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RACOON(+ANDIE)

Non-destructive examination of NPP primary circuit components, machine learning and reliability of inspection.

Interim seminar

09/04/2021 VTT – beyond the obvious

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Motivation for RACOON

In-service inspections

- Major part in nuclear safety
  - Especially in the long term operation, beyond the original design life.
- Not all failure mechanisms could be taken into account in the design phase.
- These failures mechanisms need to be detected before they become critical and cause downtime – or accidents
- **This is done with in-service inspections**

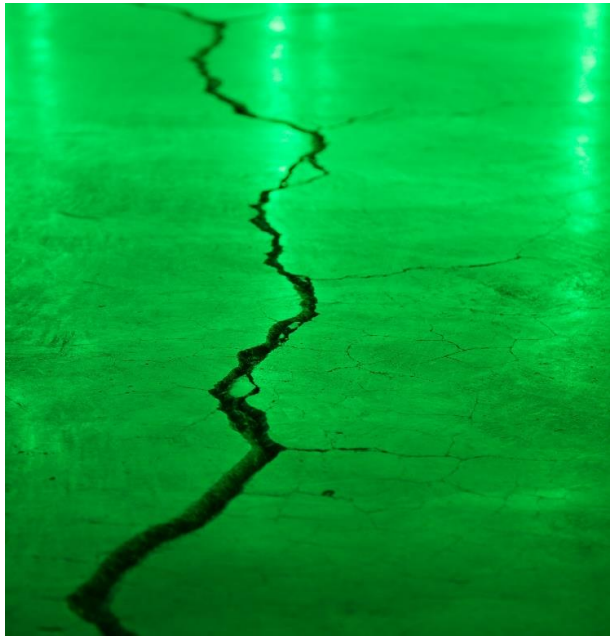


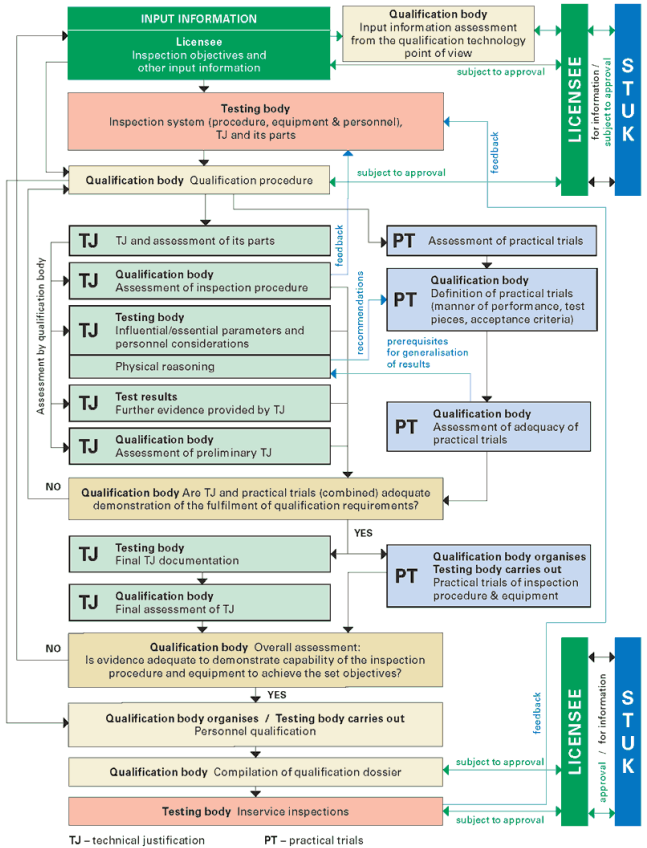
Photo by mahdis mousavi on Unsplash

Impact for inspections

- For in-service inspections to be useful
  - They need to find the flaws
- Flaws are rarely found
  - Flaws are infrequent in the system
- How to be sure that there are no flaws, if the inspector did not find any?

