Statistical analysis of dig operations leading to productive repairs

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Abstract

Inline inspection data from several runs spanning many years is available for individual pipeline segments, but compilation of this data into a comprehensive picture of pipeline integrity necessarily relies on computational tools. A critical advantage of modern data storage, analysis and visualization techniques is the relative ease of performing statistical assessments of integrity operations. Data from a single client of OneBridge Solutions Inc, Cognitive Integrity Management ("CIM") solution may comprise over 1,000 in-line inspection (ILI) runs, hundreds of pipe segments, several million aligned anomalies, and thousands of repair records. Automated alignment of ILI data allows a single physical anomaly to be reliably tracked through many years of repeated measurements of growth and correlated repair records which also factor in PODS asset data.

We present a study of cases where ILI anomaly measurements warranted a dig operation in which repair actions were either performed or found to be unnecessary. The fraction of dig operations leading to a productive repair varies with the condition triggering the dig and discretionary choices about dig condition parameters. We explore the relationship between these parameters, ILI measurements, dig-to-repair ratios and the impact to operational expenditures.

Introduction

Cognitive Integrity Management ("CIM") is an advanced pipeline integrity management end-to-end SaaS application for operators world-wide. It has comprehensive functionality to optimize and provide assessment planning and tracking; analyses of data integrity for regulatory compliance; dig management, real-time audit-readiness; instant business intelligence; and integration with other enterprise systems.

This paper will explore methodologies around how business intelligence is derived from dig operations and productive repair efforts. In partnership with a client, when trying to identify process improvements possible from the current workflow, we found an opportunity to critically examine the proportion of digs that led to a productive repair as a part of the integrity management program (IMP). In the industry this calculation is referred to as the dig-to-repair ratio, however, for the purpose of this study we refer to it as the repair fraction. Digs and repairs have the greatest impact on business optimization as they are the largest cost center of integrity operations. Critically, CIM provides pit-to-pit growth information for every anomaly using the full set of historical ILI data and allows linking this with the repair records dataset. The client provided the expertise to understand the IMP dig conditions, including regulatory conditions as well as those defined by the client's best practices.

Methodology

For the purpose of analysis, a historical repair dataset provided by one of the clients of CIM is analysed. The dataset contains records from 1,074 ILI runs spanning a time period from 1991 to 2017 on pipelines with installation dates ranging from 1920 to 2016. More than 23,000 digs were performed over a period from 1959 to 2019 which translates to 171 miles of pipeline excavation. Table 1 shows the three main categories of anomalies present in the dataset.

Table 1. Total numbers for the main anomaly categories in the dataset

Anomaly category	Count
Metal loss	14,533
Dents	5,774
Cracks	2,083

From the dig records we determine whether a productive repair was performed or whether the pipe was simply recoated without additional action taken. The ratio of digs with productive repair to the total number of digs is defined as the *repair fraction* and is the metric for dig performance that we consider in this paper. One of the core advantages of CIM is automatic alignment of anomalies in all historical ILI records and the calculation of pit-to-pit growth based on those measurements. For each anomaly that is the focus of a dig record, we have access to the ILI measurements and this growth calculation.

The repair fraction varies considerably when calculated for subsets of the full data set. There are several reasons a dig may not lead to a productive repair, including a broad category of analysis errors including mis-locating physical anomalies based on ILI records, targeting anomalies that have already been mitigated, and inability to include all available data due to computational limitations. These analysis errors can be reduced by better computational and data management tools.

Imperfect information from the ILI, mostly due to tool tolerances, means that the true threat from an anomaly is only fully known when the pipe is exposed and measured in-situ. Relatedly, proper risk management entails digging anomalies that are unlikely to be problematic in order to mitigate the few that require repair. Risk-management strategy development can benefit from analysis of the factors that are associated with a high repair fraction.

