AI-Assisted Analysis of Ultrasonic Inspections

Technical Brief — *Nondestructive Evaluation*

This technical brief provides an overview of EPRI's recent efforts to develop artificial intelligence (AI)-assisted analysis of ultrasonic inspections. It describes what AI-assisted analysis is, its envisioned value and uses, and its implementation methodology. It reviews the state of the technology for two target applications, including the results from a recent field trial supported by the industry, and considers its prospects for qualification as a credited examination. The results suggest that AI-assisted analysis has the potential to increase inspection reliability while decreasing analysis time and provide a positive outlook on its qualification.

Overview

Background

Ultrasonic testing (UT) is the main volumetric inspection method in the nuclear power industry and an essential part of every plant's nondestructive evaluation (NDE) program. UT is employed to assess the condition of several safety-related components, such as nozzle and piping welds.

Some of the UT inspections performed in the field yield large volumes of data that must be carefully reviewed by multiple qualified inspectors during an outage. Even though the vast majority of the data are benign, with no indications of interest, a detailed review of all data is still needed. This requires inspectors to maintain high levels of focus for extended periods in an environment with multiple sources of distraction and pressure. Under these conditions, human factors such as fatigue and momentary lack of focus can challenge the reliability of these inspections.

Additionally, the data analysis and review for these inspections require significant qualified resources and time. Multiple qualified inspectors (from the inspection vendor and utility) must be available over several days. This adds stress to the industry workforce and outage schedules.

AI-Assisted Inspections

Artificial intelligence (AI) can alleviate these inspection challenges. AI-assisted inspections can lead to increased inspection reliability in shorter analysis times by enabling the qualified inspectors to focus their time and energy on the portions of data that most require it. This is illustrated in Figure 1.

- In the traditional inspection, the qualified inspector is presented with all the data. This typically represents a large volume of records, most of which are benign. Having no alternative, they must distribute their time, energy, and attention equally across all data, even though only a small fraction of the data (the red records in Figure 1) is expected to contain suspicious indications that require most of their concentrated attention and review. In this approach, much of the inspector's energy and the analysis time is inevitably spent on benign portions of the data (the white records in Figure 1).
- Instead, AI technology prescreens the data volume and flags the suspicious portions of the data volume. Thus, it enables qualified inspectors to adequately focus their energy on those regions. This is expected to effectively reduce inspector fatigue, minimize distraction-induced errors, and decrease overall analysis time.

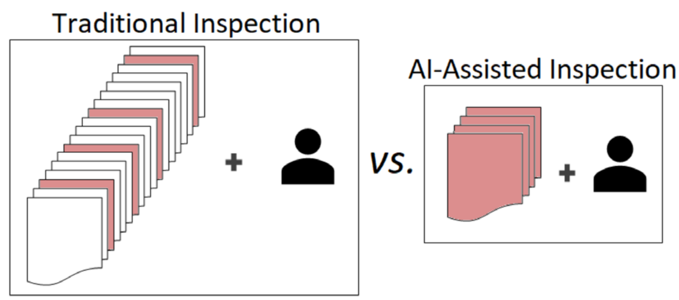

Figure 1. In the traditional inspection, the inspector is forced to distribute their energy over all the data records, even though only a small fraction (indicated by the red shading) includes conditions that need review. AI technology can prescreen the data and present only the records that need the inspector's attention.

Note that in the AI-assisted approach, the AI technology simply identifies regions for the inspector to review, and does not make final calls. Final disposition of the flagged indications remains the responsibility of the qualified inspector. It is expected that most flagged indications, although a small fraction of the entire data volume, still represent normal operating aspects, such as weld interference or other fabrication conditions, and not necessarily service-induced degradation (see field trial example). An inspector's expertise is required to make such determination.

There are two main methods by which AI can flag the data for the inspector. At the first level, AI can flag a relatively small region without precisely indicating where the potential indication(s) is (are); this is illustrated in Figure 2. At a more detailed implementation level, it can directly flag the indication itself, specifying bounding boxes to indicate its precise location in the data for the inspection to review; this is illustrated in Figure 3.

Although the more detailed implementation is preferred, it comes at the cost of requiring more training data annotated at a greater detail level and more complex models. The simpler, region-flagging approach might suffice for certain applications, whereas others will require the more detailed indication method to properly differentiate between the flaw and other non-relevant responses.

