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IDENTIFYING LOCATIONS OF ACTIVE CORROSION GROWTH FROM SUCCESSIVE IN-LINE INSPECTIONS

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Abstract

Pipeline operators use in-line inspections and corrosion control systems to manage the integrity of their systems against the threats of internal and external corrosion. Typically, operators base their excavation (dig) programs on the most severe defects reported by the inspections. Basing dig programs on reported defect severity misses an important factor that affects the future integrity of pipelines: defect growth.

Remaining life estimates can be based on estimated corrosion growth rates. These are often approximate and sometimes wrong. Excess conservatism leads to short reassessment intervals and unnecessary mitigation. Inadequate conservatism can artificially misplace resources to mitigate risk. This paper discusses how analyses of data from two in-line inspections can be used to identify areas where corrosion is taking place and estimate the corrosion growth rate. By identifying and addressing these areas, operators can minimize unnecessary mitigation in low growth areas, ensure high growth areas are mitigated in a timely manner, and extend overall reassessment intervals.

The integrated approach covered by this paper identifies corrosion activity using a combination of statistics, inspection signal comparisons, and engineering analyses. The approach relies on an understanding of in-line inspection and the mechanisms that cause corrosion and its growth. Pipeline operators can use the approach to calculate remaining lives, prioritize repairs and mitigation, and sometimes extend reassessment intervals. This process is collectively known as Statistically Active Corrosion (SAC).

Introduction

Figure 1 is a flowchart of the Statistically Active Corrosion (SAC) approach, which uses statistical analyses to identify areas where growth may be occurring and engineering assessments to identify locations that may be missed by the statistics. Two in-line inspections are required, preferably using similar technologies. Inspection signal comparisons assess whether real change has taken place, and a good understanding of corrosion mechanisms is used to estimate corrosion rates. These rates can then be used to set reassessment intervals via a deterministic model or the probability of exceedence (POE) approach^{1,2}. The SAC process addresses many of the weaknesses inherent in statistics-only approaches. The following is a brief description of the SAC process, which is described in more detail in Reference 3.

Statistically Active Corrosion Process Overview

Step 1. Data Preparation

The first step in an SAC analysis is to prepare the in-line inspection data for comparison. This begins by performing a QA/QC check on the data, after which they are aligned to a common centerline coordinate system. Next, sources of bias or systematic errors between the inspections are identified and addressed. Various types of bias exist that must be addressed prior to the statistical screening. Identifying sources of bias typically entails raw data (signal-to-signal) comparisons.

Raw data reviews are also used to identify biases between the inspections starting with a comparison of signals that have not changed between inspections. Signals from anomalies with similar

lengths, depths, and widths are examined along each inspection to verify consistency. These comparisons can include anomalies reported on the ID and OD as well as anomalies that are near and away from weld regions, wall thickness transitions, and casings.

Once sources of bias in sizing are identified, the data can be scaled to remove the bias prior to the statistical analysis. Scaling may not be done when the second (more recent) inspection reports deeper depths than the first. In this case, the apparent change in depth could be the result of corrosion growth and therefore not scaled.

Step 2. Statistical Screening

After removing any bias present in either of the two inspections, the second step is to conduct a statistical screening. The statistical screening is relatively straightforward in concept, but complicated in practice. A two-sample independent t-test is used* if each inspection reported anomalies in the length being analyzed; if not, a one-sample t-test is used versus a threshold. If the anomalies are statistically different to a given confidence level, they are considered candidates for more detailed analyses to determine whether corrosion is actively taking place and, if so, at what rate.

The statistical screening is usually based on reported depths. Other parameters, such as predicted burst pressure, length, or volume of metal loss, can also be used. Each has relative strengths and weaknesses that must be considered in the analyses. Additional statistical techniques are often required to handle unique situations.

Step 3. Raw Data Review

Step 3 involves reviewing the raw inspection signal data. The signal review allows an independent assessment of whether corrosion growth is taking place in areas where change is expected, and vice versa. In most cases, comparing the actual signals recorded in each inspection improves the statistical approach. By comparing actual signals, corrosion growth is verified or refuted and removed from consideration. Anomaly-to-anomaly comparisons are also useful when a particular anomaly needs to be reviewed over several inspections to determine its severity, origin and/or potential for growth.