Results

The overall effectiveness of a dig program can be assessed. For example, Figure 1 shows historical performance across all repair years. While there is some variation, the repair fraction is mostly stable between 40-60% of digs.

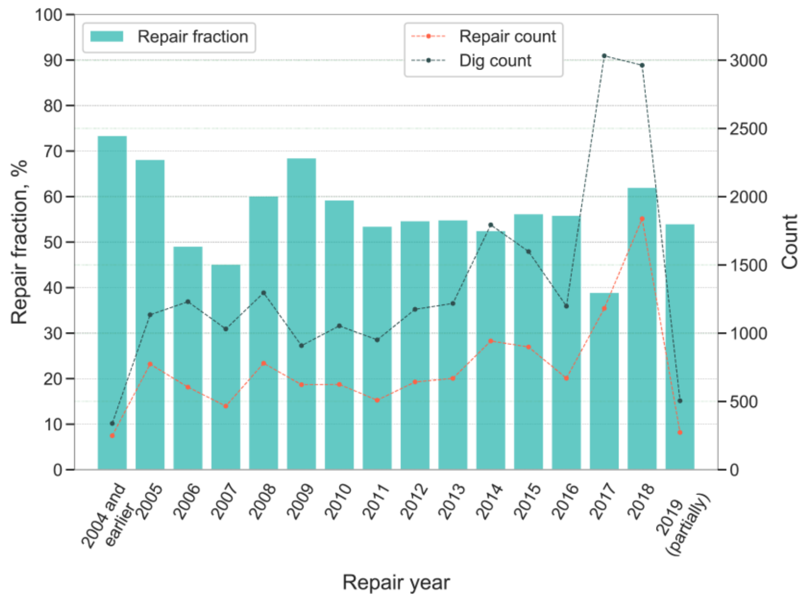

Figure 1. Repair fraction grouped by repair year .

Condition monitoring involves finding anomalies that require remediation based on regulator-established conditions as well as those that require attention based on operator best practices. Many conditions are based on anomaly depth or interactions between anomalies and pipe features. Correlation of ILI tally data and CIM-calculated alignment and growth data with the repair dataset allows us to evaluate the repair fraction against those variables. For example, Figure 2 illustrates that digs for deeper corrosion anomalies are more likely to lead to a repair.

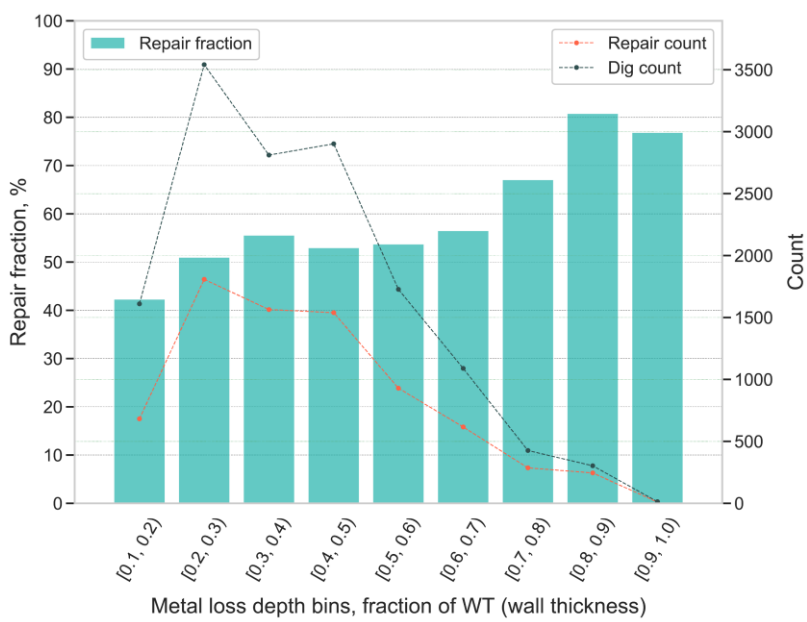

Figure 2. Repair fraction shown as a function of corrosion depth as measured by ILI tools.

