Pinnacle eBook

Increasing the Effectiveness of CML Optimization Through Condition Monitoring Optimization

This e-book will Illustrate how advanced analytics can be applied to improving inspection, mechanical integrity, and risk-based inspection programs.

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The Goal: Inspect Proportionally to Risk

The purpose of inspection is to be able to effectively quantify the damage state of an asset. If you can effectively quantify the damage state, how an asset is degrading over time, and how it's going to fail, you can then more effectively quantify probability of failure and risk. Once risk is quantified, you can better prescribe future inspection and data collection activities, be proactive with maintenance recommendations, and explore other risk-mitigation strategies. In an ideal world, it would be great if you had full inspection using advanced NDE conducted on every asset every year. But that is not practical due to constraints on people, time, and capital. The alternative option is to **inspect proportionally to risk**. By prioritizing high-risk areas, you can increase return on investment spent on mechanical integrity and inspection.

The Purpose of Inspection

- Ascertain and measure the integrity state of your assets, reducing uncertainty
- Quantify risk and predict potential failure / loss of availability or primary containment
- Proactively plan maintenance and repair tasks

Ideal World: Full Inspection of all Equipment

- Generally not possible, given constraints in manpower, inspection budget, etc.
- Attempting this usually results in spreading inspection resources too thin
- Not necessary, not a good use of limited resources

The Practical Alternative: Inspect Proportionally to Risk

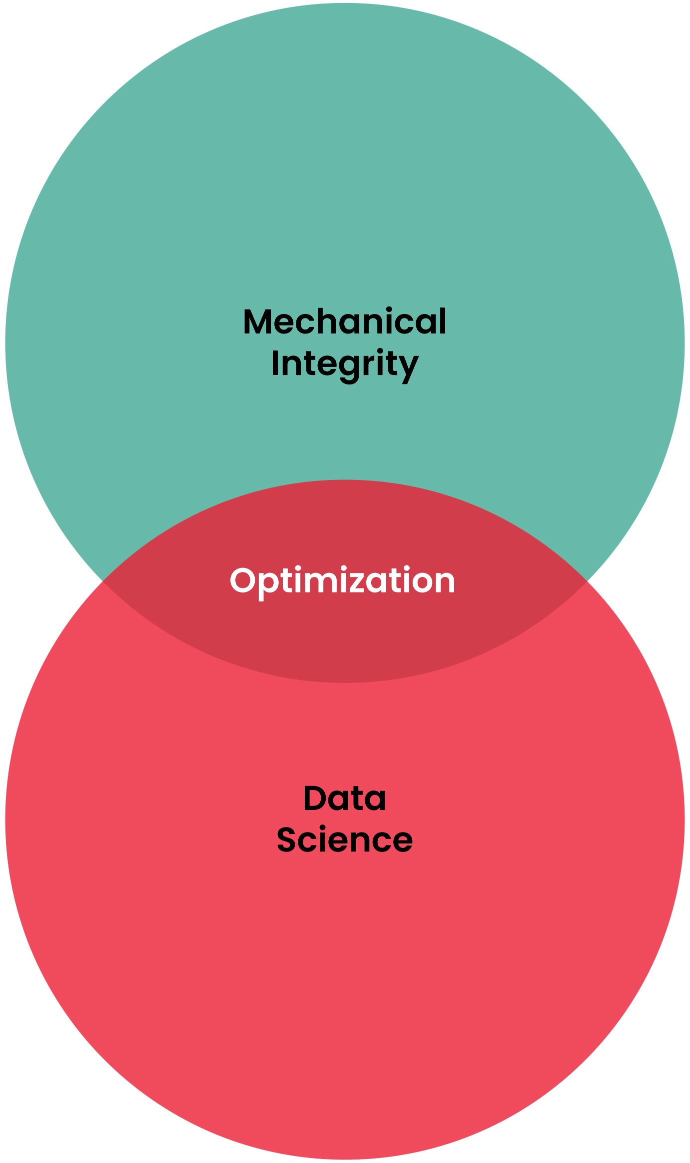
- High value assets with high risk get a larger share of inspection spend
- Focus on the areas that matter most
- Adjust coverage based on actual findings
- Target resources for the best possible ROI

Combining Mechanical Integrity & Data Science

The approach presented in this e-book blends **Mechanical Integrity** with **Data Science**. Both are very valuable, and each have different skill sets. The different strengths offset the weaknesses of one another, and by putting them together, we get the best of both worlds. The mechanical integrity side is important for understanding assets (e.g., how they're designed, how they degrade and fail) and for providing some context to the data. For example, a mechanical integrity subject matter expert (SME) can answer questions like: "What does the data actually mean? What data is useful? What data is suspect and should not be used in more sophisticated algorithms?" However, the limitations associated with relying solely on a person include possible biases, or potential over-conservativism in some cases. People also can't crunch numbers quite as effectively as computers and advanced algorithms. That's where the data science comes in.

There has been a tremendous amount of attention on data science and data-driven techniques over the past several years as computational resources have become more powerful. While data science can do quite a bit, there have been a number of examples, in our industry in particular, where data-driven methods by themselves have failed when trying to make predictions regarding damage or trying to facilitate activities within a refinery. This is because data science by itself, divorced from the human context and the mind of your subject matter expert, can end up with very misleading conclusions if left to run wild on its own.

Because of that, we're focused on combining the best of data science with the best of mechanical integrity subject matter expertise to end up with something that's better than what either could provide on their own.



Problem Setup

Assumption

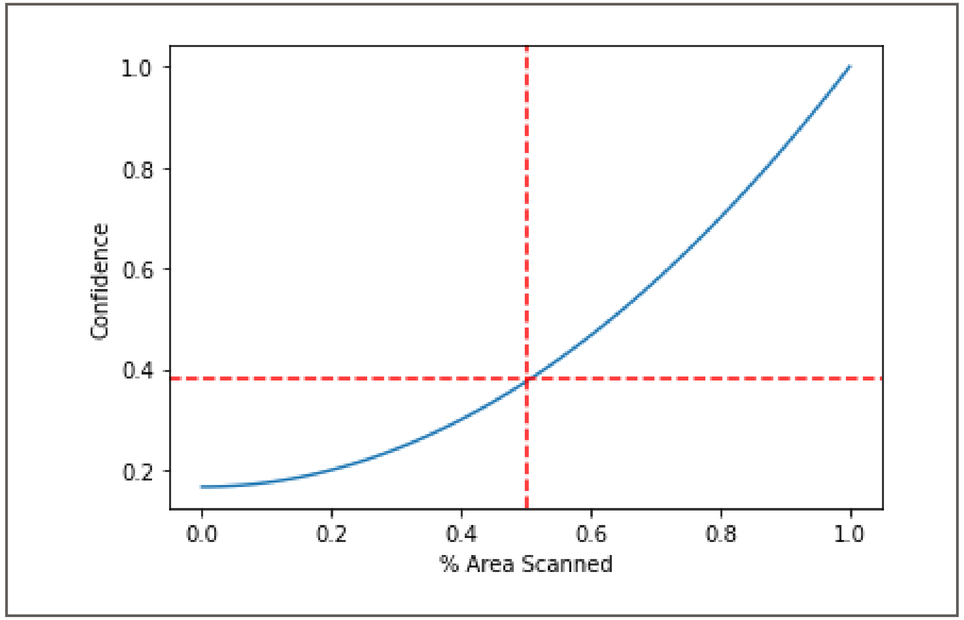
Current CML placement is sufficient to characterize damage state of each asset (i.e., if you fully inspect each CML, you have a near-perfect view of your risk).

Problem

- Identify high-risk CMLs
- Develop a strategy to focus inspection on high-risk CMLs

With this problem setup in mind, we will explore the following damage modes:

- General Degradation
- Local Degradation
- Cracking



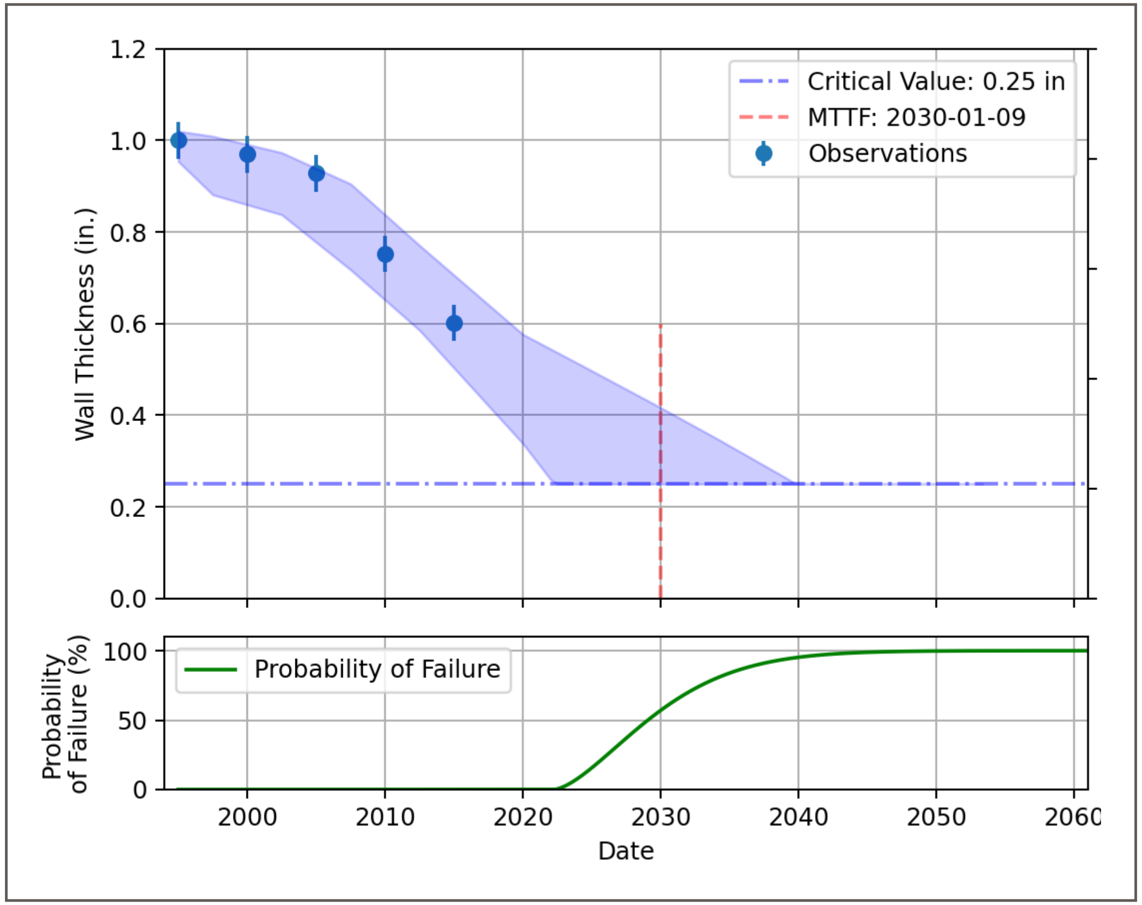
Desired Outcomes

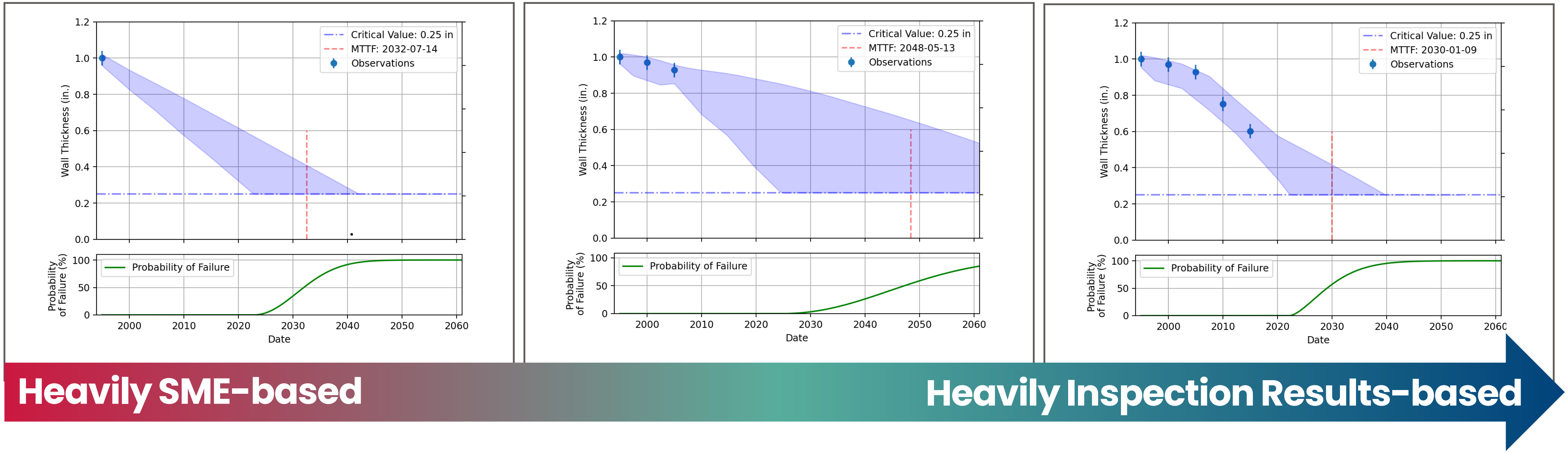
- Provide extent of inspection based on desired level of confidence and risk.
  The coverage should make sense from an SME and data science perspective,
  as well as an ROI perspective.
- Incorporate probability of detection, % susceptible area coverage, and actual inspection history
- Move away from subjectivity to more data-driven objectivity

Evaluating Thinning Risk

A Lifetime Variability Curve (LVC) is a probabilistic model that predicts asset failure through the application of data science principles combined with subject matter expertise. It creates POF and risk projection models for all asset types. Because it utilizes data science, it is not dependent on conservative assumptions and provides data-based objectivity.

An LVC model brings in expectation from subject matter expertise or mechanical integrity and inspection programs—data such as: “What damage mechanisms do we expect? Where do we expect them to occur? How bad do we think they can get? How localized do we think they could get?” It brings that information in with the actual inspection history, and as more and more data is provided, the model is going to refine itself and provide a more accurate understanding of what’s happening with the asset or flag whenever there’s less certainty about what’s going on. Rather than being a deterministic model that outputs a specific value, it quantifies the uncertainty in measurements, how the data is changing over time, or any other element that could impact the results.





Let's look at an example. The far-left graph represents a case in which an asset was just put into service. The only knowledge we have is our best estimate from a subject matter expert and industry tool such as API 581 that helps us understand the possible corrosion rate. However, there's some amount of uncertainty in the corrosion rate that's brought in with the model. Thus, it's very SME-based at the start.

In the middle slide, we see some data has been collected and there's an adjustment. The degradation is lower than expected, so we see the probability of failure and the inspected failure times pushed out to the right a little bit into the future, however, we see the uncertainty grow.

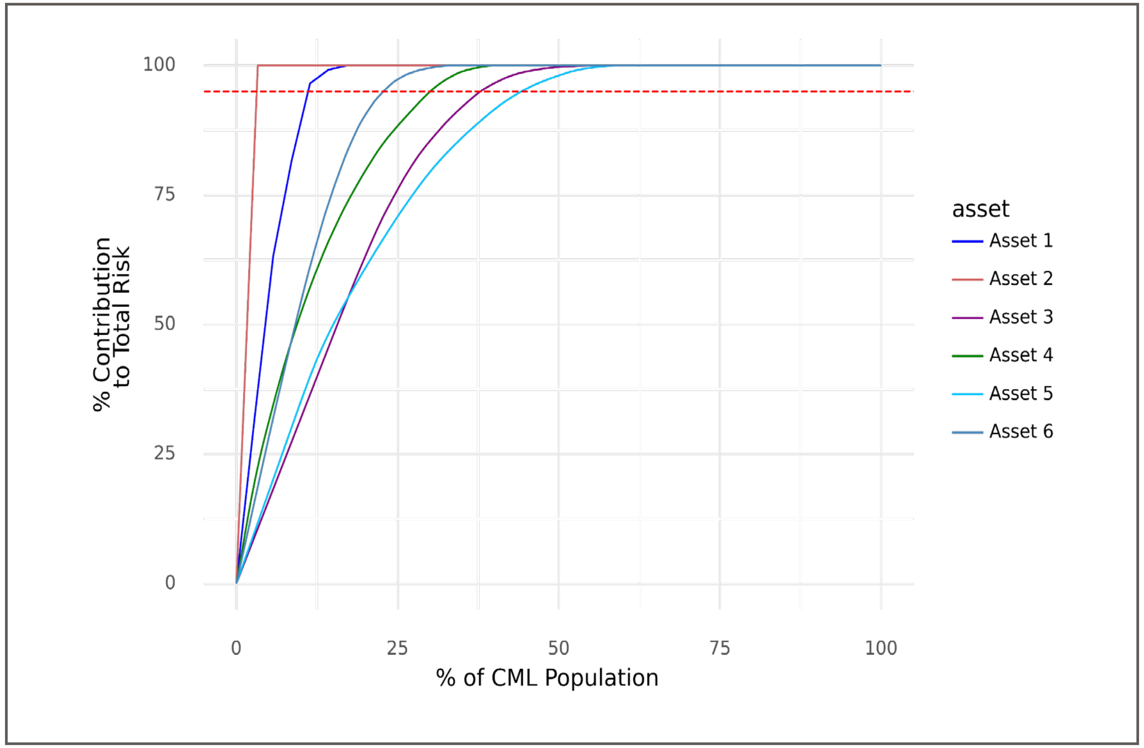
We expected damage and we didn't see as much but we only have a little bit of data. We need more data to confirm that new trend.

In the chart on the right, there was clearly a shift that occurred, bringing the corrosion rate a little more in line with the original expectation. Now, as time has marched on, the model adjusts when a possible failure is expected. Just like a hurricane tracker, the model refines itself as new data becomes available. So, we start with SME knowledge and expertise and we work our way into becoming more and more data driven, the more data we have available.