Qualification system

- Qualified procedures, equipment and personnel
- Technical justifications and performance demonstrations
- Sets the baseline for inspection performance



YVL E.5 Annex C

The way forward

- Currently the qualifications cannot improve the reliability further.
- It provide a good way of demonstrating the capability of an inspection to certain extent.
- So how to improve safety and reliability even further?
  - And make a good system even better?

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Measuring reliability

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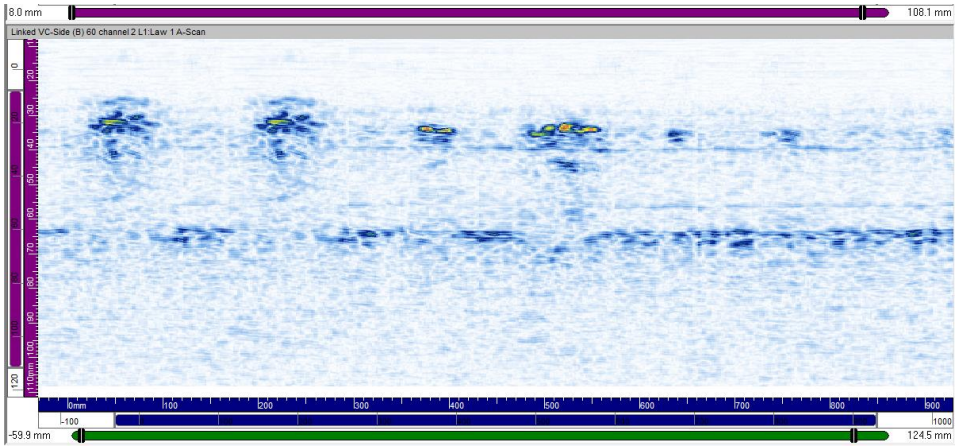
Measuring reliability

- “If you can not measure it, you can not improve it” –Lord Kelvin
- Performance demonstration shows that the system is capable of finding flaws.
  - We try to improve the system and find the same flaws again
  - Is there an improvement or not?
  - This is not the right tool for this job
- Probability of Detection (POD) quantifies the performance in more detail
  - Right tool
  - …but they require a lot more flaws

More flaws needed

- Real flaws are rare
  - Flaws needed for qualification purposes are manufactured
- Manufacturing of tens of flaws more is financially infeasible.
- Virtual flaws have been proven to be an effective way of extending the available flaw data.
  - Enable the use of POD