In the following section, we will describe a consistent analysis approach and devise changes to a condition monitoring program when a large and diverse repair dataset is available.

Optimization of the repair fraction

By collecting data about the integrity management and decision-making processes, it becomes possible to measure the effects of specific factors on the repair ratio and to identify opportunities for improvement.

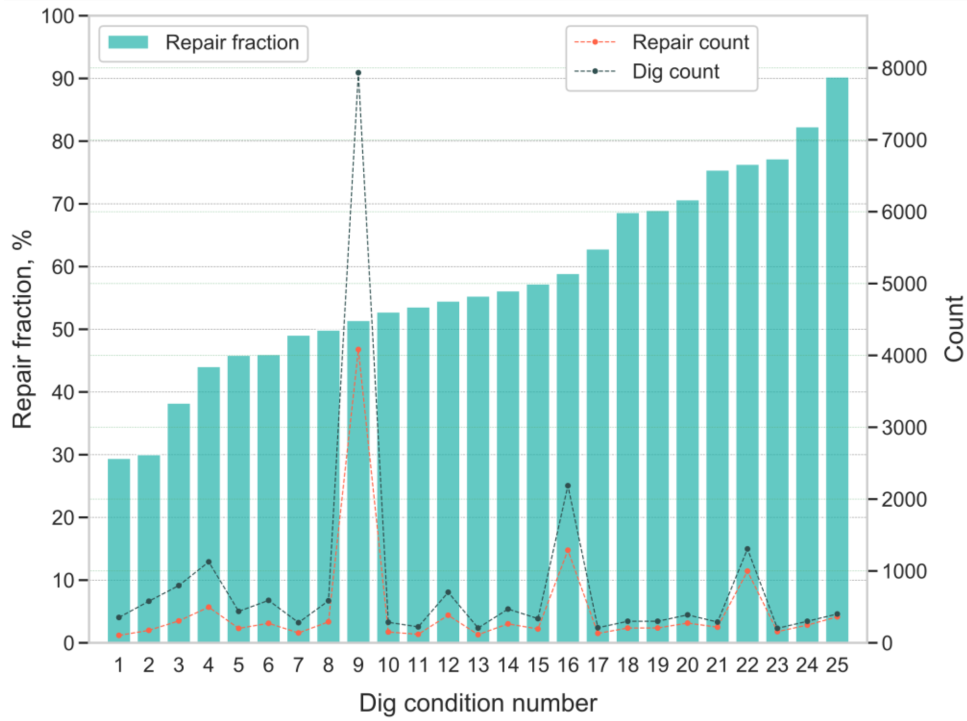

Figure 3. Repair fraction plotted across different conditions used in a dig program. The conditions are sorted in the order of increasing repair fraction.

A condition monitoring program may include more than a hundred conditions for digging and potentially repairing an anomaly. The repair fraction is shown in Figure 3 for well-represented conditions with at least 200 digs. The real conditions in the plot are encoded with numbers and ordered by increasing repair fraction. The description of all conditions can be found in Table A of the Appendix.

For this section, we consider Condition 4 for an in-depth analysis. Condition 4 is defined as *metal loss anomalies grown to exceed depth and/or pressure criteria per reassessment interval process* and have an overall repair fraction of 44%. We present a scheme to use additional anomaly depth and growth criteria to reduce the number of digs that do not lead to a repair. The scheme is generalizable to other dig conditions.

Figure 4 shows that the ratio is not distributed evenly among different values of the metal loss depth and the repair fraction increases with increasing depth. The analysis in this paper can be applied when the repair fraction varies with other anomaly parameters such as corrosion length and width, but we consider only metal loss depth here.

For Condition 4, one could add an extra criterion requiring metal loss depth > 20%, excluding the first bin in Figure 4. In absolute numbers, this means performing 51 fewer digs at the cost of not making 3 repairs. Of course, higher precision in selecting the depth threshold is limited only by the statistical power of this subset of the repair dataset.