How Does Risk Look Across Equipment?

As mentioned previously, the LVC produces a probabilistic understanding of how likely any CML within your population is to fail over time, with time being the variable you're interested in. To calculate risk, we look at the probability of failure curves that come out of the LVC model for each CML. We multiply that by the consequence of failure for each CML. We then come up with an estimate of risk over time for every CML.

Now, let's say we take a snapshot at any given point in time and we look at the total risk the facility is facing as a function of the different CMLs inside the population. When we look at a variety of CMLs distributed across multiple assets, multiple facilities, multiple clients, we consistently see that **most of a facility's risk is concentrated on a very small percentage of the overall CML population**. We typically see that about 10-20% of the CMLs are responsible for about 80-90% of the overall risk in the facility. The graphic shows one particular site where we're looking at 6 assets driving the majority of the risk in the facility.



Because risk concentrates across a small percentage of the CML population, this tells us that there is a small percentage of CMLs that are the problematic CMLs. They're the bad actors in your population. **These are the CMLs you want to focus inspection efforts on**. Without this concentration, facilities would be left trying to sample everything in the population, which is not feasible. But because this concentration exists, a facility can prioritize what is looked at and can spend resources in the most intelligent way possible to manage the risk.

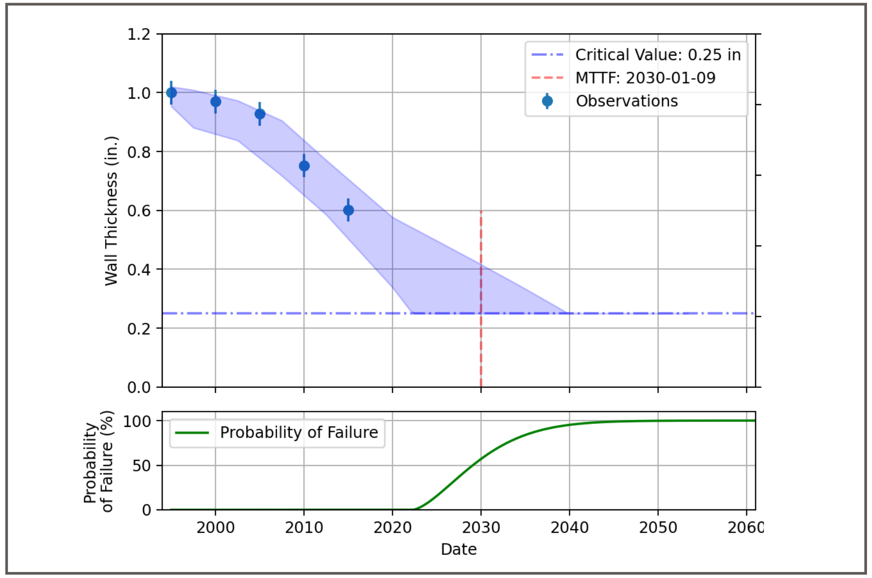
From LVC to Inspection Optimization

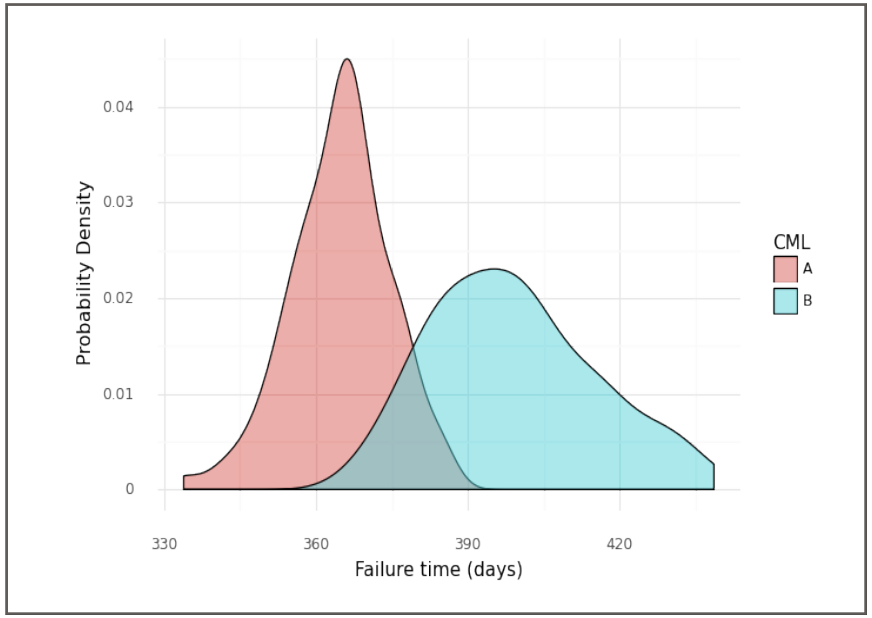
Let’s look at how the LVC model helps optimize inspection.

Key Highlights:

- The LVC model gives us a probabilistic model for the remaining life at each CML.
- We can examine these for each circuit/asset and make inspection decisions.
- The LVC model enables prioritization of specific CMLs for inspection.

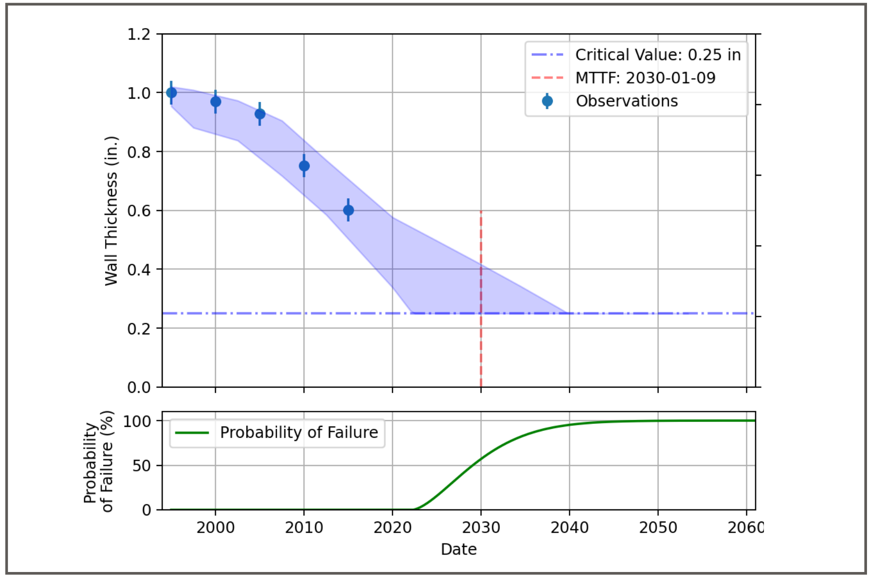
Consider an example in which we have multiple CMLs and all of them have been put through the LVC model. The model gives us an idea of when these CMLs are likely to drive failure for a particular asset. After the modeling, we may have a situation in which one CML is likely to drive failure before the other, or other cases where two or more CMLs may have a chance of being the first to fail (see graphic 1). In cases where multiple CMLS are competing to drive failure for the asset, we may have to sample multiple CMLs to get a good analysis of risk. However, oftentimes one CML is going to be the primary driver of risk on a given asset. These are the CMLs to prioritize.

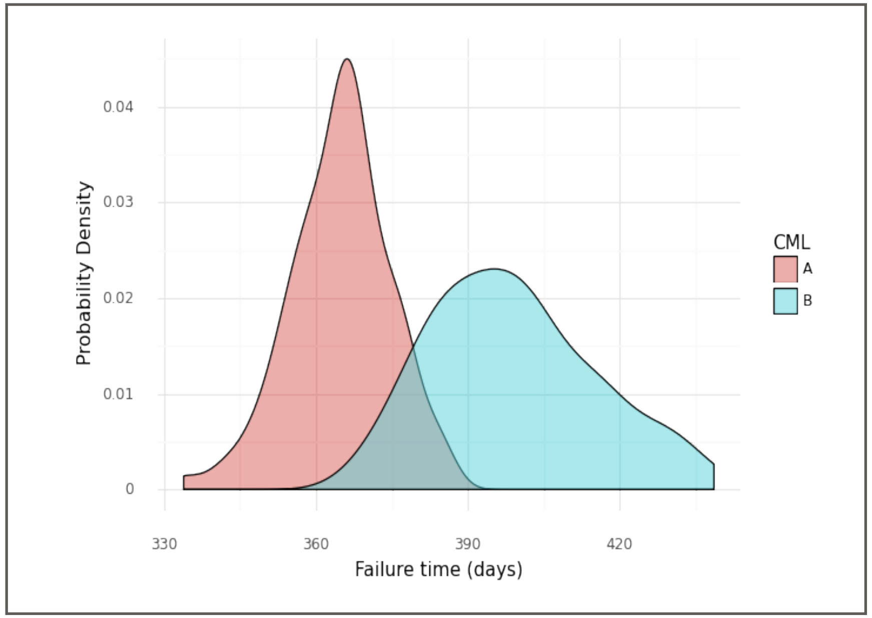




Note about CML Optimization

Depending on the CML optimization initiatives in the industry, one of the key things we're focusing on is how we're *prioritizing CMLs* for inspection rather than completely eliminating them. With that in mind, the CMLs that matter will change at different points in time, meaning, there might be a small fraction of CMLs that are very important today, but fast forwarding several years in the future, you might need to focus on some of those same CMLs plus some other ones you hadn't looked at in a while. That way you're not eliminating CMLs and exposing yourself to risk that you're not managing effectively. **This model allows you to justify not inspecting some of those CMLs for some period of time until it makes sense and adds value.**