Step 4. Cathodic Protection Assessment

Step 4 is to integrate the results of the SAC analysis with coating condition information and cathodic protection information, such as close-interval and voltage gradient survey data. The analysis considers the historical and current operating conditions of the cathodic protection system (prior to first inspection date and between inspection runs) and coating repairs.

The cathodic protection assessment provides supporting information related to the direct cause of the calculated corrosion rates. This allows the pipeline operator to identify critical areas and not only replace them when they become a threat to the safe operation of the pipeline or to implement remediation with mid and long term effects such as mitigating the direct cause.

Step 5. Establish Reassessment Intervals

The last step is to establish reassessment intervals. Using estimated growth rates, individual defects are 'grown' to determine the length of time needed remaining before the defect to reach critical size. Typical deterministic limits are when the defect depth equals 80% of the wall thickness or the predicted burst pressure is less than the maximum allowable pressure, with or without a safety factor. Alternatively, a more detailed risk based approach called Probability of Exceedance (which considers the impact of uncertainties in the depths or severities of reported flaws on the likelihood that a critical defect exists) are used, in conjunction with the SAC growth rates, to aide in establishing remaining life calculations and reassessment intervals using a probabilistic approach.

* A t-test is a statistical examination of two population means to assess whether the two sample means are statistically different.

The remaining life calculations identify defects that may fail acceptance criteria before the desired reassessment interval. Remediation can then be scheduled based on the calculated remaining lives, after including a factor of safety or a shorter reassessment interval can be established. Though, by appropriately scheduling repairs, the reassessment interval can effectively be increased by years in most cases and occasionally shortened when warranted due to actual verified high growth rates.

SAC GROWTH RATES

There are various options available in terms of the statistical analysis. A joint SAC analysis may be chosen to highlight those joints with potentially active corrosion growth but others and combinations of others are available. Regardless of what spatial components are selected a variety of statistical techniques are available to identify those joints for signal review:

- SAC Mean – identifies and quantifies the average corrosion growth where there is evidence of active corrosion at a given confidence level (usually chosen as 90% or 95%).
- SAC Max - identifies and quantifies the corrosion growth where there is evidence of active corrosion between the deepest pits in each ILI run.
- SAC Count – identifies locations where there is a statistically significant increase in the number of ILI calls over time regardless of the depth.
- SAC Bias & Pit to Pit Matching – aids in the identification of potential bias of one ILI run versus another. This uses the pits that have been automatically matched one to one across the ILI runs.
- SAC RUL – If desired, this provides both the expected and “worst case” remaining useful life of a joint. It grows the deepest pit on the joint at both the predicted SAC growth rate and the “worst case” upper 95% confidence level growth rate to estimate remaining useful life.
- SAC Individual Confidence Level – This assigns confidence levels to all corrosion growth estimates thus allowing both a ranking as well as a more in-depth evaluation of joints that just miss a given confidence level.

Table 1 presents a subset of the various types of output available that identify those joints that have statistical evidence of active corrosion between the time of the in-line inspections. The focus below is on the average (or mean) corrosion growth rates for joints with the highest growth rate on the pipeline segment.

Table 1. Sample SAC Results

| n, first run | n, second run | Confidence | Mean Corrosion Rate (mils/year) |
|--------------|---------------|------------|---------------------------------|
| 8 | 7 | 97.0% | 7.32 |
| 8 | 7 | 99.0% | 7.31 |
| 6 | 4 | 97.0% | 6.90 |
| 7 | 6 | 96.6% | 5.79 |
| 16 | 20 | 98.1% | 4.68 |
| 21 | 16 | 99.8% | 4.38 |
| 4 | 11 | 97.0% | 4.26 |
| 16 | 19 | 99.2% | 4.21 |

Reports such as shown in Table 1 along with plots of statistically active corrosion along the line allow the operator to focus their efforts on those areas of most concern. Similarly cost effective integrity plans may be developed.