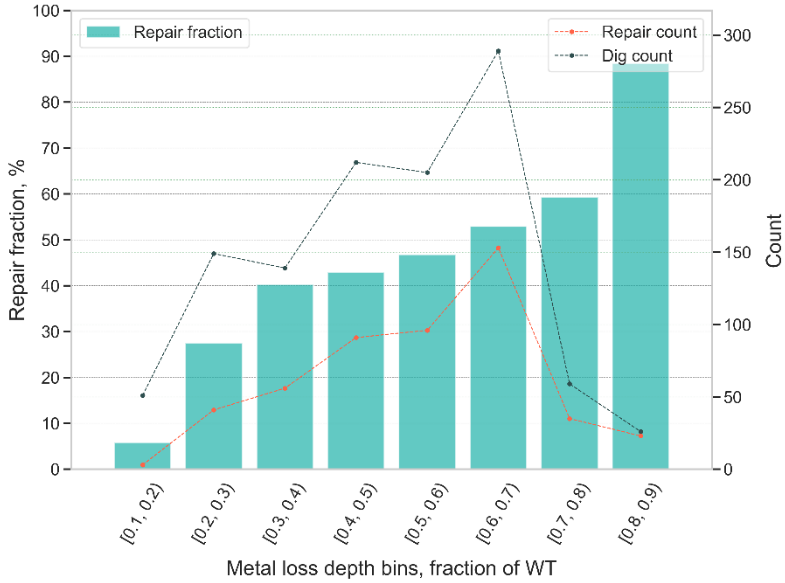

Figure 4. Condition 4 repair fraction divided into bins of ILI measured metal loss. The integrated repair fraction ratio is 44.1%

Moreover, with this idea in mind, it is possible to do a fine scan of the threshold. The scan is done by going over metal loss depth values between 0% to 30% in steps of 1%. There is no technical difficulty to perform a full range scan up to 100%. However, it would be impractical to consider higher values of metal loss threshold since it becomes too risky to exclude any digs or repairs.

Figure 5a shows the number of digs and repairs that would have been excluded by a metal loss depth threshold criterion. The orange points show how many repairs are excluded from the dataset as they fall below the depth limit. The blue points represent the number of excluded digs. The repair fraction for the digs that would be performed even with the additional criterion is shown in green. Because higher-depth anomalies are more likely to require a repair during a dig operation, this fraction increases with an increasing depth

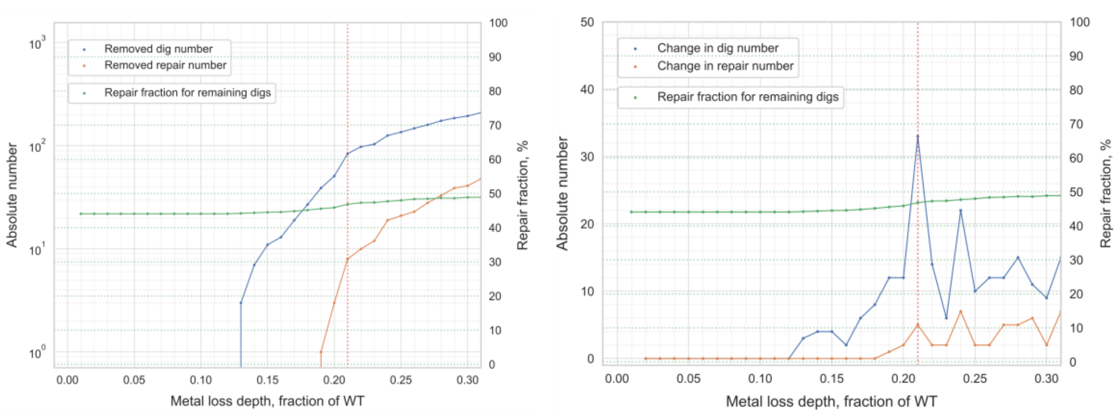

Figure 5. Results of the scan for the optimal metal loss depth. Left image (a) shows how many digs and repairs are excluded from consideration as the threshold moves along the horizontal axis. Right image (b) shows the change in the number of the digs and repairs as the threshold moves. In both images, the green line (and the right axes associated with it) shows the repair fraction for the remaining data above the threshold, and the red line indicates the threshold value discussed in the text.