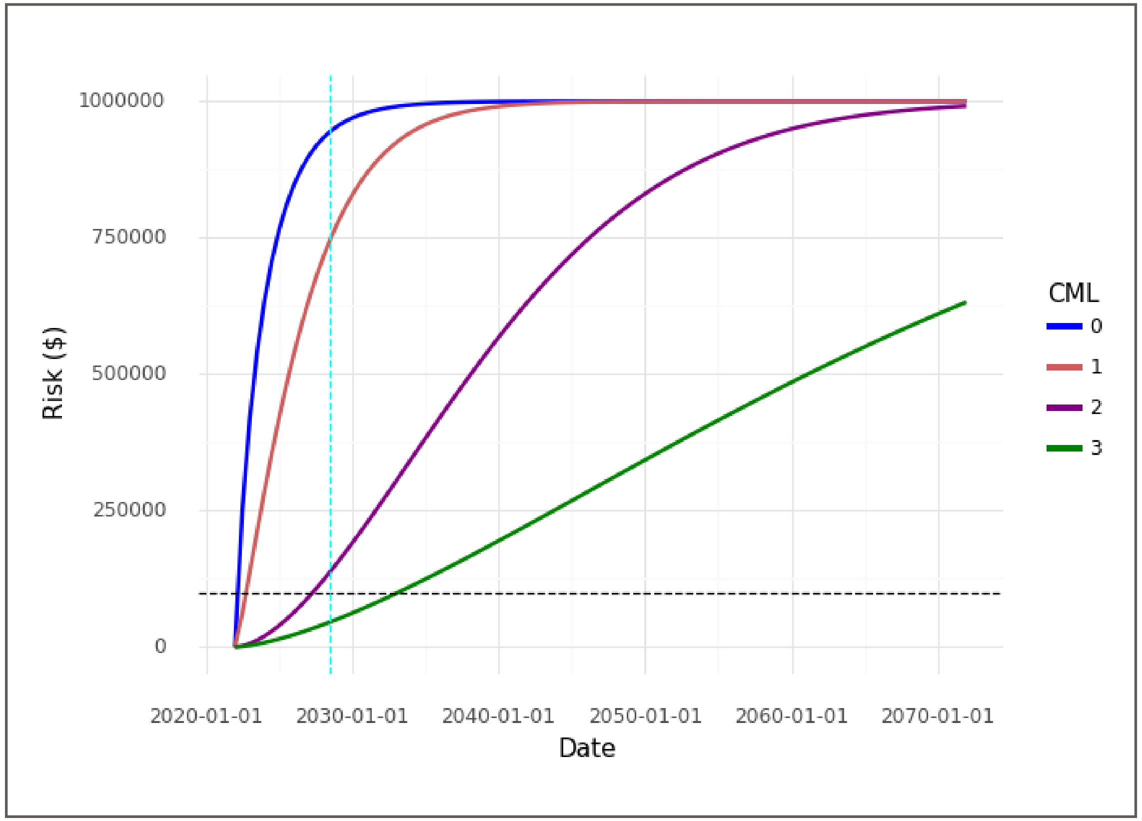




CML Risk Target

One of the ways we can do CML optimization is to define a risk threshold per CML. This is the amount of risk (in dollars) that we're willing to tolerate. Here is a synthetic example (see graphic) looking at four different CMLs. Here, we're saying we would like to make sure a CML's risk does not exceed our particular risk threshold (about $100,000), on or before a target date (January 1, 2028).

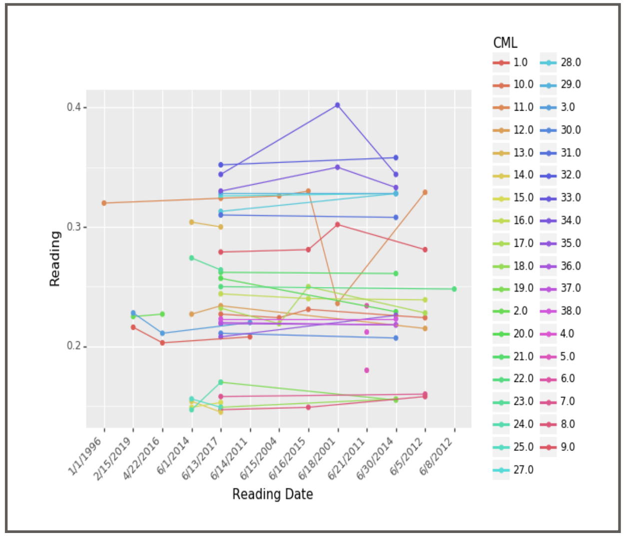
Within the graphic, we see three CMLs (blue, red, and purple) have exceeded the risk threshold for this potential inspection date. This means that these CMLs must be inspected on or before that date. Meanwhile, the green CML is still below the risk threshold, indicating that we do not need to focus on this CML now. However, we don't just delete this CML from the population because it's a CML that we'll pay attention to in the future. Right now, its risk doesn't require immediate action and we can better utilize resources by focusing on the other three CMLs exceeding the risk threshold.



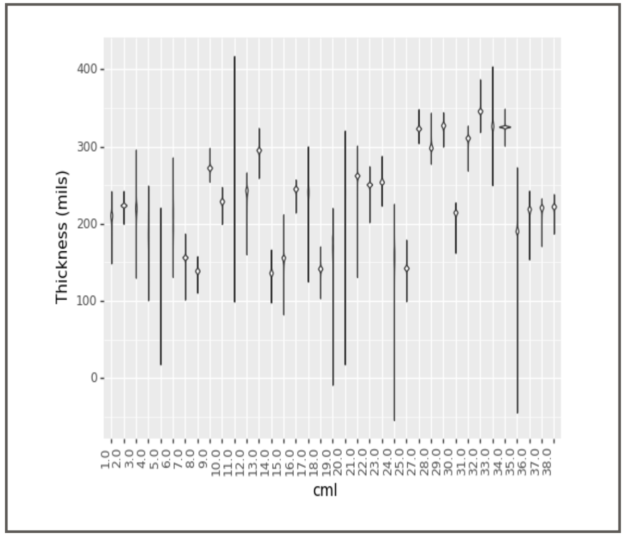
General Degradation Example

In this example, we have 38 CMLs on single piping circuit with Unspecified Internal Corrosion (UIC). We ran the historical inspection data through the LVC model to get a projection of what we think the thickness will look like in a future inspection year—2025 for this example. In the middle graphic we see that a number of CMLs can potentially have a very low thickness but other CMLs are pretty well concentrated with a fairly stable thickness—these are not CMLs that are driving a lot of concern.

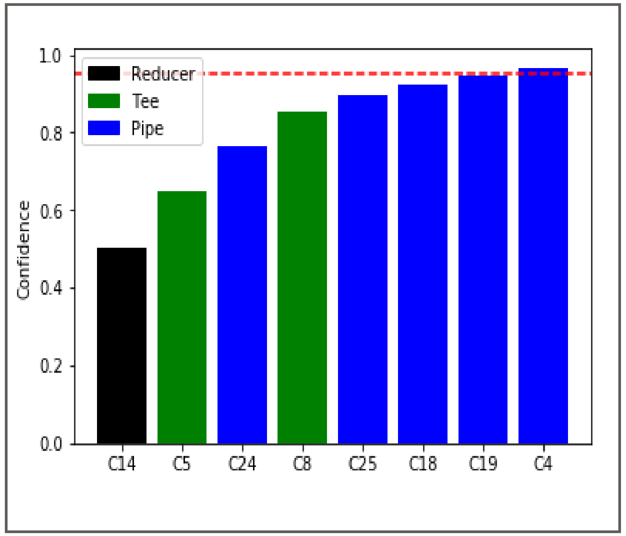
With our CML optimization methodology (see graphic 3), we only require 7 CMLs to capture 95% of the risk that's being generated on this asset. These CMLs, if we're able to inspect and mitigate these, give us a high confidence that the asset will be okay well past 2025. Again, other CMLs may be problematic in the future, but at least for this time period, this set is sufficient to characterize the damage state of the asset and mitigate risk.



Historical Readings



Projected Thickness
Per CML In 2025



CML Selection

Refinery Case Study

Now that we've walked through the analytics side, let's talk about value. We recently completed a CML Optimization project for a customer in which we analyzed six different piping systems across three different units. There were about 382 CMLs across all the systems. The assets have extremely high corrosion rates due to sulfidation and erosion. Full inspection cost was estimated at $738,000 and covered two turnarounds in the future.

With the CML Optimization methodology, we were able to keep risk about the same while better focusing inspection spend where it would add the most value. Before the optimization, money was being wasted on trying to identify every possible area where things might happen.