The sample chart in Figure 2 shows 1-1 matched pits and corresponding SAC results, highlighting areas of interest as input to the signal review process.

The sample chart in Figure 3 details the corrosion growth rates (mils per year) for each joint that was determined to be SAC Mean, providing an at-a-glance indication of the severity of active corrosion along the length of the pipe.

DISTRIBUTIONS OF CORROSION GROWTH RATES

The previous section discussed average growth rates of joints showing statistically active corrosion. In this section, a corrosion growth distribution is determined by pit-to-pit matching, independent of the SAC results. Then, the corrosion growth distribution is compared to the SAC growth rates to demonstrate that the SAC results reasonably represent the maximum growth rates along the line. Here, the following assumptions are made to simplify the discussion:

- The in-line inspection depths are assumed to have no bias (i.e., the mean error is zero) and the errors in depth are to be normally distributed.
- The growth in defect depth can be described by a lognormal distribution.

Two distributions based on these assumptions are schematically shown in Figure 4 (the blue dashed curve represents the random tool error and the dashed red line is the assumed growth). Note that the area under each curve is set to one (i.e., the distributions are normalized).

Before considering growth plus reporting error, consider the case where two identical inspections are run with no growth between them. In each case, the inspection reports the actual depth plus some amount of normally distributed (random) error. The differences between the two inspections are also normally distributed, with a mean equal to the sum of the individual mean errors.

The standard deviation of the differences is equal to the square root of the sum of the squares of the errors in the first and second inspections (σ_{ILI1}^2 and σ_{ILI2}^2 , respectively). If both inspections are assumed have the same random error ($\sigma_{ILI1} = \sigma_{ILI2} \equiv \sigma_{ILI}$), the standard deviation of the differences between the inspections can be given by:

$$\sigma_{delta} = \sqrt{\sigma_{ILI1}^2 + \sigma_{ILI2}^2} = \sqrt{2}\sigma_{ILI} \quad (1)$$

Where, σ_{delta} is the reported difference in depths in the two inspections. This equation can be inverted to calculate the random standard deviation between the inspections from the population difference between the two inspections:

$$\sigma_{ILI} = \sigma_{delta} / \sqrt{2} \quad (2)$$

So, the standard deviation in Equation (2) defines the repeatability between the two inspections. A key, of course, is identifying where corrosion has not occurred - one of the objectives of the SAC methodology previously described.

For locations where growth has occurred, the process is a bit more complicated. The mean of the resulting distribution equals the sum of the mean error from each inspection and the mean growth. Since the means of the in-line inspection errors are assumed to be zero, the mean of the distribution with growth is simply equal to the mean growth. The standard deviation, accounting for growth, is given by:

$$\sigma_{\text{delta}} = \sqrt{2 \sigma_{\text{ILI}}^2 + \sigma_{\text{growth}}^2} \quad (3)$$

Figure 5 shows an example distribution of the difference in depths reported by two inspections, generated by assuming both in-line inspection error and growth. Here, the standard deviation of the growth was taken as half the standard deviation of the in-line inspection error. As shown in Figure 5, the generated distribution of depth differences contains both negative and positive values.

Given Equation (3), it is straightforward to determine the mean and standard deviation of the growth, as shown below:

$$\sigma_{\text{growth}} = \sqrt{\sigma_{\text{delta}}^2 - 2 \sigma_{\text{ILI}}^2} \quad (4)$$

Example Problem

The method described above was applied to a pair of in-line inspections, for which about 1,700 pits were matched. Figure 6 is a unity plot showing the depths reported by both inspections. The second inspection appears to indicate corrosion growth (there are more points above the diagonal than below it). The SAC growth rates are compared to the growth rate distribution derived as discussed above to validate the SAC rates.

Figure 7 is the distribution of differences in depth for the matched pits. The mean of the distribution is 4%, which implies the average corrosion growth rate is 4% divided by the time interval between the inspections. The standard deviation of the distribution is 9.4%.

Figure 8 shows the results of the analysis. The dashed red and blue lines refer to the distributions used in the simulation, while the dashed black line shows the simulated distribution of differences between the inspections, accounting for both tool error and growth. The solid blue line is based on the actual reported depths in the two inspections. There is good agreement between the simulation and the inspection data.