threshold. Operators would select an optimal depth threshold compromising the number of digs that do not lead to repair against the small fraction of digs that do warrant a repair.

Detailed examination of the effect on repair fraction of an additional criterion allows “critical” values of the criterion to be identified, where there is a large change in the repair fraction. Selection of the specific depth criterion requires balancing the cost of digs without repair and the risk mitigation from the digs that do lead to a repair, and this process is informed by the value of the repair fraction. For example, a depth criterion of 20% excludes 51 digs including only 3 digs with repair. Increasing the depth criterion to 21% excludes a total of 82 digs and only 8 digs with repair. While this analysis considers only digs for Condition 4, accounting for 5% of the repair digs in this dataset, a similar optimization process can be applied to the other dig condition categories. In Figure 5, we see that the repair fraction has a step increase of 1-2% when a depth threshold around 20% is applied.

Inclusion of pit-to-pit anomaly growth

A large dataset with multiple dimensions gives even more opportunities for optimization studies. In addition to checking dependence on the metal loss depth done above, one can also look at the pit-to-pit growth and other data dimensions.

For a given metal loss depth criterion, an additional growth criterion retains the digs with repair while excluding digs that do not lead to repair. This process is shown in Figure 6b for the fixed depth criterion of 20%. In Figure 6a, the number of digs excluded by a combined criterion of a depth threshold and a growth threshold is shown in purple. This criterion avoids exclusion of any digs that did lead to repair, thus leaving the risk profile unchanged.

This process could also be fine-tuned with a scan of possible thresholds in order to find the best possible optimization under extra conditions of choice. Concretely, a depth criterion of 20% or greater and a requirement of any positive growth excludes 8 digs while retaining all digs that led to a repair.

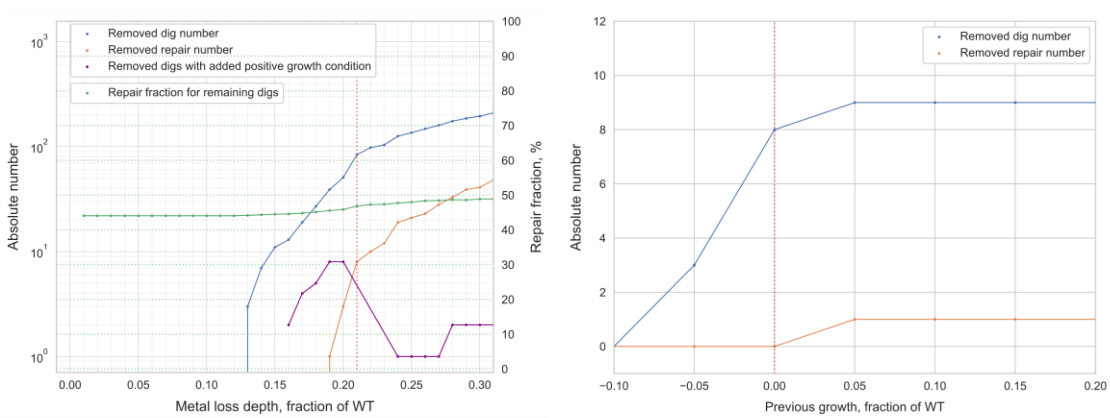

Figure 6. Left image (a) is Figure 5a with an added optimization results over pit-to-pit growth. For every value of metal loss limit, an extra scan is performed over the growth variable while requiring that the number of excluded repairs is zero. The purple curve shows the numbers of digs not leading to repair excluded by a combination growth and depth criterion that represent the maximum values found at a given metal loss threshold. Right image (b) shows an example of one of the scans corresponding to the metal loss fixed value of 20%

By adapting the selection criteria for these conditions, and by introducing additional datasets such as an advanced growth model based on pit-to-pit anomaly alignment there is an opportunity to perform fewer unproductive digs. Operators can more efficiently allocate resources towards digs that are most likely to lead to productive repairs while balancing cost-efficiency and risk.