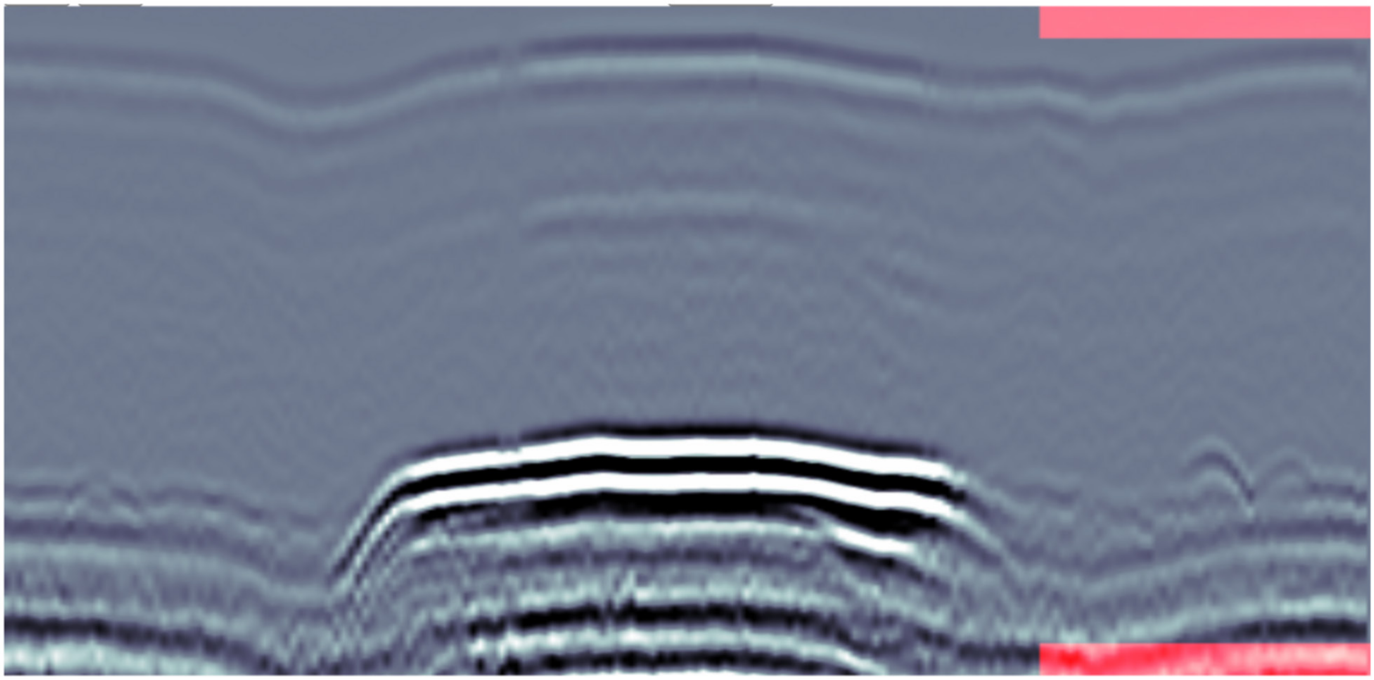

Figure 2. At the first level, AI flags a small region for review (indicated by red highlights). The specific triggering indication is not localized in the flagged region.