The calculated in-line inspection error between the two inspections has a standard deviation of about 4.1% of the wall thickness (and an assumed mean error of zero). A typical MFL tool specification is +/-10% of the wall thickness, 80% of the time, which corresponds to a standard deviation of about 7.8% of the wall thickness. So, this inspection was more accurate (repeatable) than the typical MFL performance specification.

For the lognormal growth distribution, the standard deviation is about 7.5% of the wall thickness and the location factor is equal to -1.0. This distribution is compared to the SAC rates in the following section.

Comparing SAC Rates to Growth Distribution

The calculated lognormal growth distribution is compared to the SAC mean values in Figure 9, which shows the growth component of the inspection differences. The SAC mean values follow the generated growth distribution for higher growth rates but not for low growth rates. This is as expected because the SAC process focusses on joints with significant growth. Hence, SAC mean growth rates appear to be good representation of the peak growth rates that occur along a pipeline segment, as determined using a distributional analysis of the pit-to-pit matched depths.

CONCLUSIONS

The SAC methodology is used for identifying corrosion activity and calculating corrosion growth rates in pipeline sections that have multiple inspections. The ability to predict local corrosion growth rates and improve long-term failure predictions benefits operators because mitigation are more effectively targeted to specific pipeline sections where corrosion is actively growing.

This paper presents methodologies that are used for validating active corrosion and growth rate predictions, including statistical analyses, reviews of the inspection signal data, integration of CIS data, and field verification. The SAC growth rates compare well with a growth rate distribution determined from pit-to-pit matches.

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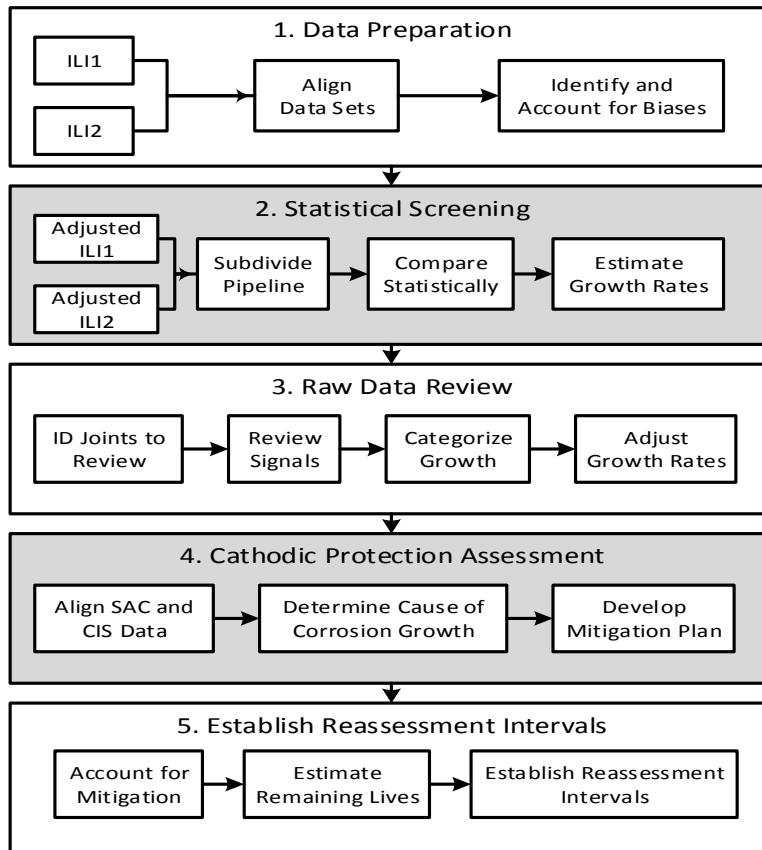