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Progress in 2019-2020

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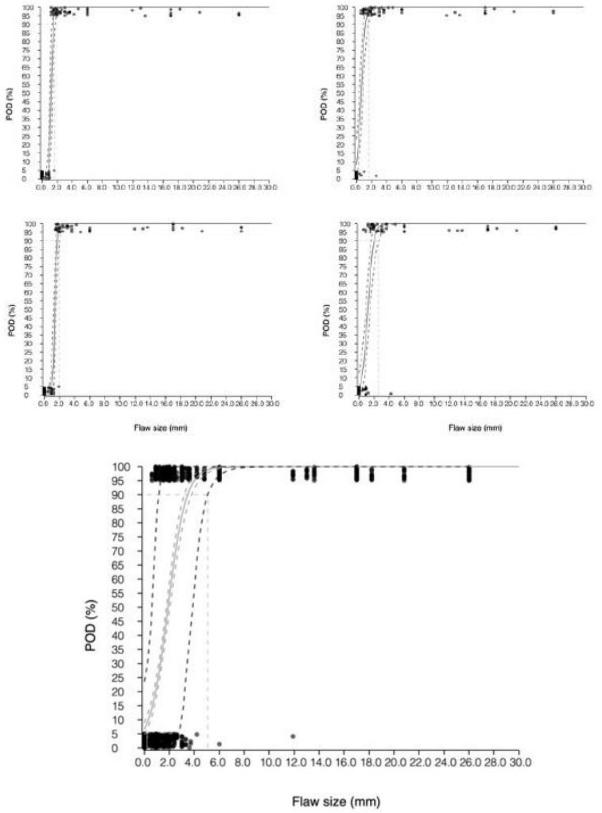
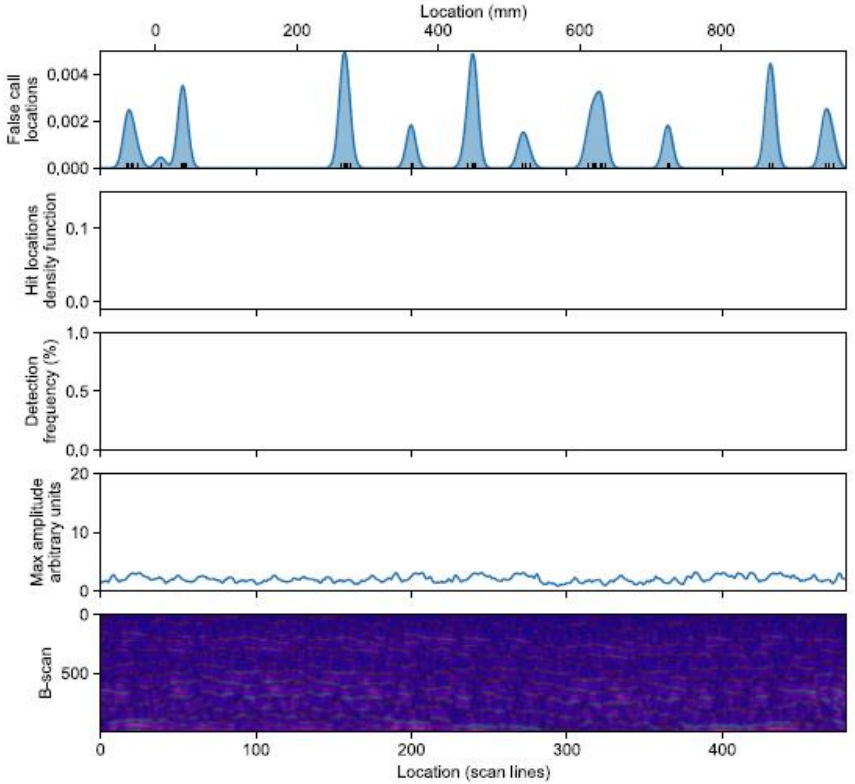
Probability of detection and virtual round robin

- 2019 – 2020 Virtual round robin was conducted for a DMW weld with virtual flaws.
- No logistics of physical mock up.
  - Quick and cost effective approach
- Single DMW mock-up scanned with few additional DMW plates.
  - Total of 6 different flaws
  - 12 inspection data-files generated from the scan data and distributed globally.
  - Total of 12 individual inspectors



Virtual round robin

- Proved to be effective way of demonstrating and testing reliability
- Valuable information on inspection performance
  - Performance varied from $a_{90/95}$ 1.7 – 7.1 mm
  - False calls rate 1 - 9 %
- Some inspectors missed couple of big flaws!



Reality of inspections

- Why are flaws missed and false calls made?
- Conducting inspections and interpreting the inspection data is reparative work.
  - Flaws are really infrequent
  - Inspector should still find every flaw
  - While making no false calls in the process.
- Inspectors require high attention span on the task for long periods of time.
  - Humans are notoriously bad at this.
- There has to be a better and more reliable way of doing this

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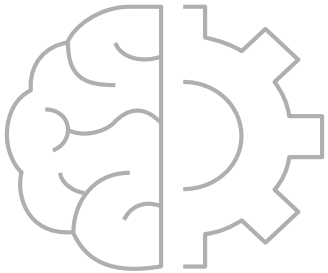
Improving reliability – Machine learning powered NDT