Many conditions depend on values measured in a single ILI run. Optimization of their performance can have a large impact on the overall cost effectiveness of a dig program as it has been illustrated above. In the next section, we examine how the repair fraction can be used to evaluate growth models, including the CIM-alignment based pit-to-pit growth calculation.

Repair fraction under different growth model scenarios

In Figure 7, we calculate the repair fraction for different selections of corrosion anomaly growth using two different models: the pit-to-pit growth model based on CIM anomaly alignment and a half-life growth model based on pipe installation date.

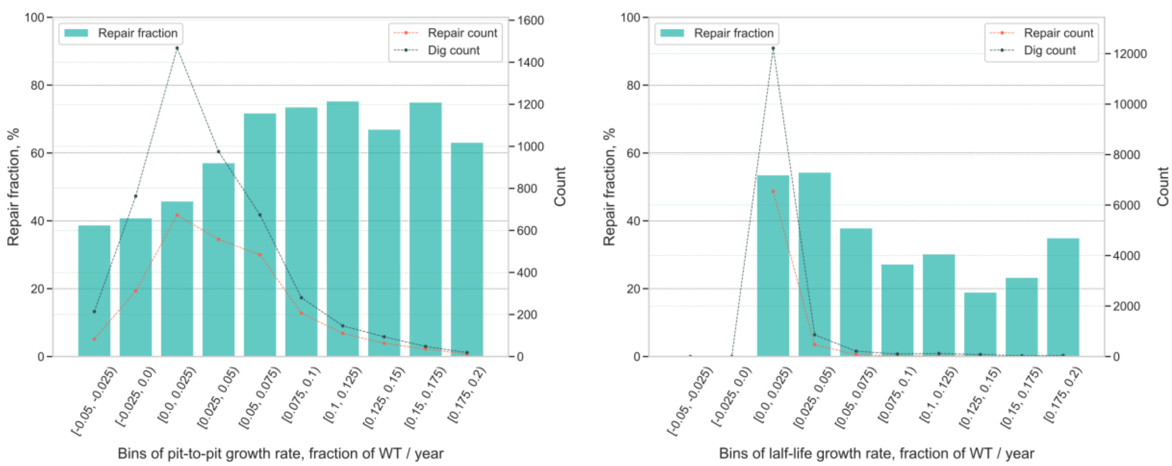

Figure 7. Left plot (a): Repair fraction as a function of the pit-to-pit growth. Right plot (b): Repair fraction as a function of the growth based on the half-life calculation.

Anomalies with higher growth rates should merit a repair more often than those with low growth rates. We see that the pit-to-pit growth model does exhibit this trend, but the half-life based model shows a flat or negative correlation between repair fraction and anomaly growth. This indicates that the half-life model does not correctly indicate the anomalies that are riskiest or most in need of repair.

Future Work

This analysis can be applied to additional datasets as they become available. A unified data collection and analysis framework allows for easy addition of new datasets. The correlation between a parameter and the repair fraction indicates how useful the parameter is for determining the riskiest anomalies. Pipe environmental data, pipe coating, close interval survey data are examples of datasets where such parameters as soil acidity (humidity) or cathodic protection current have potential to improve optimization.

Beyond the addition of diverse datasets, it is important to note that a significant increase in the volume of data would allow the development of a predictive model, in contrast to the *post-hoc* analysis in this paper. A larger parameter space and total data volume is necessary for data-validated models that predict dig outcomes and the repair fraction with a satisfactory level of statistical accuracy.