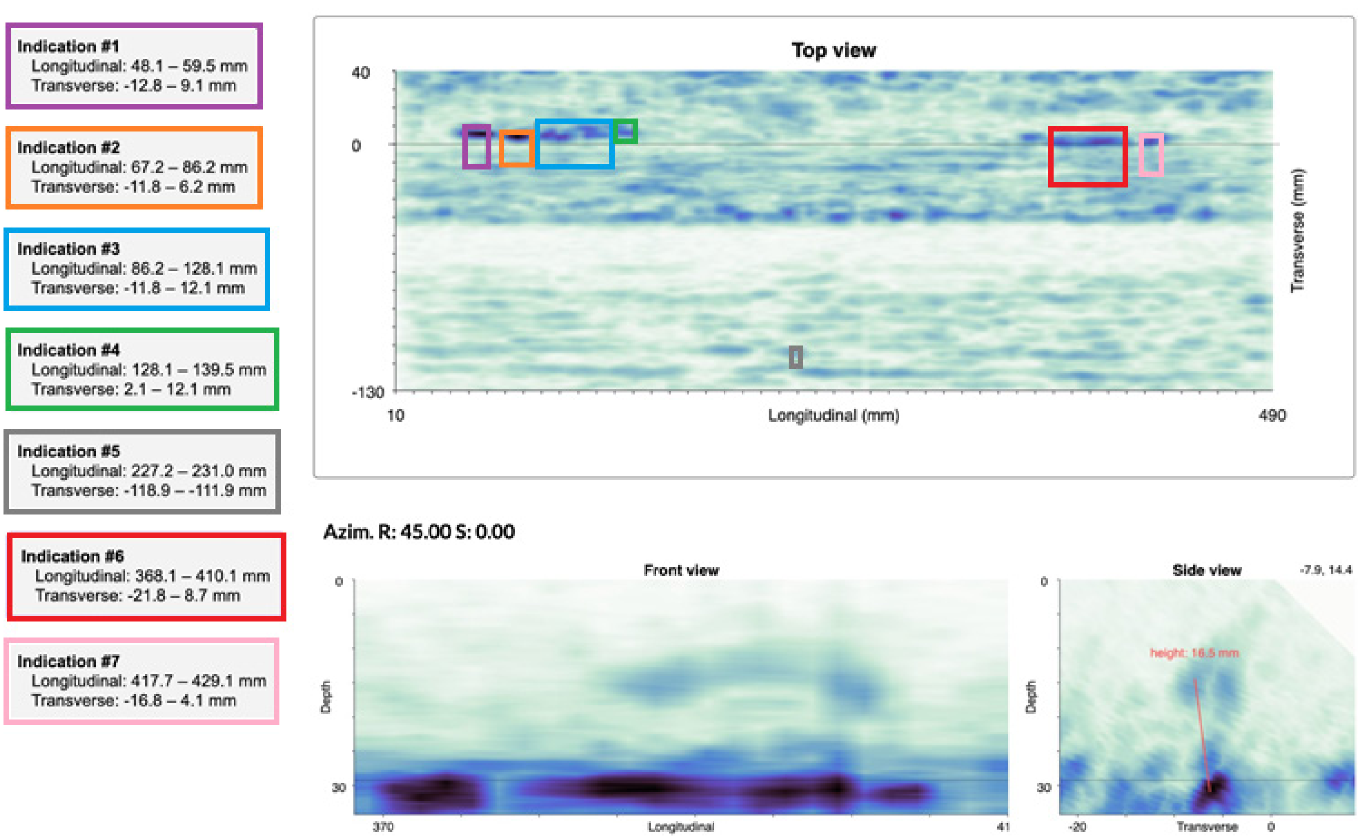

Figure 3. At the mode detailed level, the AI directly localizes individual indications in the data, as illustrated by the color bounding boxes. The data can then be automatically gated to each indication for review.

Added Value: Envisioned Uses

The main envisioned use of the technology is as part of a credited, qualified inspection. Although that requires qualification (see later section on qualification prospects), the technology can be leveraged to bring value to the industry even before that is accomplished.

Additional, more immediate uses that do not require qualification include:

- ***To aid in utility oversight.*** Review of the data and results provided by their inspection vendors is an important oversight activity for the utility. However, a comprehensive review in the traditional approach would require considerable resource allocation from the utility staff during the outage, which makes this valuable review difficult to perform. By automatically identifying a subset of the data for review, the AI-assisted approach makes it possible for the utility to perform a meaningful review of the results, enabling them to conduct a more efficient oversight of the activity.
- ***To assess needed resources.*** Utilities can quickly obtain an estimate of the fraction of the data that is flagged for review by applying the technology to the data from the last outage. This can be accomplished through automated reports, without requiring data review. Having an estimate of the volume of data needing review allows utilities to plan and allocate resources for the next outage accordingly.
- ***To prioritize inspection order.*** Utilities can leverage the technology to quickly review the last outage data to identify which components are more likely to contain relevant indications and prioritize the inspection order accordingly. Because data analysis is much faster than in the traditional approach, this can be accomplished even after the plant is offline but before the specific inspections begin.
- ***To familiarize examiners with component conditions.*** The technology enables inspectors to perform a meaningful review of previous inspection data in minimal time, even in between the time the outage has begun and the time the specific inspection starts. This would allow the inspectors to quickly familiarize themselves with the expected condition of the component immediately prior to the examination, making it easier to identify changes that might indicate evolving conditions.

Another benefit of the technology is that it is well suited to automation of the otherwise time-consuming, error-prone clerical tasks related to reporting. Also, AI technology can be leveraged to facilitate data comparison across different outage inspections.

Simple and Secure Implementation

The implementation methodology is illustrated in Figure 4. No changes are required during data collection—data are acquired according to the qualified procedure as usual. After collection, the UT data file is copied to the machine learning (ML) box which acts as an external drive. The ML box automatically detects and processes the UT data file, generating the output for review. It is expected that the entire process will take less than a minute.

Data security and simplicity are key aspects of this approach, as follows:

- ***Data security.*** The data do not leave the site. No cloud or other remote resources are used. The UT data and output can be erased from the ML box after the results are copied to the desired location on site.
- ***Simplicity.*** No specific training or knowledge is required to use and run the models. The ML box automatically detects the presence of compatible UT data files and generates the output. Also, no custom or special software is required for data analysis: the results are presented as HTML files that can be reviewed in any common browser. Lastly, the browser interface is simple and intuitive, requiring no training.

Reactor Vessel Upper Head Penetrations

The first application for which AI-assisted inspection is developed is reactor vessel upper head (RVUH) penetrations. This examination commonly uses time-of-flight diffraction UT techniques to inspect all penetrations on the vessel head. Given the number of penetrations, this yields large volumes of data for analysis. Furthermore, industry operating experience (OE) has suggested that data analysis is challenging.

