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Quantifying the Value of Your Inspections

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Introduction

The US refining industry's average availability realized a 15% increase between 1980 and 2000 as facilities implemented proactive maintenance practices and fixed equipment inspection programs. However, the increases in availability since 2000 have been 2 to 3% despite significant advances in technology that have changed the way the industry collects and analyzes data. Risk-based inspection enabled the industry to leverage relative risk models to focus mechanical integrity (MI) programs, and facilities have access to more software than before to monitor trends and improve data analysis. These relative risk-based models have improved our understanding of where the facility risk is concentrated, but more leading-edge quantitative risk models have several advantages:

1. Ability to quantify the inspection method probability of detecting damage, allowing quantification of the value of an inspection when compared to the inspection-related cost.
2. Ability to link a specific condition monitoring location (CML) to an asset and calculate the impact on asset risk.
3. Ability to quantify the impact on unit or facility performance to calculate the impact of a specific asset's failure on facility production.

Even in today's data-rich environment, using relative models makes it difficult for MI leaders to confidently define and justify future inspection plans to key decision-makers. Facilities need to begin leveraging advanced modeling to quantify uncertainty and probability of failure (POF), thereby helping to confidently drive valuable inspections and ignore those that provide little or no value.

In this article, we're going to explore how more advanced modeling addresses the above challenges and drives increased performance for two facilities:

1. **Quantifying Business Value of Targeting Specific Condition Monitoring Locations (CMLs) in a Reformer:** A refinery leveraged quantitative modeling to quantify the value of its CML placements and optimize its budget on value-adding CMLs. This optimization yielded a high ROI, equating to about $800,000 in total value gain while maintaining or improving asset risk and availability.
2. **Quantifying Business Value of Targeted Inspections in a Flare Header:** A refinery experiencing leaks in one of its flare headers leveraged quantitative modeling to identify the top contributors to downtime by accounting for the uncertainty associated with different inspection techniques. This optimization resulted in the refiner recognizing a cost savings of $75,000 per flare header system, extrapolated across six units for a total cost savings of $375,000 and a projected 0.4% increase in availability over the next five years.

Quantifying Business Value of Targeting Specific Condition Monitoring Locations (CMLs) in a Reformer

Primary Value: A refinery leveraged quantitative modeling to quantify the value of its CML placements and optimize its budget for value-adding CMLs. As a result of this optimization, this refinery is on track to recognize a total value gain of nearly $800,000 over the next five years while maintaining or improving asset risk and availability.

Managing risk correctly doesn't necessarily involve reducing the number of completed inspections; it focuses on reducing the number of inspections that do not add value while adding additional inspections where necessary to ensure adequate coverage. Many risk models are heavily dependent on outdated, deterministic algorithms and the conservative estimates of subject matter experts. A data-driven approach is required to modernize existing algorithms and remove the inherent subjectivity of current models.

The refinery recently implemented an RBI program to improve risk management after it continued to experience an increased number of leaks despite having a mature program in place. The refinery's leadership knew they were overspending on their inspections but had no approach that could identify which CMLs had little or no impact on the risk of their facility with their existing RBI program.

A quantitative model was developed for a hydrocarbon reformer unit comprised of a variety of circuits, including vessels, drums, exchangers, air-fin coolers, regular process piping circuits, dead-leg circuits, injection points, and mix points. The unit had recently completed an RBI validation study, and while it exhibited relatively low corrosion, the facility had not removed or delayed any of the existing CMLs before the project. In addition to determining cost-saving opportunities, the facility wanted to quantify opportunities to further mitigate risk by adding inspections that would help reduce the unit's POF.

The pilot scope of work included creating a system model for the unit and calculating the POF and uncertainty for each CML. The facility's IDMS data was used to create a baseline modeling scenario that predicted future inspection costs and unit availability based on the ten-year planned inspections. This baseline scenario was used to evaluate the impact of inspection program changes on both inspection spending and unit changes in future availability and associated production. All future planned inspections were loaded into the model to calculate the uncertainty and POF for each CML and circuit and, ultimately, calculate the projected availability of the unit over ten years. The team modeled three scenarios to determine the impact of specific inspections on the unit's costs, risk, and projected availability:

- **Scenario 1a:** Scenario 1a modeled the projected availability and costs of the facility's current plan, which included inspecting all existing CMLs on their next scheduled inspection due dates. This is the expected availability based on the facility's current CMLs and planned inspections.
- **Scenario 1b:** Scenario 1b uses the planned inspections modeled in Scenario 1a but adds CMLs without inspection history for 48 circuits. This is the true projected availability of the facility's current inspection plan and, as expected, has a lower availability than in Scenario 1a.
- **Scenario 2:** Scenario 2 models the facility's existing plan for Scenario 1a after optimization removes the CMLs that do not have a statistical bearing on the unit's future projected availability. The projected availability is the same as Scenario 1b but reflects lower inspection costs.
- **Scenario 3:** Scenario 3 models the impact of the proposed optimized inspection plan defined in Scenario 2 but adds inspection for three localized corrosion circuits with insufficiently planned inspections and 48 missing circuit CMLs. Compared to Scenario 2, this scenario shows an increase in cost and availability through the uncertainty reduction achieved by adding inspections.

Table 1. Impact of Scenarios.

Scenario	Total CMLs	Total Cost	Projected Availability
1a	13,500	$500,000	95.8%
1b	13,500	$500,000	94.7%
2	2,300	$65,000	94.7%
3	2,350	$80,500	94.8%

More than 13,000 of the unit's CMLs were planned to be taken over the next five years. To quantify the difference between the facility's current inspection plan and the recommended plan generated by the quantitative model, the costs from Scenario 1a and the availability from Scenario 1b are compared to those from Scenario 3. A list of optimized tasks was then exported. This list included the techniques and dates for the facility's planned CMLs, which CMLs should be removed or pushed out, and additional inspections that should be considered during the next revalidation. In some cases, these additional inspections reflect higher-cost methods such as automated ultrasonic scanning.

The pilot revealed two critical insights. First, the it supported the hypothesis that the facility was overspending on the inspections within the unit. Additionally, the quantitative nature of this analysis provides the basis for identifying which CMLs can be confidently removed since they do not produce a statistically significant change in the amount of uncertainty present in the unit's performance.

Second, even in units with numerous inspections, there may be opportunities to further impact risk and availability by identifying which assets continue to contribute the most to risk and availability. Adding asset inspections in this use case resulted in a projected availability improvement of 0.1% over five years. The projected availability increase correlates directly with an additional 6% risk reduction achieved through added inspections in small areas that showed higher degrees of uncertainty due to a lack of data.

The value captured from this project can be measured in two ways:

1. **The total cost reduction captured with the removal of non-value-adding inspections between Scenarios 1 and 2.** By identifying and removing more than 11,000 CMLs that add cost without adding value, the facility is projected to save more than $400,000 over the next five years.
2. **The availability improvement gained (0.1%).** The projected improved availability expected for Scenario 3 over the next five years is estimated at another $400,000 in increased production.

The total value gained over the next five years from both cost reduction and increased availability was about $800,000.

Quantifying Business Value of Targeted Inspections in a Flare Header

Primary Value: A refinery experiencing leaks in one of its flare headers leveraged quantitative modeling to identify the top contributors to downtime by accounting for the uncertainty associated with different inspection techniques. This optimization resulted in the refiner recognizing a cost savings of $75,000 per flare header system, extrapolated across six units for a total cost savings of $375,000 and a projected 0.4% increase in availability over the next five years.

It's common for facilities to compensate for the uncertainty in the life of an asset by adding inspections to similar services after a failure occurs. In many cases, these additional inspections often add little to no value, resulting in wasted spending and an increase in the strain on resources. To determine which inspections are valuable to perform, facilities need to quantify the uncertainty of the life of their assets.

This refiner had a significant issue with leaks within its flare header systems. To prevent these leaks from occurring, the refiner planned to inspect all circuits within each flare header system. However, many of these inspections did not provide insight into the specific assets that were causing the flaring and resulted in unnecessary expenses.

