) 3-D laser plot (b) GP inference (c) Uncertainty plot

**Figure 10.** Comparison of real and predicted depth profile for MFL data.

BEM technology uses a pulsed eddy current coil probe sensor. The sensor is excited by a pulsed voltage and this time varying excitation induces eddy currents in a test piece. The sensor then reads a voltage induced by the magnetic field. The induced voltage is then characterised to derive the average thickness of the test piece or the pipe wall. Similar to the work done with the MFL technology, a GP model is used to interpret the average pipe wall thickness from the sensor readings. The results for Pit 3 of research run inferred by the learned model were compared with the ground truth and one such comparison is shown in Figure 11. The difference between the ground truth and the inferred results was also computed and the particular segment shown in Figure 11 produced a mean absolute difference of only 1.95 mm.




(a) 3D laser plot (b) GP Inference (c) Uncertainty plot

**Figure 11.** Comparison of real and predicted depth profile for BEM data.

## CONCLUSIONS

A research test-bed has been established at a Sydney Water site to gain a better understanding of the current condition and performance of buried water mains, and to evaluate and possibly enhance condition assessment technologies. UTS, together with Sydney Water, have put in place a protocol to correctly reference pipe sections that are exhumed for further forensic investigation, producing accurate and reliable estimates of pipe thickness. Combining 3D laser scanner data with discrete ultrasonic measurements can increase the reliability of the pipe thickness estimates. Data from different technology providers together with this associated ground-truth has then been used to develop models that can predict remaining thicknesses of pipe sections together with the corresponding measure of uncertainty. Accuracy of these predictions increases with the amount of data available. Thus, attaining reliable estimates of the exhumed pipes is critical for the success of the proposed CA data interpretation technique enhancements currently being researched by UTS.

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