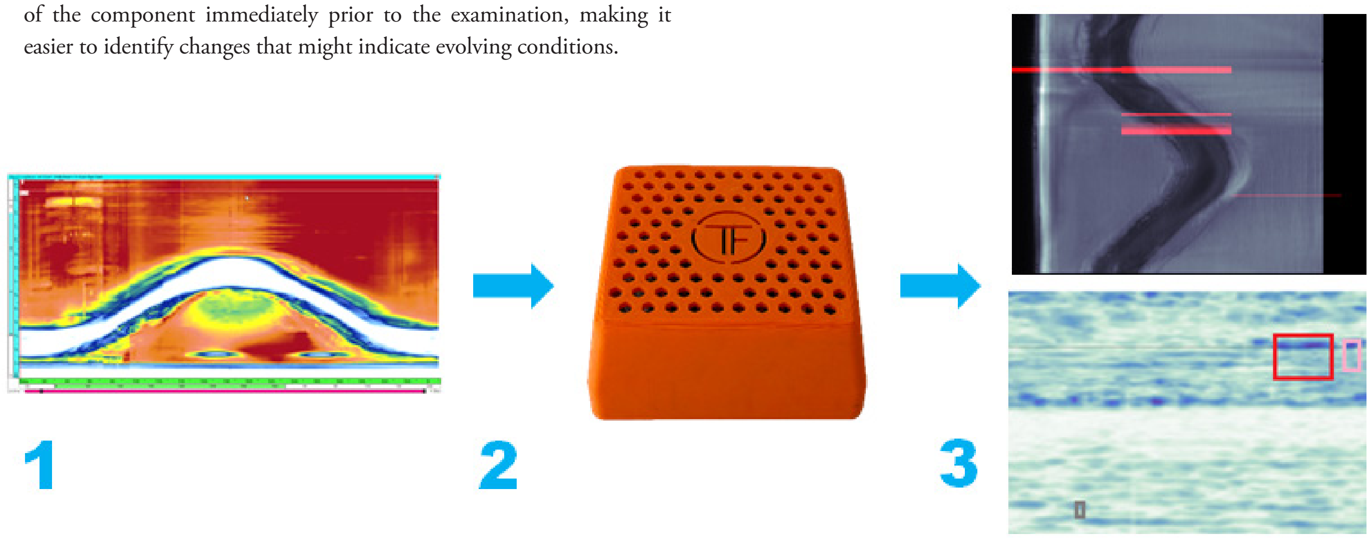

Figure 4. Implementation: 1) UT data are collected as usual; 2) the data are copied into the ML box, which automatically detects and processes the UT data; and 3) generates the output for review.

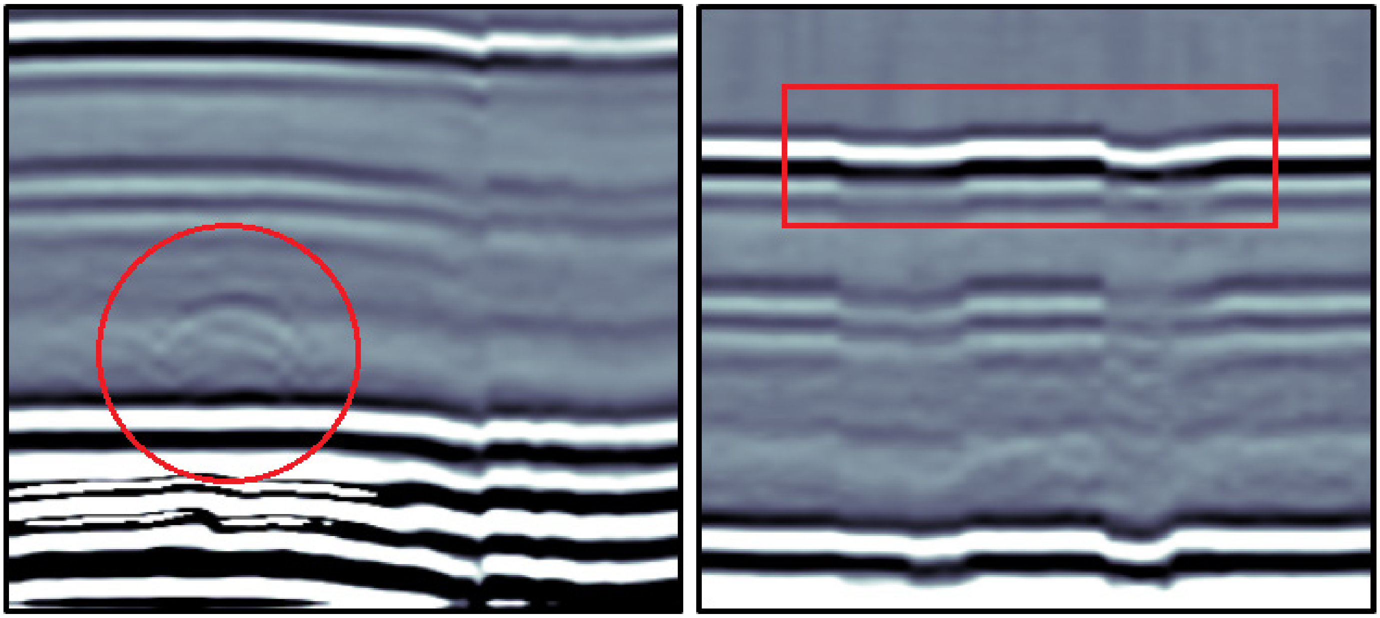

Figure 5. The RVUH model was trained to identify the arc-like responses caused by ID and OD flaw tips (left) and the disruption in the lateral wave caused by ID flaws (right).

