Remote Monitoring Methodology for Underwater Laser Cutting in Nuclear Facility Dismantlement

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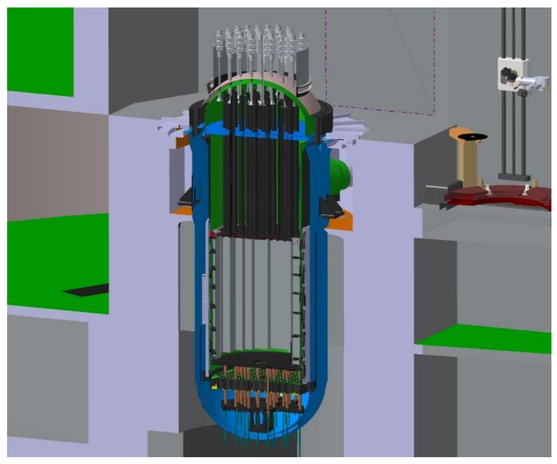
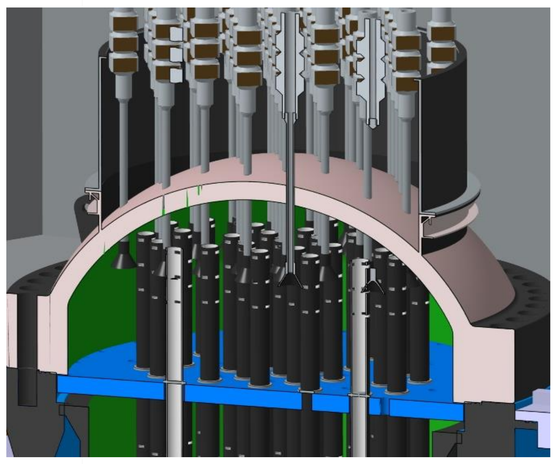
1. Introduction

- Dismantling the RPV internal structures
  - ✓ High radioactive part and has very complex geometry
  - ✓ Remote cutting with and an automated cutting system
  - ✓ Remote monitoring is required for safety



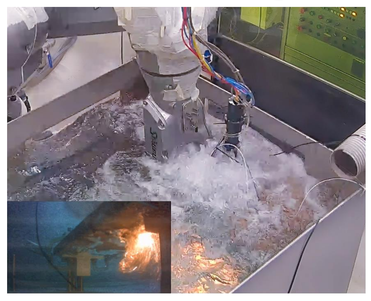
RPV Cross section

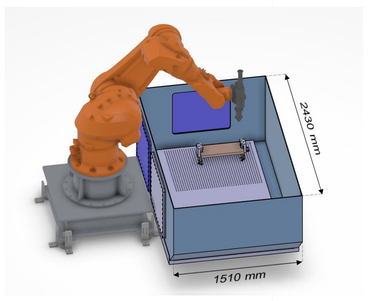


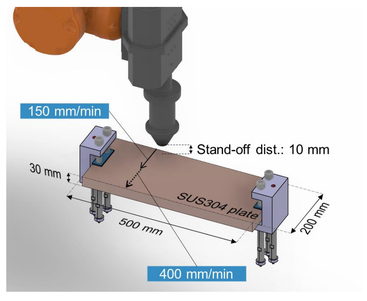
Upper support plate (blue part)

- Challenges in remote monitoring:
  - ✓ Limited visual information due to bubbles and debris
  - ✓ Bright laser light diffusion underwater surpasses dynamic range of visual sensors

- Testbed Configuration

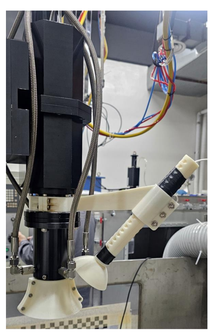


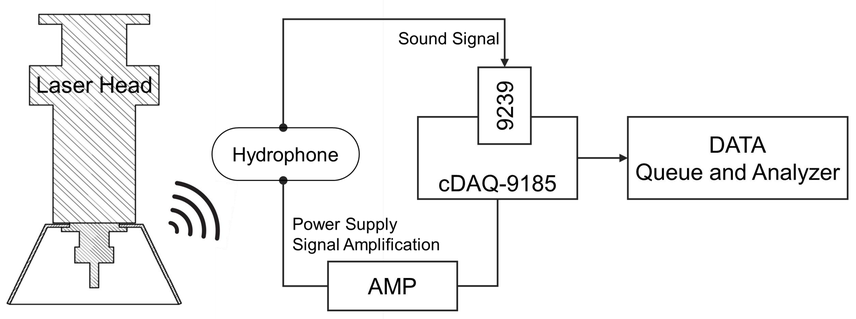




  - ✓ Initially moving the laser cutter successfully for the first 100 mm at a speed of 150 mm/min
  - ✓ Subsequently, we accelerate the laser cutter to 400 mm/min, exceeding its cutting speed limit, resulting in improper cutting of the remaining part of the plate