Conclusion

This analysis demonstrates the correlation between positive repair results and more advanced growth models based on a comprehensive picture of historical inline inspection data and pit-to-pit anomaly alignment. The repair fraction can be a valuable tool to assess the effectiveness of additional datasets or new methods of analysis, and to compare the relative performance of alternate methods of growth forecasting and criteria for dig selection.

The study suggests that new tools and methodologies made available through advances in data science and machine learning allow clients to tune their IMP and de-risk operations. With a structured approach to integrity decision-making, more rigorous collection and management of integrity data, and the use of modern tools which leverage the computational power of the cloud, there is significant opportunity for deeper analysis and inspection of the integrity management program. The types of analysis presented here can guide operators toward a more effective integrity program and to reduce overall risk by improving the allocation of dig program funds.

Appendix

Table A. Description of the real conditions shown in Figure 3

Condition number	Condition description	Type of condition
1	Any change since the previous assessment	company best practice
2	Dents located on the pipeline that have any indication of metal loss not meeting immediate/priority conditions	company best practice
3	Predicted metal loss greater than 50% of nominal wall that is in an area that could affect a girth weld	regulator-established
4	Metal loss growth anomalies: metal loss anomalies grown to exceed depth and/or pressure criteria per reassessment interval process	company best practice
5	Dents located on the bottom of the pipeline with a depth greater than 6% of nominal pipe diameter, and greater than 0.25" for NPS 4 and smaller pipe	company best practice
6	Dents located on the top of pipe (above 4 & 8 o'clock) with a dent depth greater than 2% of pipe diameter (and greater than .025 inches for pipes less than 12-inch in nominal pipe size)	regulator-established
7	Anomalies that are in the judgment of the person designated by the operator to evaluate the assessment results	company best practice
8	Historical correlation/verification features - previously evaluated and/or repaired metal loss or dent anomalies that can be correlated to the current tool run.	company best practice
9	Features required for validation of tool performance	company best practice
10	Laminations (field evaluation are not required if a 1.25 hydrostatic test has been previously performed)	company best practice
11	Dents located on the bottom of pipe (below 8 and 4 o'clock) that has any indication of metal loss, cracking, or a stress riser	regulator-established
12	Dents located on the top of pipe (above 4 & 8 o'clock) with a dent depth greater than 3% of nominal pipe diameter (or greater than .25 inches for pipe less than 12-inch in nominal pipe size)	regulator-established
13	Metal loss of or along the long seam weld	company best practice
14	Dents located on the top of pipe (above 4 and 8 o'clock) that has an indication of metal loss	regulator-established
15	Predicted metal loss greater than 50% of nominal wall that is located at a crossing of another pipeline	regulator-established
16	Safe operating pressure that is less than current established MOP at anomaly location	regulator-established
17	Corrosion of or along a longitudinal seam weld	regulator-established
18	Dents located on the pipe (above 4 and 8 o'clock) that has any indication of metal loss and MOP is greater than or equal to 40% SMYS.	company best practice
19	Metal loss greater than 80%	company best practice
20	Metal loss greater than 80% of nominal wall	regulator-established
21	Top side dents with depth greater than 6%	company best practice
22	Metal loss features where SOP pressure less than MOP at the anomaly location	company best practice
23	Stress corrosion cracks (crack-field calls by the ILI Vendor with depths equal or less than 80% of the nominal wall thickness.)	regulator-established
24	Crack fatigue remaining half-life anomalies: crack anomalies grown to exceed depth and/or pressure criteria per API-579 or log secant method.	company best practice
25	Stress corrosion cracks (crack-field calls by the ILI Vendor with depths equal or less than 80% of the nominal wall thickness or with a calculated predicted burst pressure less than MOP at the anomaly location)	company best practice