After the CML Optimization methodology, the number of CMLs were reduced from 382 to 190 and inspection cost was reduced from $738,000 to $358,000.

We'd like to note again, as previously mentioned, this methodology is not about completely eliminating CMLs—it's about better focusing inspection. For this project, we did recommend increased inspection frequency in some specific areas. At the same time, resources are not being wasted—they are being prioritized for key areas where inspection is going to be the most valuable. Overall, with this methodology, **we were able to keep risk at about the same level and eliminate a lot of unnecessary spend.**

	Total Cost	# CMLs	Risk
Current Inspection Approach	$738,000	382	$97,163
Risk-Based Inspection Approach	$358,000	190	$99,860

CML Families

- Subset CMLs that behave similarly within a corrosion loop or across corrosion loops
- Beyond location, some CMLs have similar function
- Opportunity: Can we consider functional groups that behave the same and focus efforts at this level?

The exmaples on the next two pages demonstrate the following:

- Mechanical Integrity identified families of CMLs with similar configurations and damage mechanisms
- Data Science used families as basis for shared corrosion experiences
- Data Science additionally found other families not originally identified in the Mechanical Integrity investigation
- These families are used for CML grouping – we do CML optimization within each family to better mitigate risk

Up to this point, we've talked about pooling all your CMLs together and identifying any that are crossing your risk threshold. Going beyond that, we'd like to introduce a concept called CML Families. These are sets of CMLs that may not be closely located—these may not be adjacent CMLs on a piping circuit, for example—however, they share very similar functional and damage-based characteristics. For example, the first elbows coming out of a set of piping circuits leaving a furnace—they aren't close together spatially but have the same function, expected damage profiles, etc.

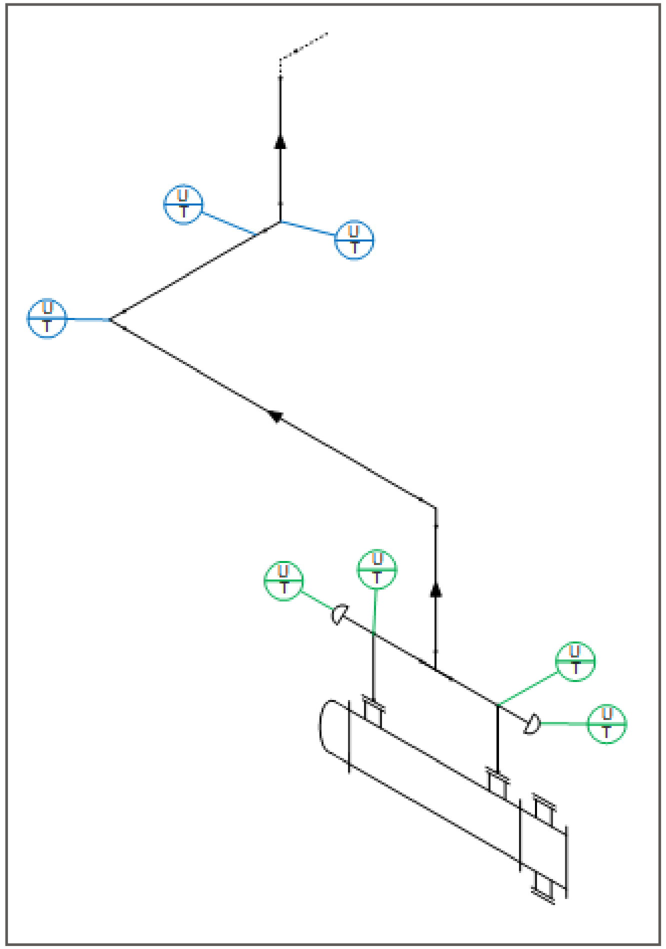
With CML families, we can group CMLs in the same functional family and treat them together for CML Optimization. By doing this, we are further mitigating risk by making sure we include the worst actors from every single CML family in our analysis.

Heat Exchanger Outlet Example

Let's look at a heat exchanger example. Here, a mechanical integrity subject matter expert identified two CML families within a corrosion loop. We have CMLs that are labeled in blue and another set of CMLs labeled in green. The blue CMLs are horizontal in condensate locations. These are places where fluid may sit in your pipe for a long period of time, causing a particular type of damage and degradation. Dead leg corrosion will potentially be observed on the green CMLs.

Once the CML families were identified, the data science team then looked at the actual data from the inspections done at these locations to either confirm or reject what the subject matter expert was finding.

After analysis, data science confirmed potential accelerated corrosion on horizontal condensate locations. This required almost immediate mitigation for the client. However, for the dead leg there wasn't a lot of corrosion present at that point in time. An interesting note is that the data science team would likely not have found this area based on the data alone, so this is a great example of combining the mechanical integrity expertise with data science for a fully rounded view.



Furnace Outlet Example

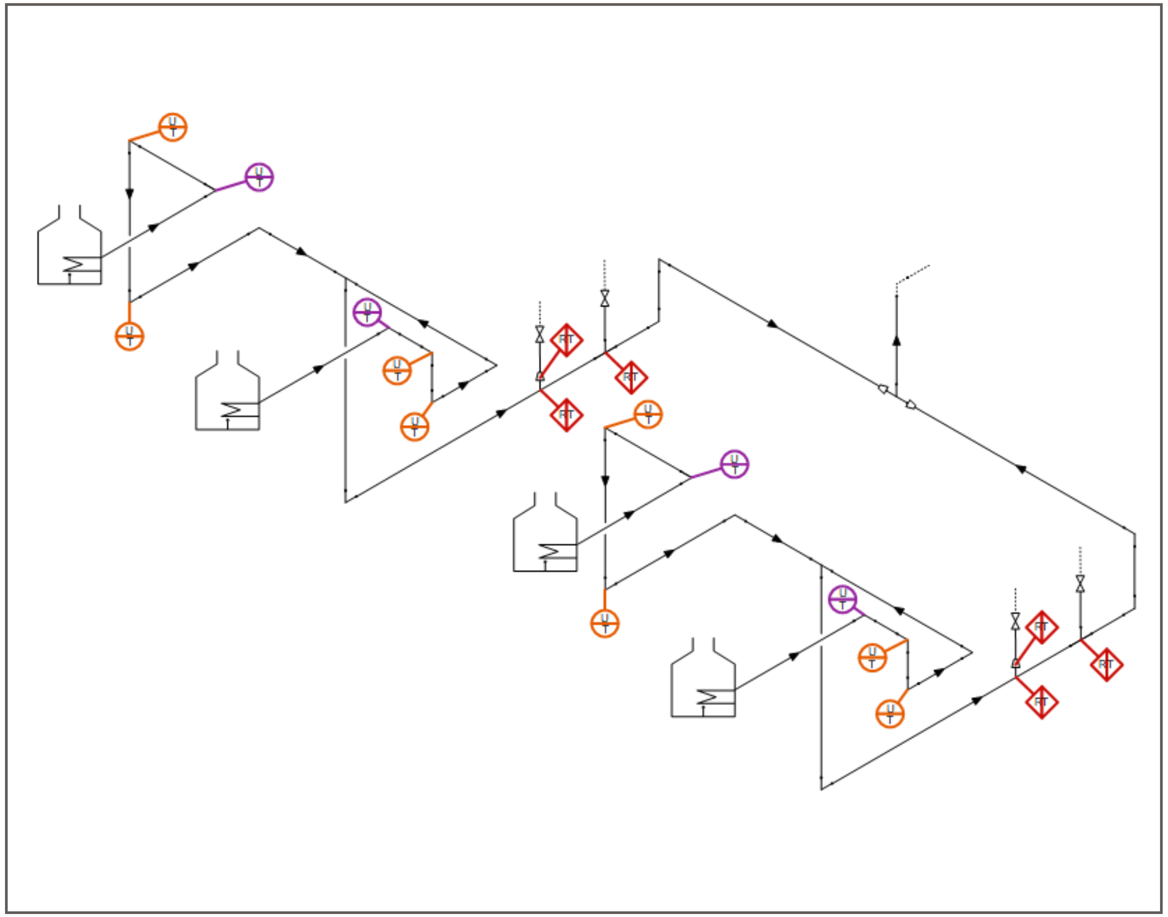
Here's another example looking at a furnace outlet. Here, the mechanical integrity SME identified two CML families across four corrosion loops:

1. The first elbows after furnace outlet (purple)
2. Second and third elbows after furnace outlet (orange)

After running the analysis, the data science team confirmed these to be areas of high degradation. In addition, the data science team found a third area that was not originally identified:

3. Vertical risers (red)

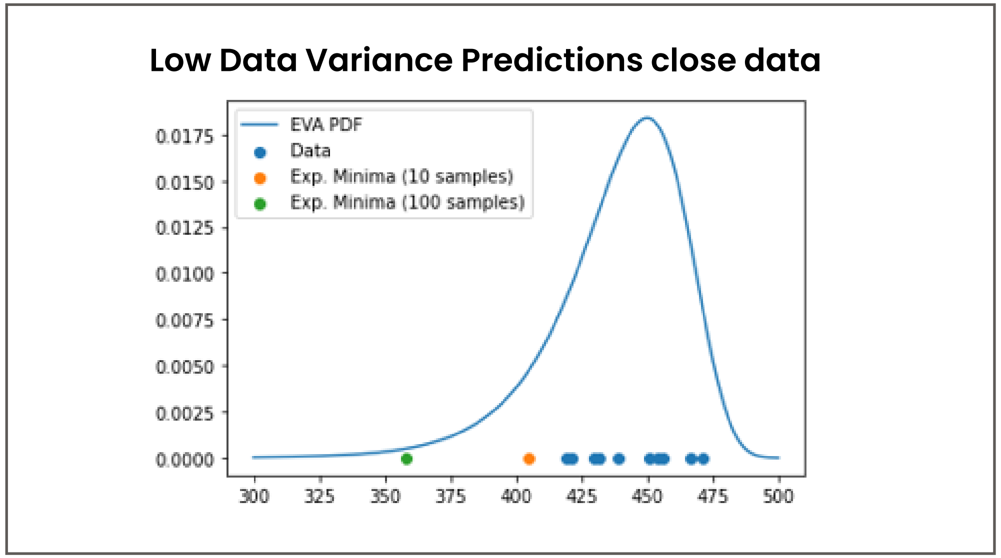
The CMLs labeled in red were vertical risers where the MI SME had not conceived of a problem at these locations. Data science was able to see that these CMLs were experiencing accelerated damage and that they had a very similar damage profile. After this identification by the data science team, the mechanical integrity SME confirmed the finding. This is another example of mechanical integrity and data science working together. The mechanical integrity helps the data science team be more effective at what they're doing, and the data science team can also give analytics back to the subject matter expert, resulting in a rich collaboration.

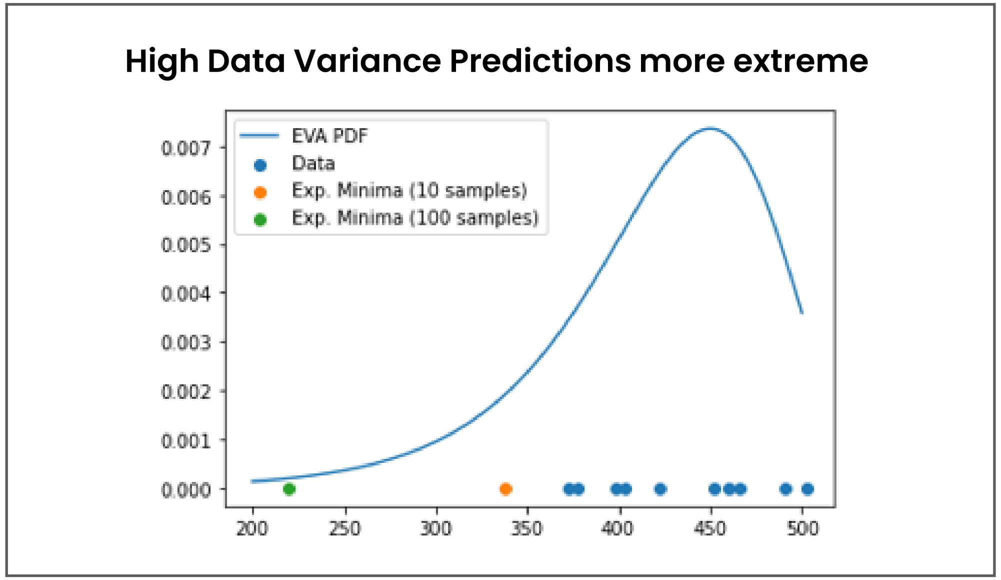


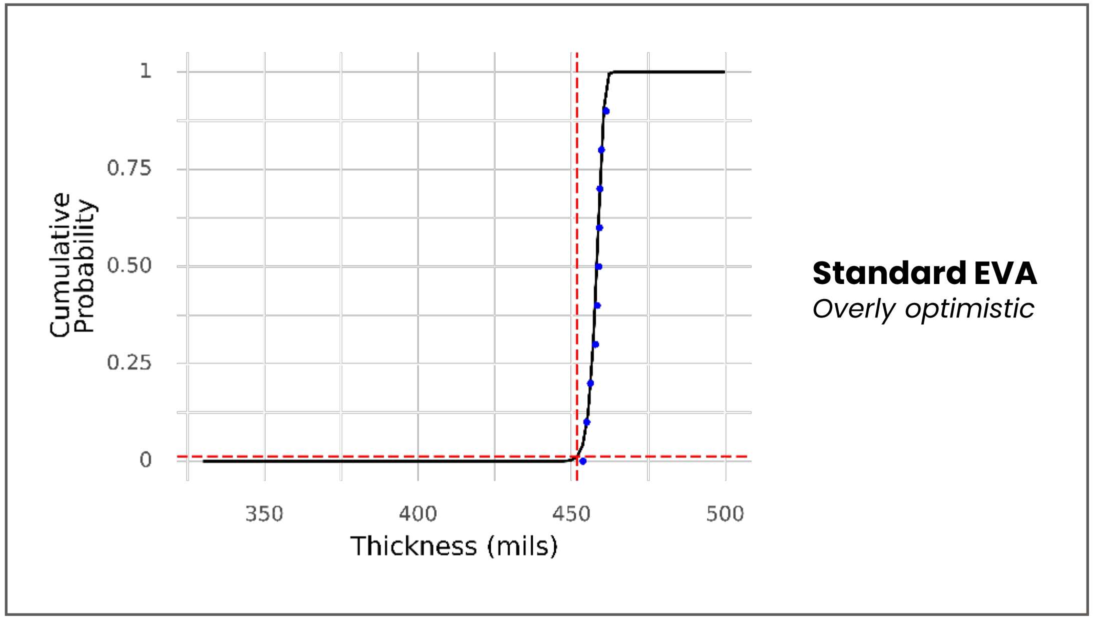
Local Degradation and Extreme Value Analysis (EVA)

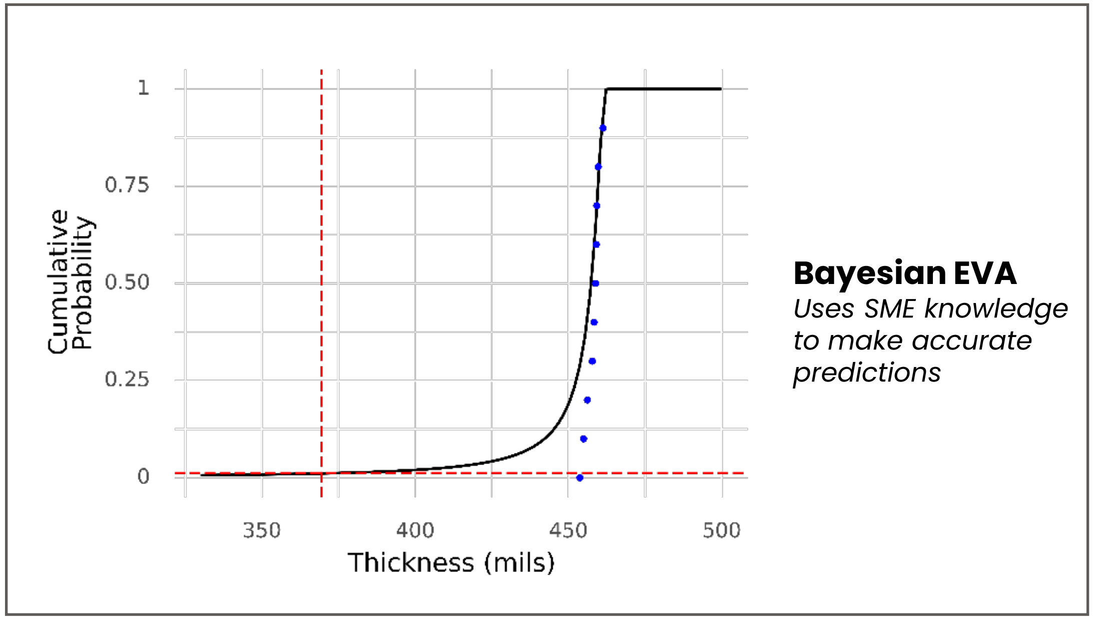
In cases where local degradation is of particular concern, we do what's called an Extreme Value Analysis (EVA). This analysis uses thickness data to predict minimum thickness of the uninspected areas. The two charts show an example. In the first chart, there's less variability in the data. Based on what's being seen, the data is much tighter here compared to the second chart.

As a result of that, the lowest expected thickness in the first chart is higher than the lowest possible expected thickness in the second chart. That's due to how variable the degradation is, relative to how much it's been inspected. In this case, not a lot was inspected, so there's a good chance it's significantly lower than what's been observed. Therefore, an inspection should be performed to either confirm or deny a low thickness. Thus, as data variability increases, required inspection increases.