To address this challenge, the refiner needed a data-driven approach that would help them determine the value of specific inspections and decided to build a quantitative model for one of its flare systems using historical data. This model outlined the assets that experienced external and internal corrosion failures and their impact on the overall flare system. While the refiner had a substantial amount of historical data and existing inspection work recommendations (IWRs) in place for the unit, they were unaware of the specific circuits that were the primary drivers of the system's downtime. The system model leveraged the facility's

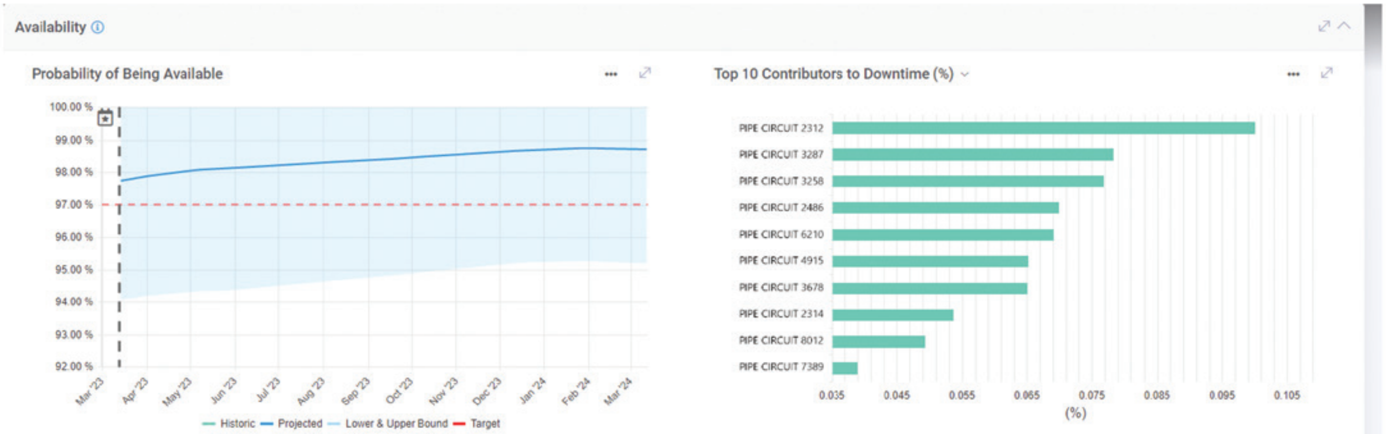

Figure 1. Projected Availability of a Flare System with the Top 10 Contributors to Downtime

existing data to provide a holistic view of the entire flare system and how each piece of equipment impacted others within the system to identify the top contributors to the system's downtime at the circuit level. The model also projected the availability of the system based on the refinery's current plan, as shown in Figure 1. A list of inspection and replacement tasks for the top contributors to downtime was also generated to mitigate the impact of these assets on downtime.

In addition to identifying the top contributors to the system's downtime, the model highlighted areas that were susceptible to failure and were missing from the current inspection plan. As a result, the facility can pinpoint areas where inspections are critical, ensuring that any inspections added to their plan provide value.

The team also plotted the historical and predicted failure dates of individual CMLs within the flare header system further to analyze the impact of inspections on the flare system using corrosion profiles and uncertainty. This analysis accounted for the uncertainty associated with different inspection techniques, such as spot UT, manual scanning, and automatic scanning, a calculation that has not been attainable through previous methodologies. At the conclusion of the analysis, the team determined that the refiner only needed to inspect 25 of the 85 circuits within one flare header system that they currently planned to inspect.

The optimization opportunities that were generated from the quantitative model resulted in the refiner recognizing a cost savings of $75,000 per flare header system, extrapolated across six units for a total cost savings of $375,000. Additionally, the refiner is expected to recognize a 0.40% increase in availability over the next five years with the plan generated during the analysis. The next step for this refiner is to build the system model for the remaining flare systems to identify the top contributors to downtime in those systems and better prioritize the techniques and actions needed to mitigate future flaring.

Conclusion

With the data available today, a data-driven approach to reliability is critical to identifying which inspections provide the most value. By leveraging a methodology that helps quantify uncertainty on a task level and connect that to overall unit performance, facilities can quantify the impact of specific tasks on an asset's POF and determine where inspections are the most effective in reducing uncertainty.