Models were developed for this application based on field data from retired vessels, pre-service inspection (PSI) data, and open mockup data. The approach leveraged virtual flaw technology to augment the available datasets to generate the amount of data needed for training ML models. The model was trained to identify both the arc-like tip response signals from inner- and outer-diameter (ID and OD) flaws as well as disruptions in the lateral wave (LW) usually caused by ID flaws (see Figure 5). Note that the available data for training contained only axial flaws; support for circumferential flaws was added through virtual flaw technology.

The performance of the model was initially assessed on the following two case studies:

- ***Industry OE.*** In this case, the model was presented with data from inspections at a U.S. plant where ID axial flaw indications were unidentified or mischaracterized for multiple sequential examinations. The AI tool flagged 13% of the data volume review, which included all the flawed regions in every opportunity. Most datasets in this case use an inspection setup that is underrepresented in the training data. In the tests, this is seen to lead to a relatively higher flag rate (see Table 2 for a comparison with the other study cases) but not to affect detection capabilities.
- ***Pre-service inspection.*** The model was presented with PSI data for 65 penetrations on a new vessel head that included tapered configurations. The AI tool flagged less than 1% of the unflawed data volume for review.

Field Trial

The most significant performance assessment was conducted during a field trial at a volunteer U.S. host utility. A team of EPRI analysts and the AI contractor performed an AI-assisted data analysis during a regularly scheduled outage inspection. The field trial provided an opportunity to evaluate the performance of the AI in a field setting, the implementation methodology, and the potential time savings offered.

This analysis was performed in parallel to, and independent from, the traditional inspection performed by the qualified inspection vendor engaged by the host utility. Following an established communication plan, there were no interactions between the EPRI analysts and their contractor and the utility's inspection vendor, except as directed and reviewed by the utility lead NDE staff responsible for the inspection. The utility lead NDE staff provided the UT data as they were collected and was briefed on and reviewed the results of both analyses. The parallel AI-assisted analysis did not interfere in any way with the schedule, analyses, or results of the traditional inspection.

The activity began by performing an AI-assisted analysis of the previous outage data. This was done after the outage had started but before the scheduled RVUH examination started. This enabled the team to obtain a preliminary assessment of the tool's performance and the implementation method in preparation for the current outage examination. The observed overall performance of the tool in this analysis was good. It flagged approximately 5% of the full data volume for review, which allowed the full analysis to be completed in 4 hours; based on the analyst's experience, it would have taken nearly three days to complete the same analysis without the AI tool. Previously repaired locations with embedded indications were correctly flagged.

At the same time, the team noted a known end-of-tube condition that, although benign, consistently triggered flags, and identified an opportunity for improvement. The EPRI team and AI contractor then leveraged three files from the previous outage to retrain the model on site to inform the model about the identified condition. The retrained model was validated against benchmark data to ensure that detection performance was not degraded. All this was accomplished on site, after the outage had begun but before the scheduled RVUH examination started.

The results of the retrained model on the field data were positive. The identified issue was addressed, and the flag rate was reduced to 2% of the entire volume, which represents a 60% reduction in the amount of data flagged for review while maintaining the same detection performance. This result showcases the notable value in including site-specific data in the model training, highlighting the benefit to utilities when they share their data for inclusion in the model development.

The new model trained on site was applied to the current outage data as they were collected on the site's 78 penetrations. It flagged approximately 2% of the data volume for review. The AI-assisted analysis averaged ~4 minutes per penetration, and that included time to fully record the trigger reason of all flagged regions. This was done for learning purposes in the field trial; such level of detailed characterization would not be required in a typical data analysis. The tool successfully flagged all relevant locations and yielded the same results as the traditional analysis from the qualified inspection vendor while only reviewing 2% of the entire data volume. Table 1 compares the amount of data requiring inspector review in each approach: over the 78 penetrations inspected during the field trial, the 2% flag rate leads to a reduction from 4.4 miles (7.0 km) of data to 463 ft (141 m). The relevant indications were all contained in the 463 ft (141 m) of data identified by the AI tool.

Table 1. Approximate amount of data requiring review in each approach at field trial.

Traditional Inspection	AI-Assisted Inspection
4.4 miles	463 ft
7.0 km	141 m

The results of the detailed analysis of the conditions leading to a flag trigger are shown in Figure 6. The analysis indicates that most of the flags (~56%) were triggered by weld interface or mechanically induced responses. These types of responses require inspector review to proper characterization and disposal; therefore, their flagging is deemed adequate. Only ~13% of the flags were true "false flags" from the underlying ML model and had no identifiable trigger reason related to tube condition.

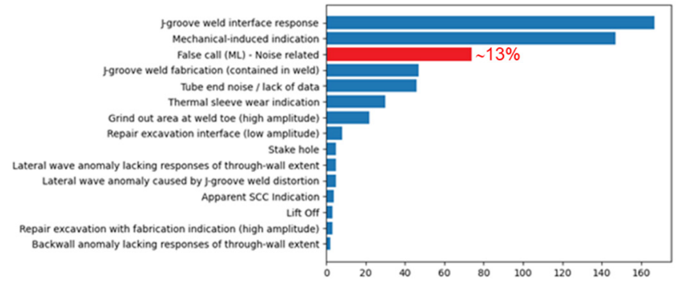

Figure 6. Types of responses flagged by the AI tool during the field trial. High weld interface disturbances and mechanically induced indications triggered most flags (about 56%); only ~13% of the flags were true ML false calls triggered by noise.