FIGURE 1. SAC PROCESS FLOW CHART

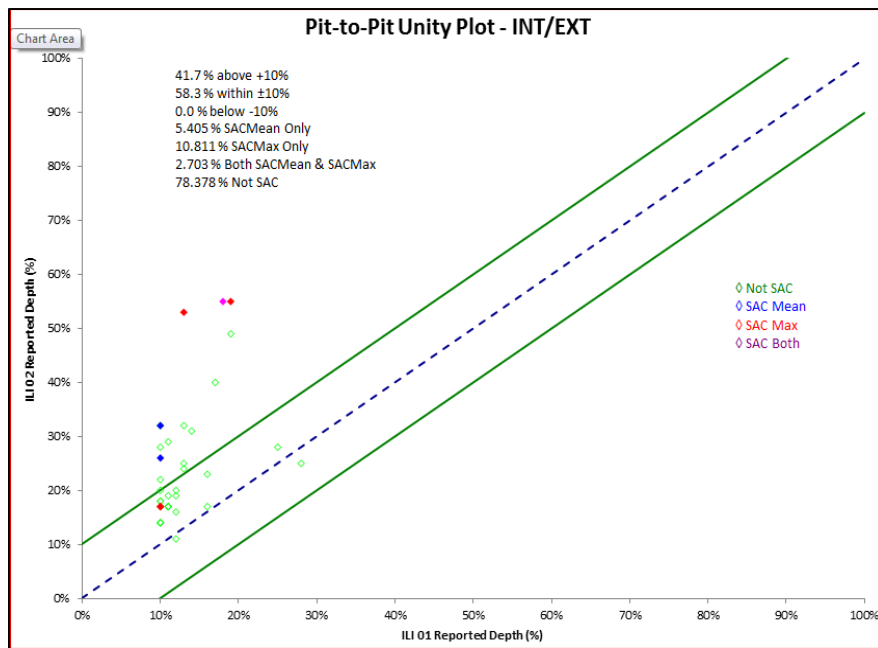


Figure 2. Sample Unity Plot

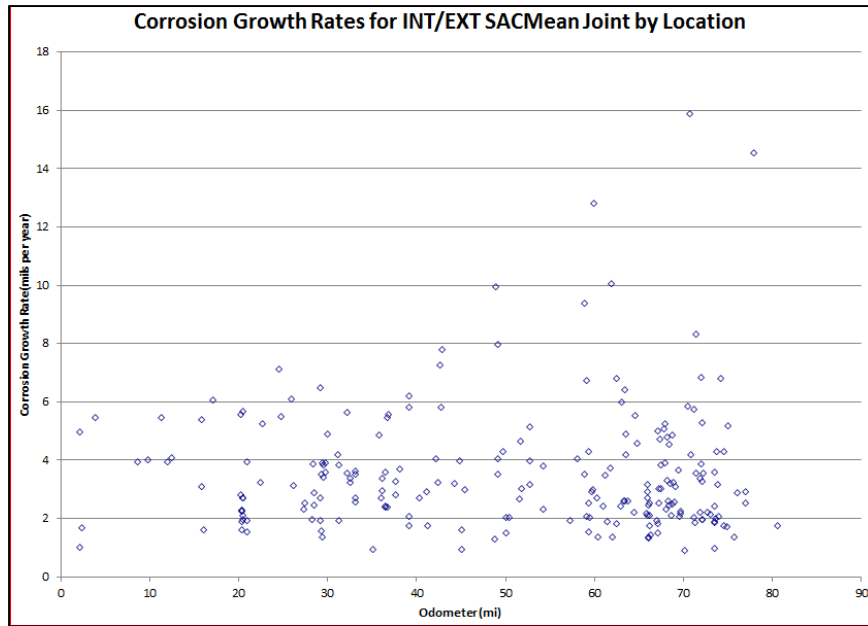


Figure 3. SAC Corrosion Growth Rates Along Pipeline