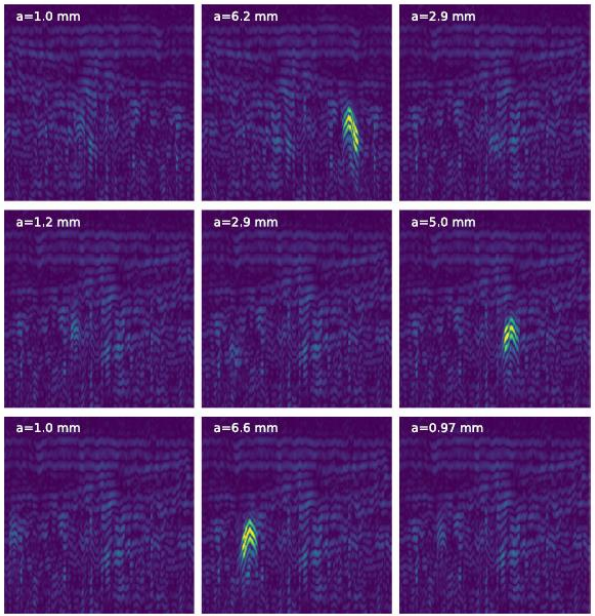
Why machine learning

- Humans are intuitive and skilful of finding the small flaws.
- But it is only human to make mistakes
  - The VRR demonstrated; inspectors were able to find the small flaws. However, some of the inspector made couple of BIG misses.
    - The big flaws are the ones critical to find!
  - Not to mention avoiding false calls at the same time.



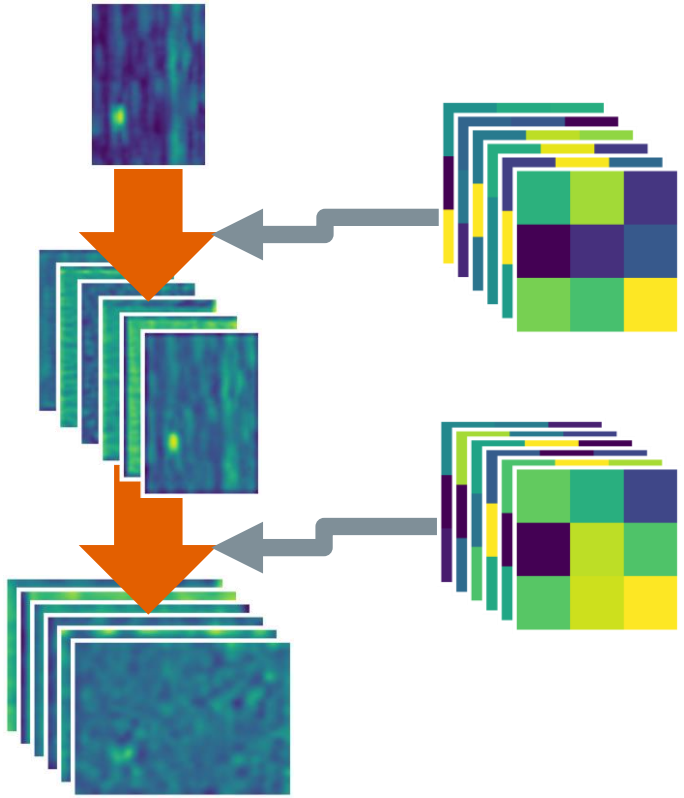
First steps in machine learning NDT (ANDIE)

- Machine learning powered NDT started as a small project in 2019
- As virtual flaws enable the POD estimation and VRR, they can also be used to train a machine learning model.
- Proved to be viable approach on finding flaws



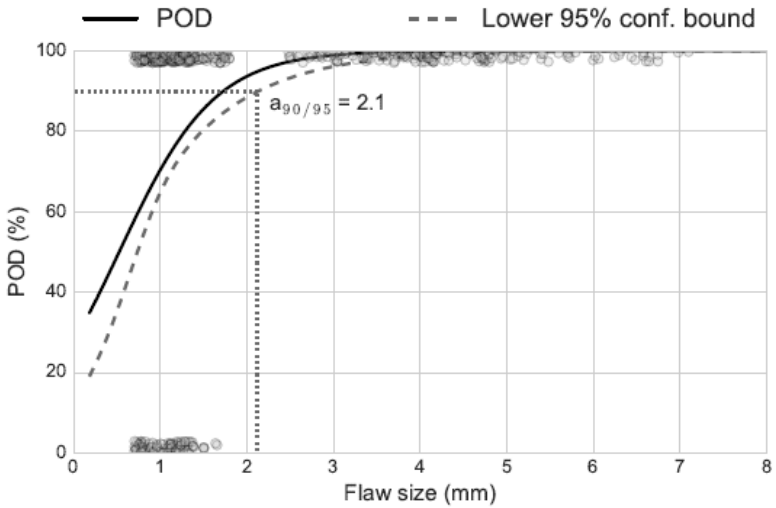
Real phased array data for machine learning