The field trial provided the opportunity to identify further ways the AI-assisted analysis can benefit the inspection process. Namely, it was noted that the automation of clerical tasks (such as recording certain inspection attributes) that it enables can bring considerable added value to the activity in that it reduces time and minimizes opportunities for errors. Furthermore, it was noted that the simplicity of the tool can be leveraged to allow inspectors to more easily compare the results from the current and previous outages. These areas are noted for further evaluation and development.

The field trial activities, results, and timeline are summarized in Figure 7.

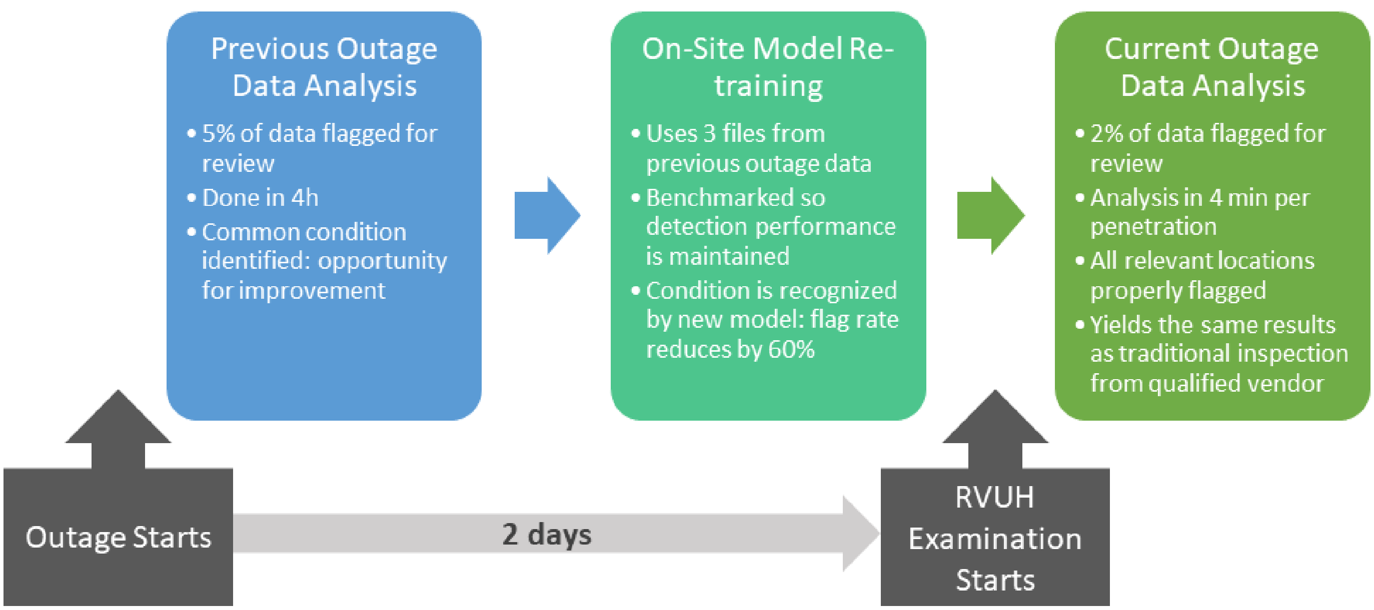

Figure 7. Summary of field trial activities.

Dissimilar Metal Welds

The second target application for AI-assisted analysis is dissimilar metal welds (DMWs). Encoded examinations of these components commonly include multiple skew and refraction angles. This multitude of ultrasonic beams is valuable to improve detection capabilities because different target flaws respond better to different beams. At the same time, it also leads to voluminous and laborious data analysis because each channel needs to be reviewed independently.

For this case, the AI-assisted solution under development leverages the more detailed approach, where it localizes each individual indication for review. The process is illustrated in Figure 8: the AI tool exhaustively goes through all channels in detail, localizing areas of interest in each; then, it consolidates related responses into indications and provides a C-scan-type overview with bounding boxes, complete with an indication table, as illustrated in Figure 3. Once an indication is selected, the user can review the corresponding response from each channel where it appears. The interface also allows simple preliminary measurements (see detail in bottom-left image of Figure 3).

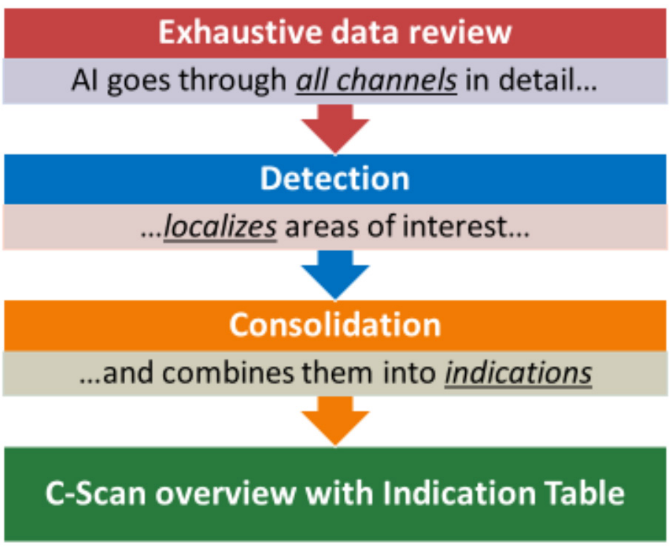

Figure 8. AI analysis process for DMW application.