2. Sound Data Collection

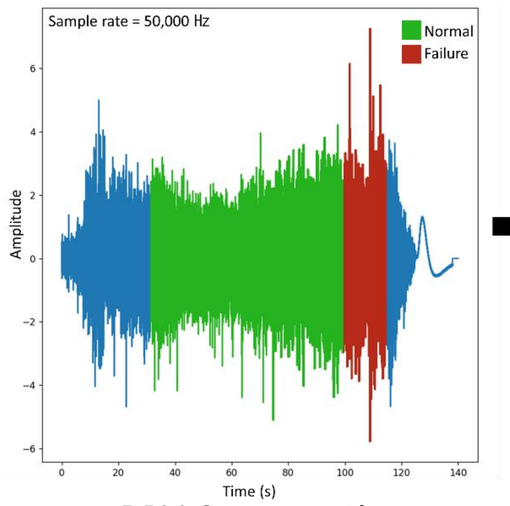




Device	Model	Maker	Specification	Note
Hydro-Phone	Type 8103	BRÜEL & KJÆR	• Frequency range: 0.1 Hz to 180 kHz • Receiving sensitivity: –211 dB re 1 V/µPa • 50 × 9.5 mm	Miniature Hydrophone
Chassis	cDAQ-9185	NI	4-Slot Ethernet	
Sound signal Acquisition (ADC)	9239	NI	• BNC, 4-CH +/-10 V • 50 KS/S PER CHANNEL, 24-BIT • CH-TO-CH ISOLATED ANALOG INPUT MODULE, ADC	Plugin to c-DAQ-9185
AMPLIFIER	TYPE 2692-A-0I1	NEXUS	1-channel Charge Conditioning Amplifier with Single and Double Integration	IEPE compatible

  - ✓ Data acquisition: NI cDAQ-9185 with NI 9239
  - ✓ moduleSampling rate: 50,000 HzAnalysis: 512 sample segments (duration: 0.1024 seconds)

- Sound data pre processing
  - ✓ Short-Time Fourier Transform (STFT) for frequency analysis
  - ✓ 257 frequency bins with ~98 Hz interval up to 25,000 Hz



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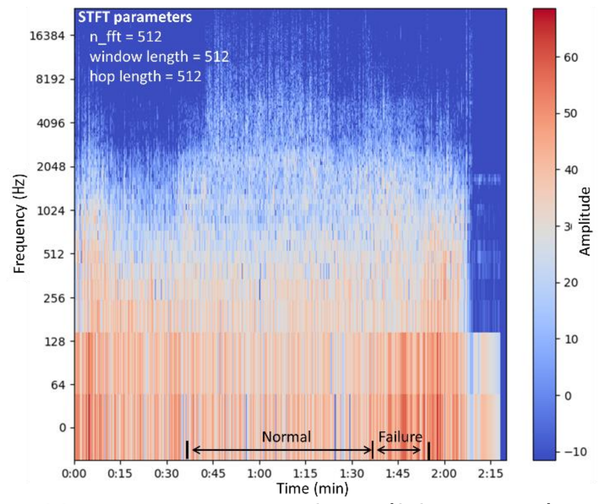
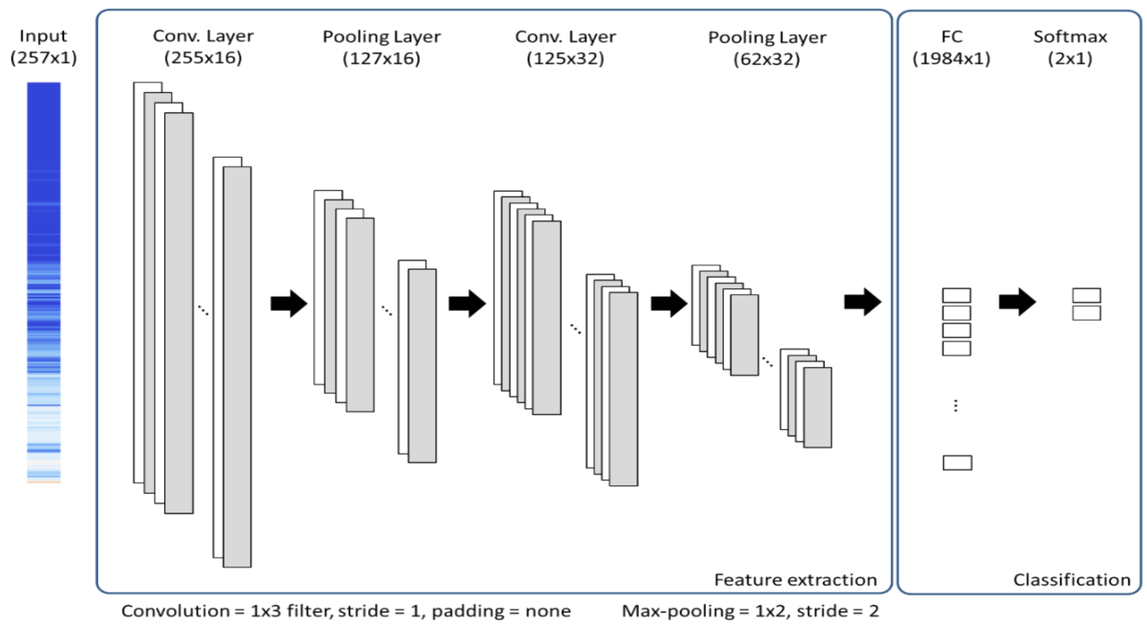


Upper support plate (blue part)

3. AI Model Development

- CNN-based architecture
  - ✓ Input: Frequency spectrum data (257x1 shape)
    Layers: 1D convolution filters (1x3) and pooling layers (1x2)
    Output: Binary classification (normal/abnormal cutting state)
  - ✓ Model designed to capture localized frequency patterns and their correlations
  - ✓ Training data: 6358 samples, Validation data: 2726 samples, Test data: 5177 samples



- Results
  - ✓ CNN model Accuracy: 94.73%
  - ✓ Outperforms other machine learning methods:
    Support Vector Classification (SVC): 85.45%
    Multi-Layer Perceptron (MLP): 88.92%

4. Conclusion

- Successful differentiation between normal and abnormal cutting states
- Enables monitoring of complex, highly radioactive structures like reactor internal components
- Future Work
  - ✓ Investigate optimal hydrophone positions for improved sound capture
  - ✓ Develop restarting methodologies for cutting failures
  - ✓ Precise identification of failure positions
  - ✓ Strategies for resuming cutting from point of failure
  - ✓ Presure sensor data integration