- In 2020 ANDIE was merged with the RACOON project
- TVO case to inspect austenitic stainless steel weld with phased array inspection and machine learning model.
  - Same inspection procedure as for real inspection
- Train and test welds representing a real weld in NPP
- Total of 16 different flaws for training and 8 separate flaws used for testing.



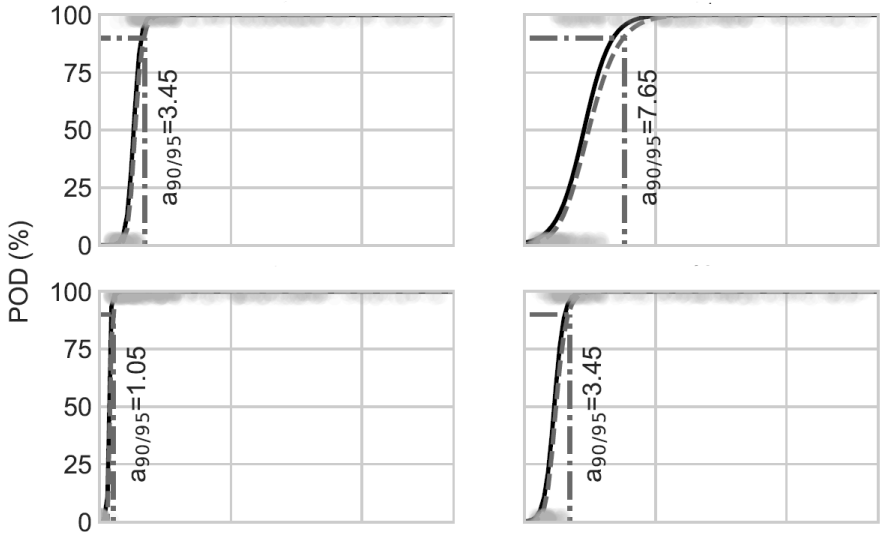
Excellent results

- $a_{90/95}$ 2.1 mm (1.7 mm at best for humans in VRR)
- False call rate of 2.3% (4.17% for humans in VRR)
- Human level performance achieved
- With no missing of large flaws



The effect of flaw data to machine learning

- Performance greatly related to the flaw size and type
  - The $a_{90/95}$ can be adjusted with the size of flaws used in training
- ML model can constantly find the target flaw size, without missing the large ones.
  - With minimum false calls.



Highlights 2019-2020

Measuring reliability with VRR

- Cost effective
- Possibility to improve and measure the true performance of difficult inspection targets.
- **Focus on improvements which have the most impact.**

Improving reliability with ML powered NDT

- Human level performance on austenitic and DMW welds
- False calls are rare
- Models don’t miss any big flaws
- **Consistent, predictable and efficient analysis for inspection data**

Scientific publications

- Koskinen, T. Virkkunen, I. Siljama, O. & Jessen-Juhler, O. 2021. The Effect of Different Flaw Data to Machine Learning Powered Ultrasonic Inspection, J Nonde-struct Eval, 40, 24. https://doi.org/10.1007/s10921-021-00757-x
- Siljama, O. Koskinen, T. Jessen-Juhler, O. & Virkkunen, I. 2020. Automated flaw detection in multi-channel phased array ultrasonic data using machine learning, Unpublished : In review
- Virkkunen, I., Koskinen, T., Jessen-Juhler, O. et al. 2021. Augmented Ultrasonic Data for Machine Learning. J Nondestruct Eval 40, 4. https://doi.org/10.1007/s10921-020-00739-5
- Virkkunen, I. Koskinen, T. Jessen-Juhler, O. 2020. Virtual round robin – a new opportunity to study NDT reliability. Unpublished : In review