Data from EPRI open-qualification samples have been extensively used to support the development of this application, again augmented by virtual flaw technology. Some additional data from thermal fatigue flaws are also being leveraged.

As of the writing of this brief, the model has been initially trained and assessed on open samples with good results. Further evaluation on blind samples is underway, as well as efforts to fine-tune the reporting and workflow to fully leverage the more detailed output provided by the model. Qualification prospects will also be assessed.

Based on the experience with the RVUH application, a field trial of an AI-assisted DMW ultrasonic examination is crucial to support the further development and assessment of the approach. The field trial will provide a unique opportunity to assess the performance of the model and the proposed workflow under real field conditions. Therefore, EPRI is seeking volunteer utilities to host such a field trial in 2023. As with the RVUH field trial in early 2022, the activity is to be performed in parallel to but completely independent from the traditional inspection by the qualified vendor, without interfering with the outage schedule. Data security will be maintained—all data remain on site. EPRI member utilities interested in supporting this effort by hosting a field trial are encouraged to contact EPRI.

Qualification Prospects

As mentioned, the main envisioned use case for the technology is as part of a credited inspection, for which qualification is required. The natural question then is, what could qualification of an AI-assisted analysis be like? Although the answer is not yet clear and definitive because this is a first-of-its-kind technology in the industry, some prospects for qualification can be discussed.

First, the AI-assisted analysis would likely be subject to a procedure qualification, where 100% detection is required. Assuming the hypothetical procedure specifies that the inspector reviews only the regions flagged by the tool, this would require the underlying AI model to flag all the flawed regions within the scope of the procedure for inspector review. Otherwise, the inspector would not have an opportunity to detect all flaws, and the procedure qualification detection requirement cannot be met.

To assess whether the AI model can meet such a high detection performance demand, the RVUH model was exposed to more than five times the amount of data required for a traditional Performance Demonstration Initiative (PDI) procedure qualification. The results show that the model accurately flagged all flawed regions, which included:

- Craze cracking
- Axial, circumferential, and off-axis oriented flaws
- Small and large through-wall flaws
- ID and OD surface-connected flaws

The observed flag rate varied from 13% to 59%. The considerably higher value when compared to the other case studies is explained by the fact that the specimens are much more flaw-dense in this case. Notwithstanding, review of the results still indicates the capability of the model to distinguish between flawed and non-flawed regions. As discussed, the final determination (flawed or non-flawed) is still the responsibility of the inspector reviewing the regions flagged by the model. This result simply indicates that the human analyst would have the opportunity to detect all flaws within the scope of the procedure, as required for successful procedure qualification. Therefore, the observation from this study is that the AI-assisted analysis is expected to be able to meet the qualification requirements.

A potential qualification approach is illustrated in Figure 9. First, a procedure would be updated to include a defined process for the AI-assisted evaluation. All necessary AI algorithms for qualification would be provided to the qualification body prior to the activity; at this stage, the model version is frozen and would no longer be able to change without

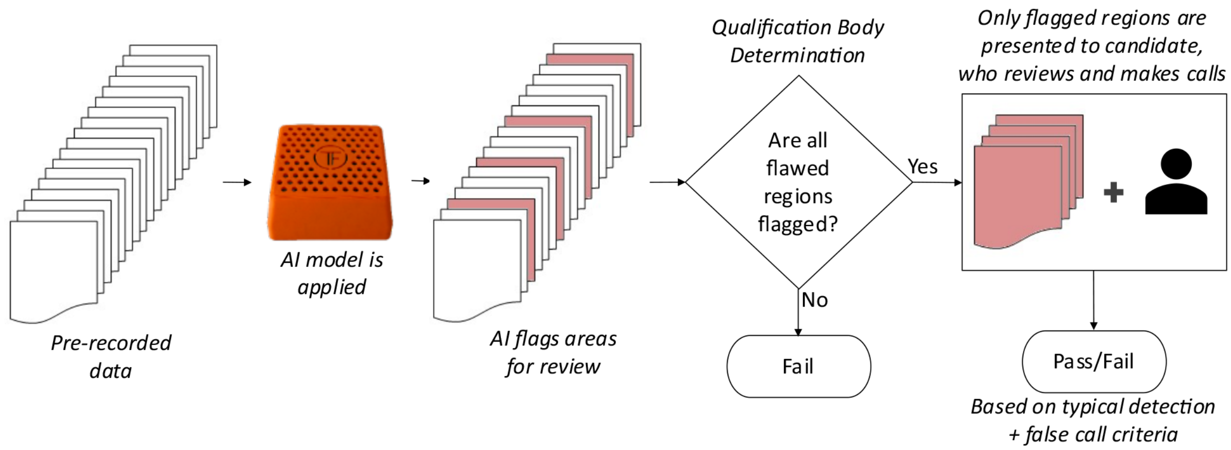

Figure 9. Potential qualification process. The AI model is provided to the qualification body and frozen prior to the activity.