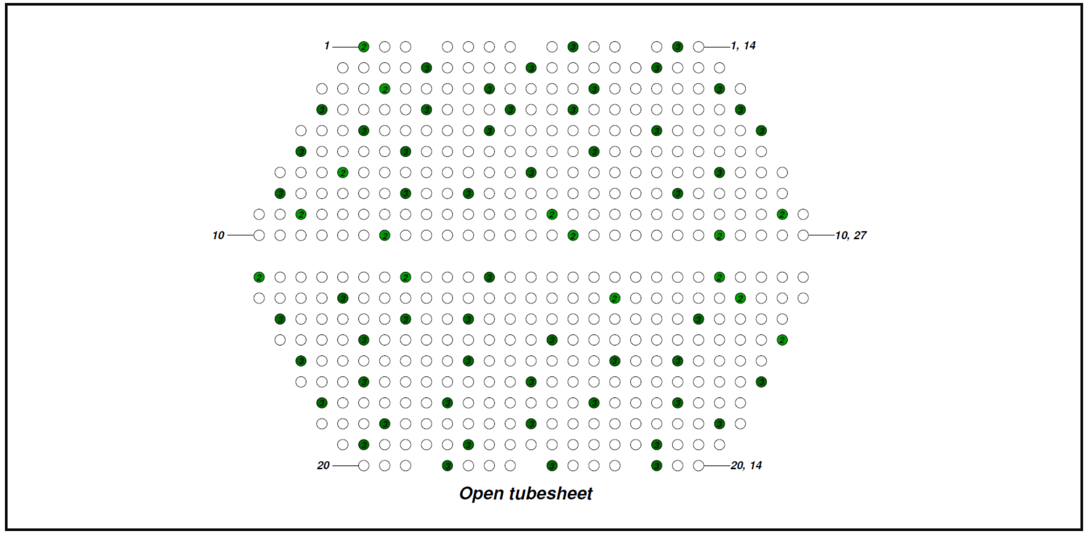
EVA has been brought up in the industry before but it hasn't been widely adopted, partly because a traditional EVA approach can fall short in this industry. Why? The data you have available does not necessarily effectively represent the asset and the damage that exists.

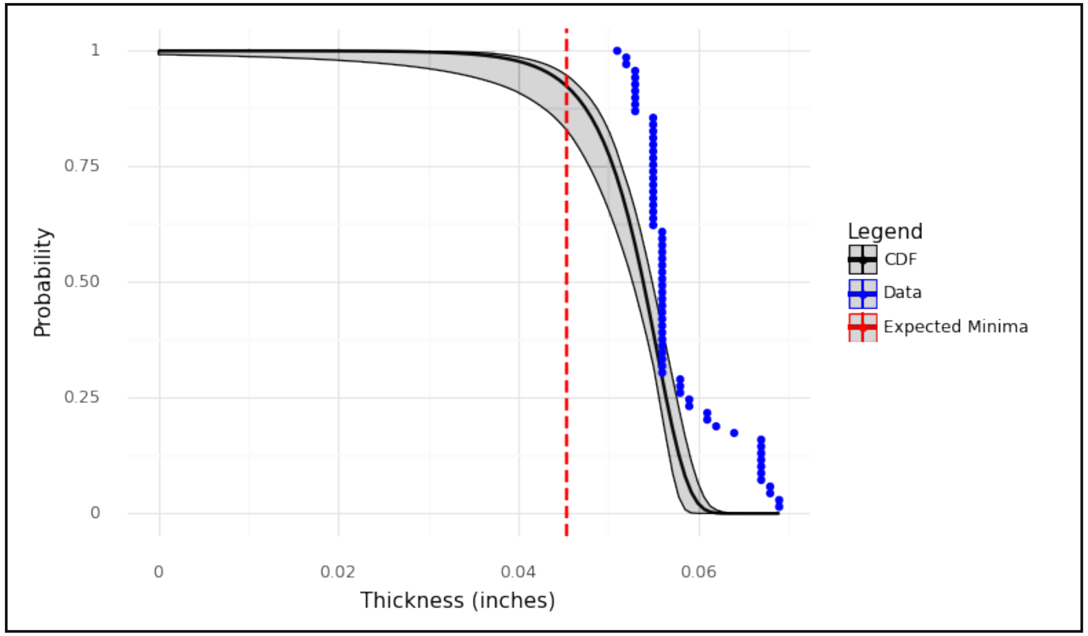
If data supports indication of localized degradation, an EVA is valid. If data does not support indication of localized damage due to poor CML placement or coverage, we can use a Bayesian EVA approach. Similar to LVCs discussed earlier, we blend "what do we expect?" with "what are we seeing in the data?" and we leverage both data science and SME support to improve CML placement. With more data from inspection, SME expectation is either reinforced or denied. So, we're becoming more and more data driven but we're not losing data that is available.

Heat Exchanger Tube Bundle Example

To give a more concrete example of using Bayesian EVA, we have an example looking at a heat exchanger tube bundle. Here we have 450 tubes in the entire bundle, 69 of which have been inspected. The second plot shows the actual measured data in the blue dots. Every one of these represent the smallest thickness registered across the given tube. The data science team's job is to give bounds on how bad the rest of the 381 tubes could be, given the available data and what the subject matter expert says could potentially occur in the local damage profile of this asset.

After running the Bayesian EVA, the data science team created the curve that is on the black line in the second plot. The gray shaded region gives a notion of confidence—we believe that the reality of that asset is going to be somewhere within that gray envelope. And what we come up with is that we are reasonably certain that the absolute worst-case tube on this asset isn't probably much lower than 45 mils of thickness, so we can feel pretty good that inspection has adequately characterized the damage of this asset and that risk is low right now. This is not something the plant needs to worry about—no further inspections required at this time.



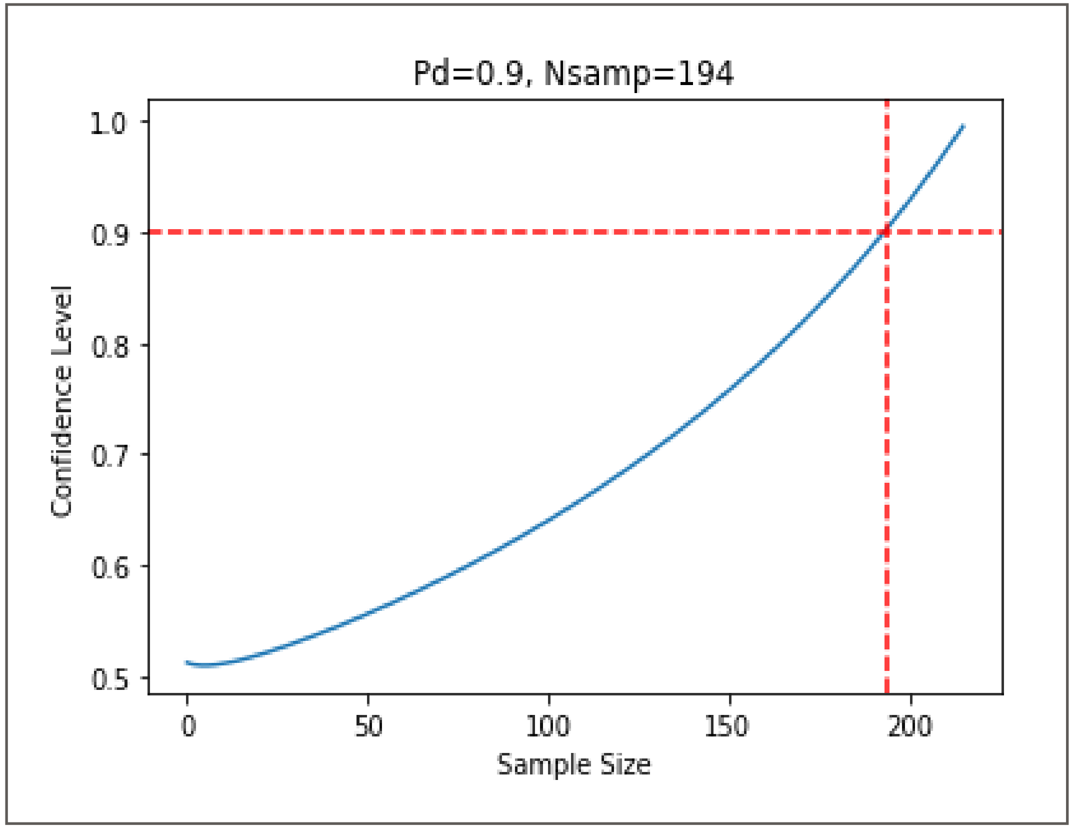


Cracking Methodology

Switching gears, let's talk about cracking. We're going to look at a heat exchanger tube bundle with 216 tubes. Walking into this problem, we're going to assume that this tube bundle has a very low susceptibility to cracking. We don't believe that there's a high probability of a crack being present, but we still have to go through the motions and do the inspection to verify this.

No previous cracking inspections have been done and API gives us guidelines for how we'll evaluate the a priori of a crack being present given the scenario. The technique that we're going to use for inspection has a 90% probability of detection. Meaning that if we inspect a tube that has a crack, there is a 90% chance that our inspection will find that crack and a 10% chance that it will not find the crack.