However, these types of living programs must be continuously maintained and improved upon to ensure inspections are added, delayed, or eliminated as needed. Quantitative modeling provides the basis for a living program that dynamically updates as additional data becomes available to provide guidance on where inspection is most valuable in managing risk, availability, and costs. ■

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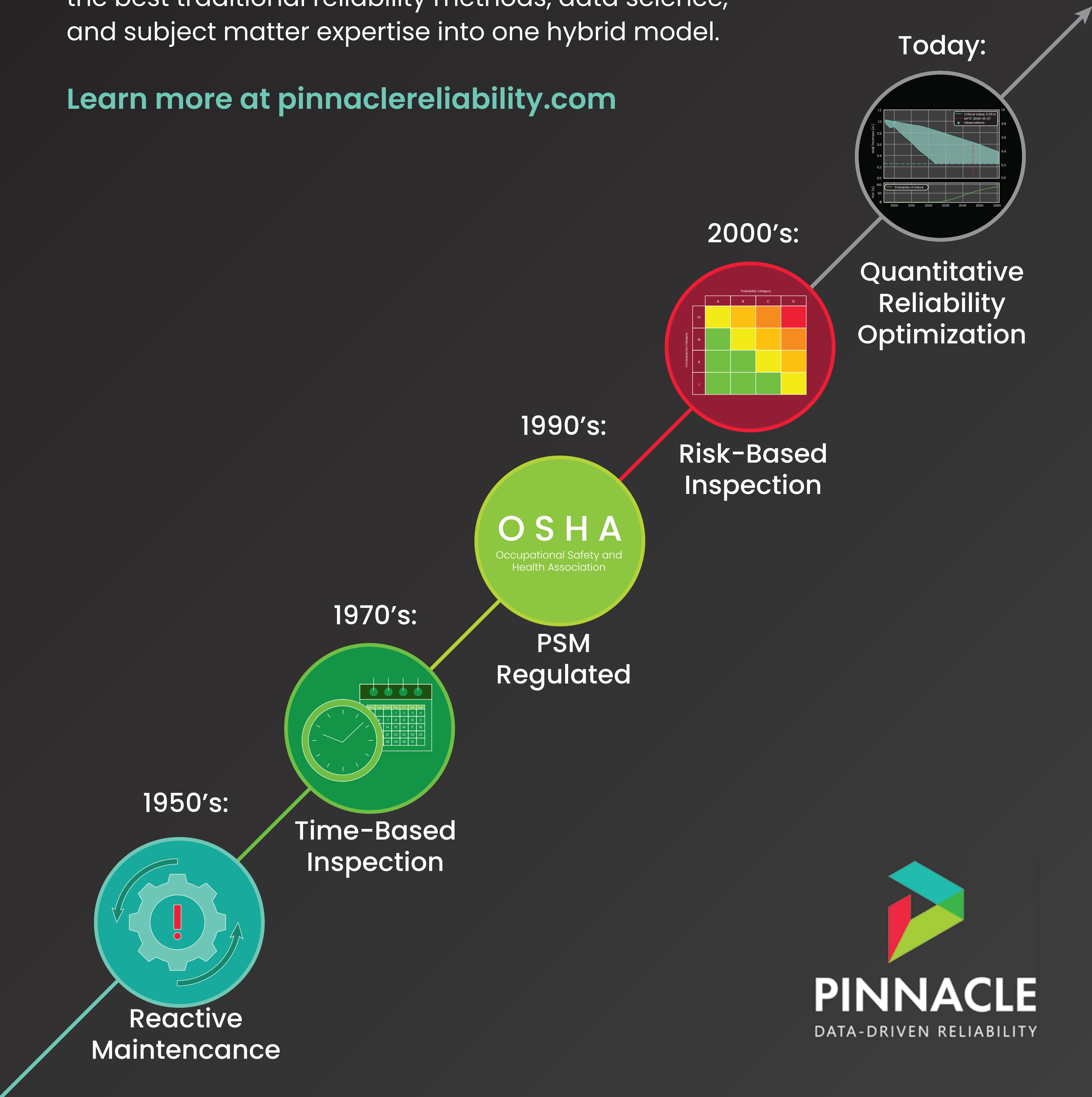

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Lynne Kaley, Director of Reliability Strategy at Pinnacle, has over 30 years of refining, petrochemical, and midstream gas processing experience. Lynne was an owner/user plant metallurgist/corrosion and corporate engineer for over 10 years and has 20+ years consulting with plant management, engineering, and inspection departments, including Risk-Based technology (RBI) development leader, the development of implementation work process for plant application. Lynne is a member of API committees for the development of API 580 and API 581 recommended practices, project manager of API RBI Project from 1996-2009, and master editor for API 581 and 580.

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