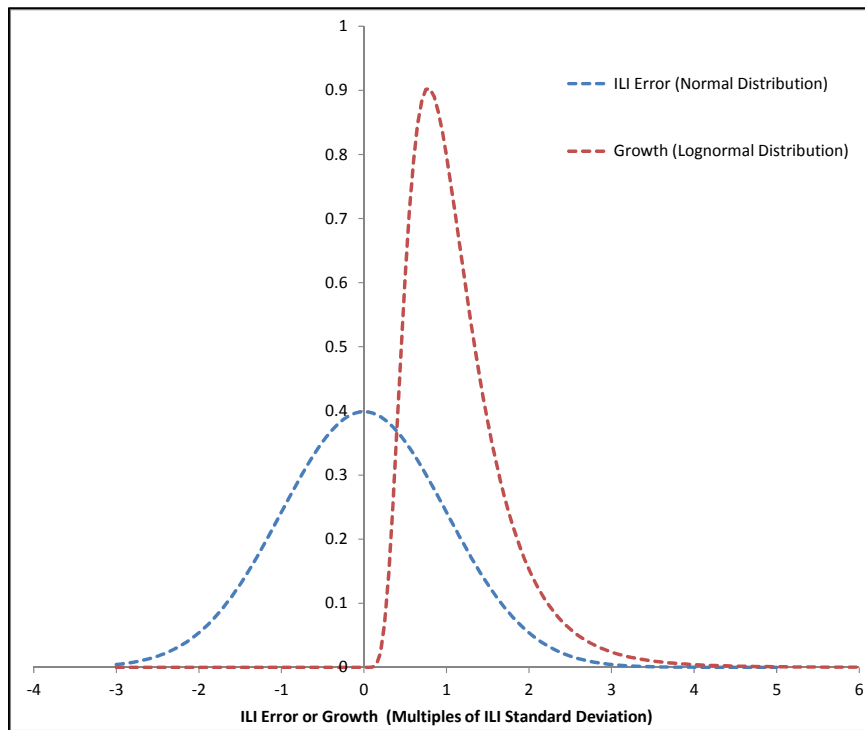


Figure 4. Expected Difference in Reported Depths

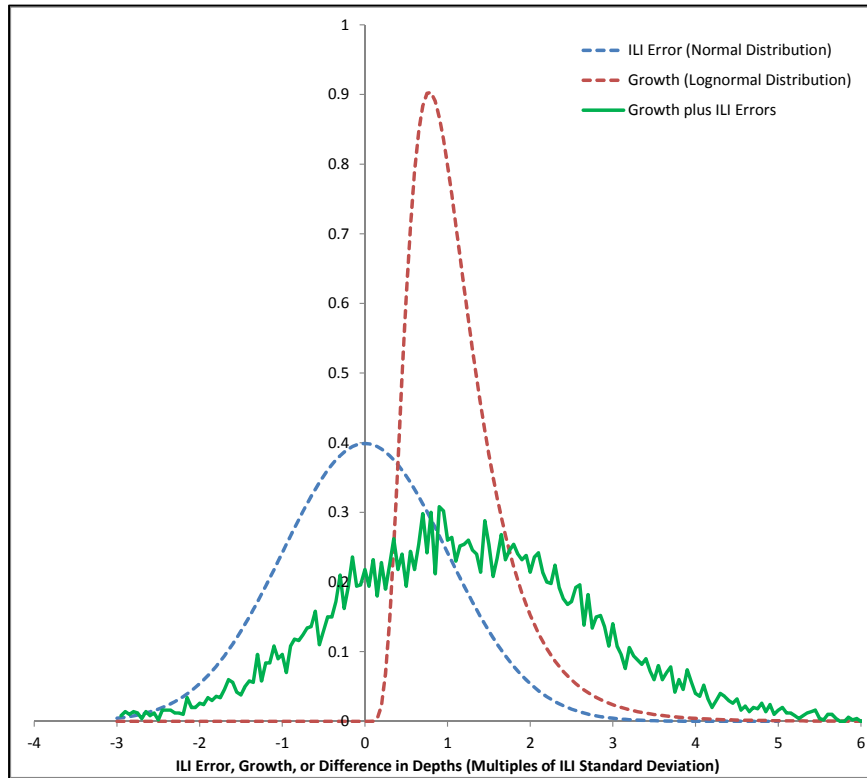


Figure 5. Example Distribution of Differences in Depth

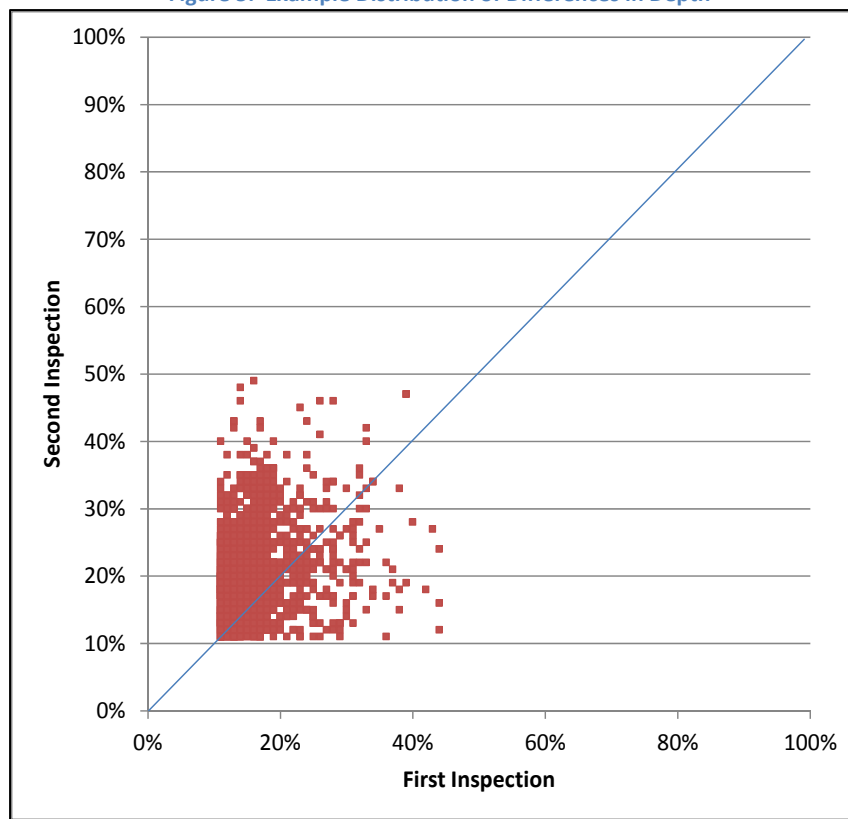