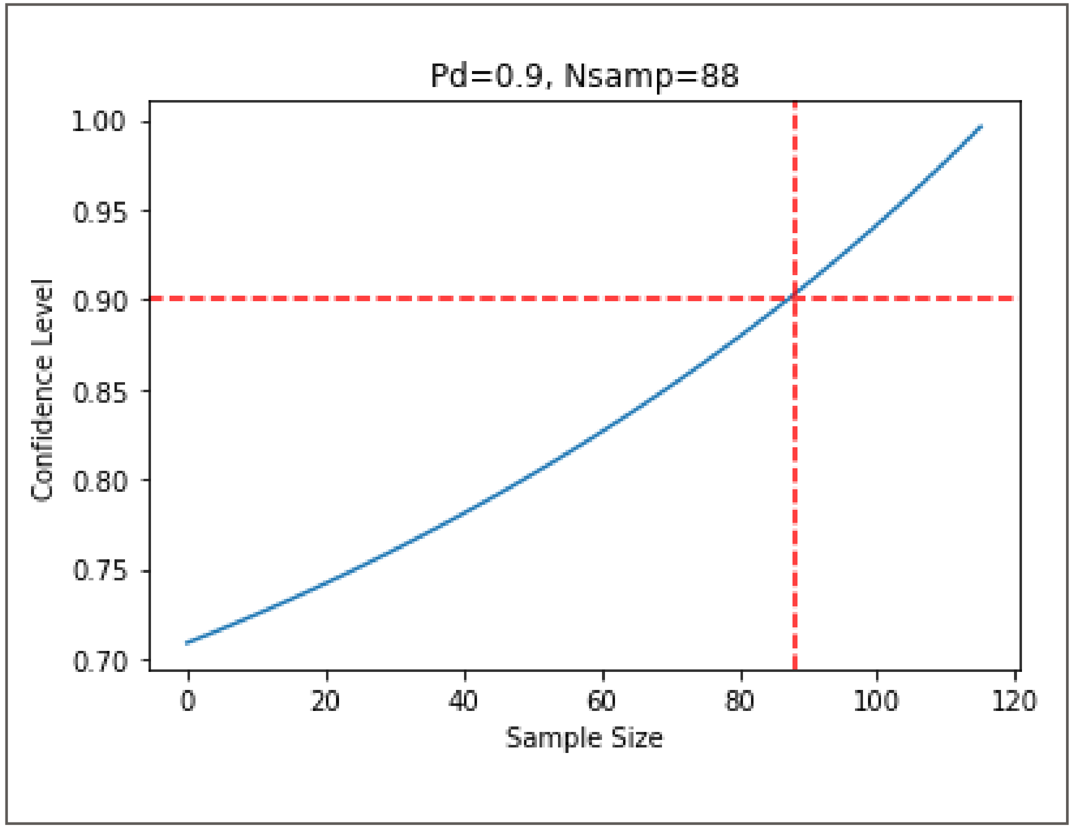
Let's say we want to achieve a 90% confidence that the tubes are completely crack free. In this case, it's a bit of a needle in a haystack, so we need to sample 194 of the 216 tubes to have that 90% level of confidence.



Adjusting Inspection Coverage with New Data – No Cracks

Let's say a future inspection happens and we do find a crack on one of the tubes. Now we'll ask the question, "How many more tubes do I need to inspect to be able have confidence I found every problem, every defect in this population?"

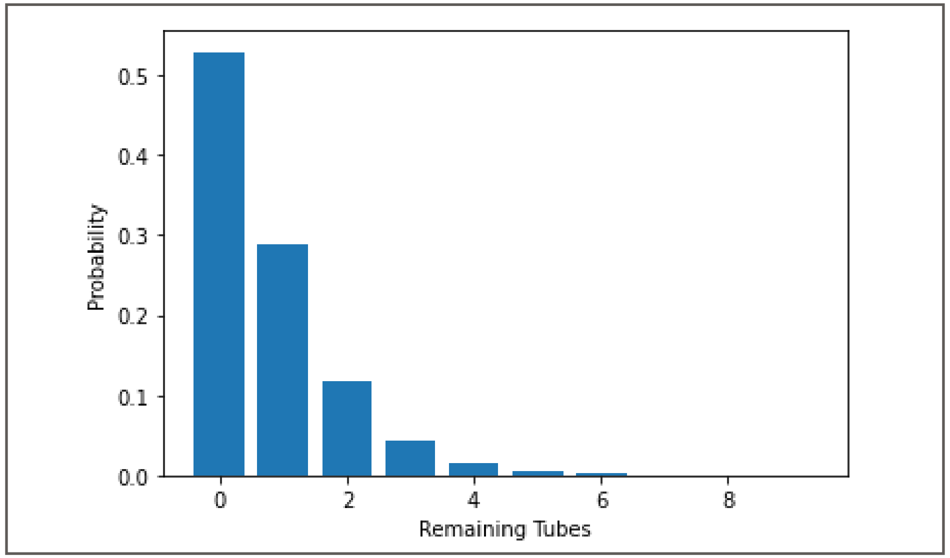
So, let's say we found our first crack and we inspected 101 of the 216 tubes. The first plot gives a probability distribution of how many remaining cracks could be in the population. This plot shows that there's about a 55% chance that there are no other cracks in the population. That's not the 90% level of confidence we want, though—there's still a 45% chance that something is wrong in the population. And in this case, a 45% chance that at least one or more cracks is/are present. If we want to rule out that possibility, the second plot shows us that we'll need to inspect another 88 tubes, such that if we don't find any damage, we can reach that 90% confidence level that we found all the defects in our population. If we find more defects, we will probably have to do more inspections to reach that confidence level.

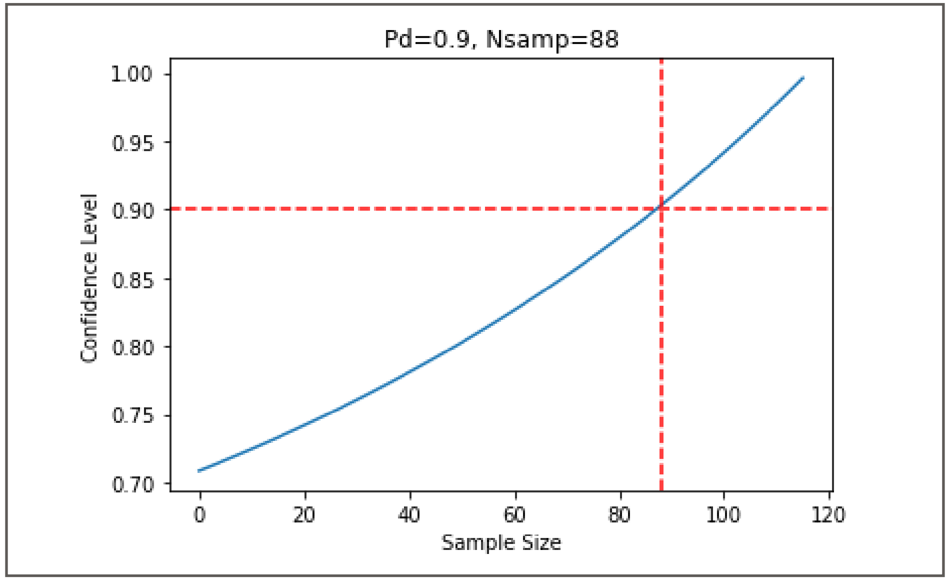


Adjusting Inspection Coverage with New Data – Presence of Cracking

Moving forward, let's say we've done our inspection—194 tubes—and found no cracks. Coming back several years later, we now have a new probability of cracking that's given to us by API. We've done a good inspection previously, so the number should be a bit lower.

To remain at a 90% confidence level, the next inspection requires 101 of the 216 tubes to be sampled. So, because we've done a good inspection in the past, mathematically and statistically, we can now get away with doing less and still have a good level of confidence.





Benefits of Condition Monitoring Optimization

- Eliminate subjective assumptions and rules of thumb
- Specific inspection plans include e.g., # tubes, # of CMLs, area of coverage
  - Prescriptive CML coverage recommendations, meaning high confidence can be achieved with less but highly targeted inspection
- Inspection Recommendations based on expected and actual results
  - If damage is less severe than expected, future inspection coverage and frequency can be decreased
  - If damage is more severe than expected, current and future inspection coverage and frequency can be increased
  - Accept lower level of confidence in asset condition
- Focus limited resources where they add the most value

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info@pinnaclereliability.com

+1 281.598.1330

pinnaclereliability.com

Conclusion and Takeaways

This e-book has discussed how we can combine mechanical integrity subject matter expertise with data science principles to revolutionize the way that we do inspection. We're excited to see where this can go in the future as we explore new damage methodologies, new damage types, and different ways of leveraging the power of data science and subject matter expertise together to change the way we do inspection and make facilities safer for everyone.

Major Takeaways:

- Use quantitative methods to better allocate fixed inspection resources
  - Identify locations that are likely to drive failure and exceed risk thresholds within some time window
- Drive quality by jointly leveraging data science and SME experience
  - CML Families: cluster CMLs based on shared corrosion profiles for better interpretability to drive quality
- Leverage statistical methods to quantify inspection effectiveness and mitigate risk when inspection coverage is limited
  - Bayesian EVA for local thinning
  - Quantitative Inspection Effectiveness for cracking