invalidating the qualification. The potential qualification process illustrated in Figure 9 is as follows:

1. Data are collected as determined in the procedure. Typically, this follows the same data collection approaches used today.
2. The pre-recorded data are loaded into the ML box, which applies the AI model and generates a report identifying the flagged regions for review.
3. The qualification body then reviews the output from the ML box to determine whether all flawed regions in the scope of the procedure have been flagged. If they have, the process continues with the flagged regions being presented to the candidate for review. If all flawed regions were not flagged, the qualification exam is unsuccessful because the candidate, if exposed only to the flagged regions, would not have the opportunity to detect all flaws and achieve the required 100% detection for the procedure.
4. The candidate reviews only the regions flagged by the ML box and makes his or her calls. The qualification body reviews the final candidate's calls and assesses pass/fail based on the typical applicable detection and false-call criteria.

The preceding generic outline assumes a procedure in which the candidate reviews only the regions flagged by the model, and it is perhaps more directly applicable to a model that provides the screening output (like for the RVUH application covered previously) rather than the indication table. Several variations can be incorporated; for example, it could call for the flagged regions plus a certain extent to either side of it to be reviewed by the candidate inspector. The specific desired approach needs to be defined in the procedure.

Summary

Table 2 summarizes the results of the studies covered in this brief. They suggest that the AI-assisted analysis significantly reduces the data volume for review because it maintains low flag rates while still providing the analyst with all the available opportunities to detect the flaws. This enables them to focus their attention and energy on the portions of data that need it the most. Inspection reliability is increased by minimizing opportunities for human performance issues caused by momentary lack of focus or fatigue, and data analysis time is shortened considerably.

Qualification prospects were also assessed, and it is expected that the AI-assisted analysis can meet the qualification exam requirements. A potential qualification process that leverages the existing industry qualification framework is proposed; it can be adapted or used as a starting point toward defining a method to qualify AI-assisted procedures.

Finally, work in this area continues for other applications. In particular, models for AI-assisted DMW examinations are in advanced stages of development, and EPRI is seeking volunteer utilities to host a field demonstration of the technology to support further assessment and development.

Additional EPRI Resources

Refer to the following EPRI resources for more information on this topic and other ways AI can be leveraged to benefit NDE and the nuclear sector.

- *Automated Analysis of Ultrasonic Inspection of Reactor Vessel Upper Head Penetration Welds* (3002021043)
- *Quick Insight Brief: Leveraging Artificial Intelligence for Nondestructive Evaluation* (3002021074)
- *Quick Insight Brief: Leveraging Artificial Intelligence for the Nuclear Energy Sector* (3002021067)

Table 2. Summary of performance case studies.

	Industry OE	PSI	Field Trial	Mock Qualification
Flag rate	13%	<1%	5% initially; 2% after on-site retraining	13–59% (higher flaw density)
Detection	All flawed regions flagged	—	Provided same results as independent analysis from qualified inspection vendor	All flawed regions flagged in more than five times the amount of data typically required for procedure qualification

DISCLAIMER OF WARRANTIES AND LIMITATION OF LIABILITIES

EPRI prepared this report.

THE TECHNICAL CONTENTS OF THIS PRODUCT WERE NOT PREPARED IN ACCORDANCE WITH THE EPRI QUALITY PROGRAM MANUAL THAT FULFILLS THE REQUIREMENTS OF 10 CFR 50, APPENDIX B.THIS PRODUCT IS NOT SUBJECT TO THE REQUIREMENTS OF 10CFR PART 21.

NOTE

For further information about EPRI, call the EPRI Customer Assistance Center at 800.313.3774 or e-mail askepri@epri.com.

About EPRI

Founded in 1972, EPRI is the world's preeminent independent, non-profit energy research and development organization, with offices around the world. EPRI's trusted experts collaborate with more than 450 companies in 45 countries, driving innovation to ensure the public has clean, safe, reliable, affordable, and equitable access to electricity across the globe. Together, we are shaping the future of energy.

Contact Information

For more information, contact the EPRI Customer Assistance Center at 800.313.3774 (askepri@epri.com).

EPRI Resources

EPRI members interested in engaging in and supporting this effort should contact EPRI for further discussion.

Thiago Seuaciuc-Osorio, *Principal Technical Leader*
704.595.2841, tsosorio@epri.com

Leif Esp, *Program Manager*
704.595.2697, jesp@epri.com

Nondestructive Evaluation

3002023718

October 2022

EPRI
3420 Hillview Avenue, Palo Alto, California 94304-1338 • USA
800.313.3774 • 650.855.2121 • askepri@epri.com • www.epri.com