Figure 6. Example Problem Unity Plot

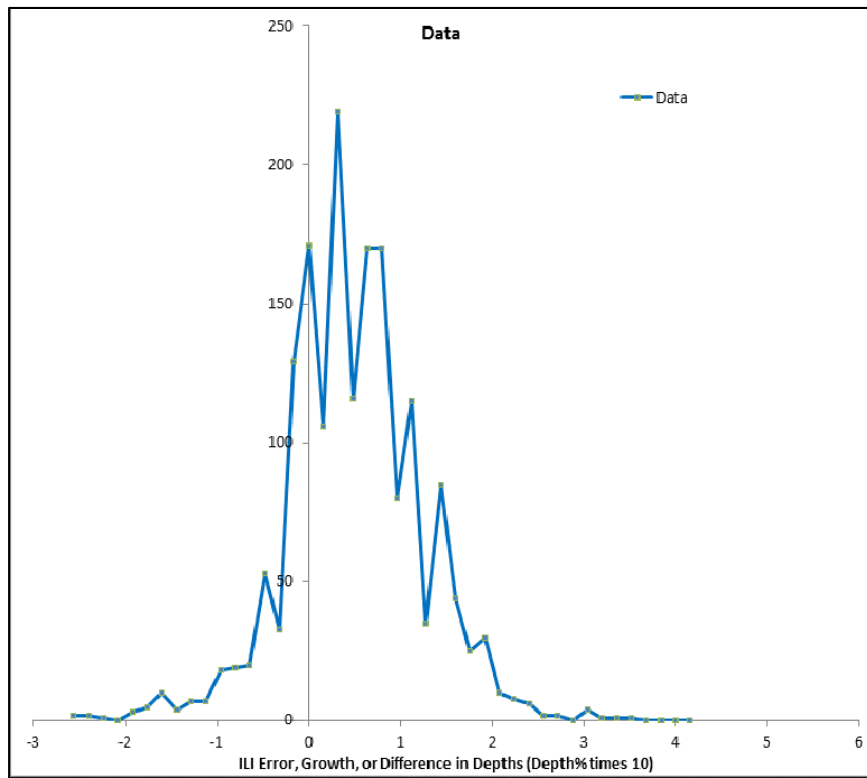


Figure 7. Example Problem Distribution of Depth Differences

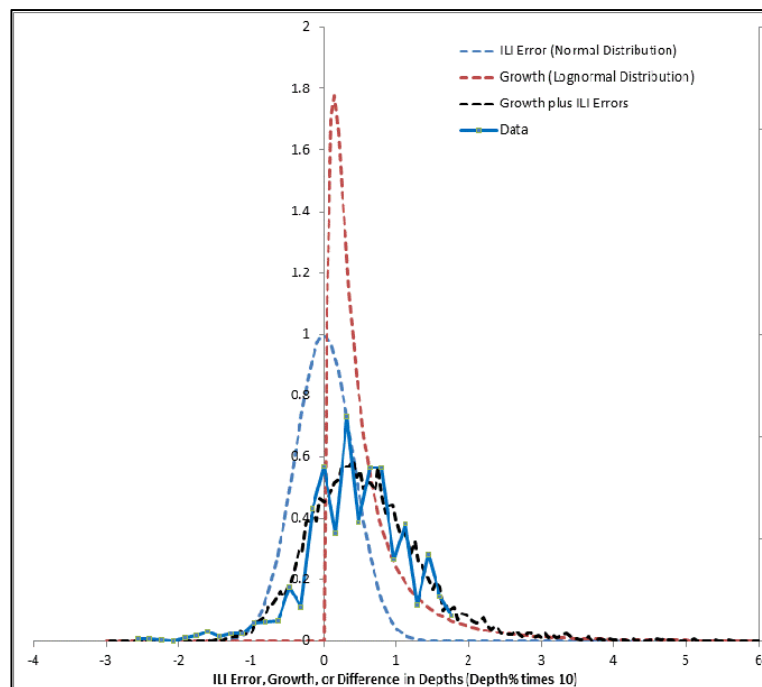


Figure 8. Comparison of Generated Difference Distribution with Data

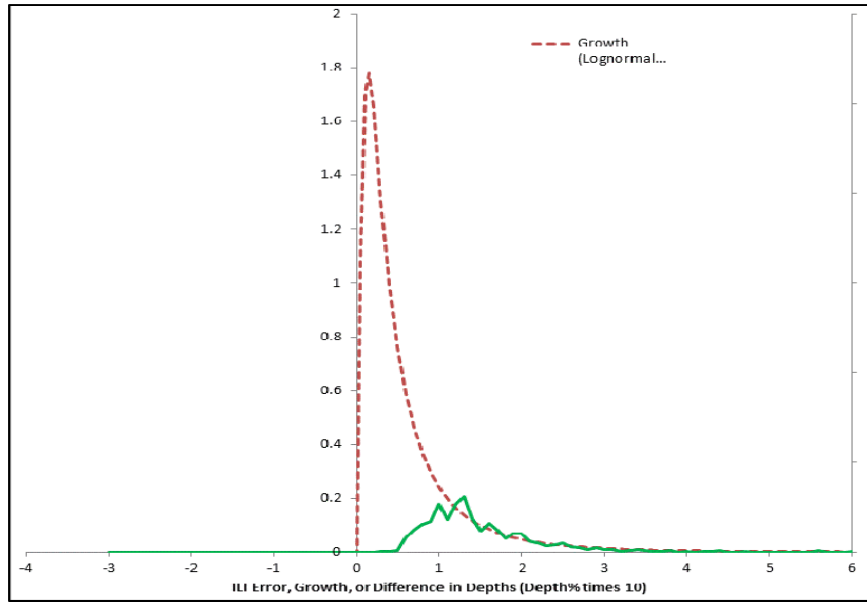


Figure 9. Comparison of SAC Mean Results with Generated Distribution of Growth from Pit-to-Pit Matches
