Eddy Current Testing for Research Reactor Fuel Rods via Deep Learning

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ECT is needed to inspect the coating layer defects

» Safety problem caused by the flaws in cladding layers can be prevented by ECT

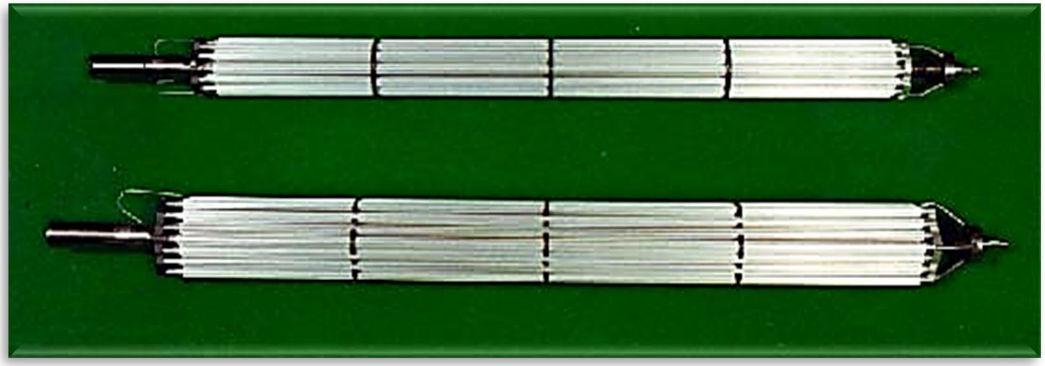


Fig. 1 HANARO Fuel Assembly

- Nuclear fuel rods for research reactors used in HANARO require a cladding layer
- Cladding surrounds the nuclear fuel core to effectively transfer heat and smooth coolant flow
- The flaws that is present in the coating layer lead to the leakage of the fissile material
- The leaked can migrate into the cooling water in research furnace, which causes safety problem
- Eddy current testing (ECT) should be performed to inspect the coating layer defects

Deep learning can improve the reliability of ECT

» The reliability of ECT defect inspection can be improved via deep learning

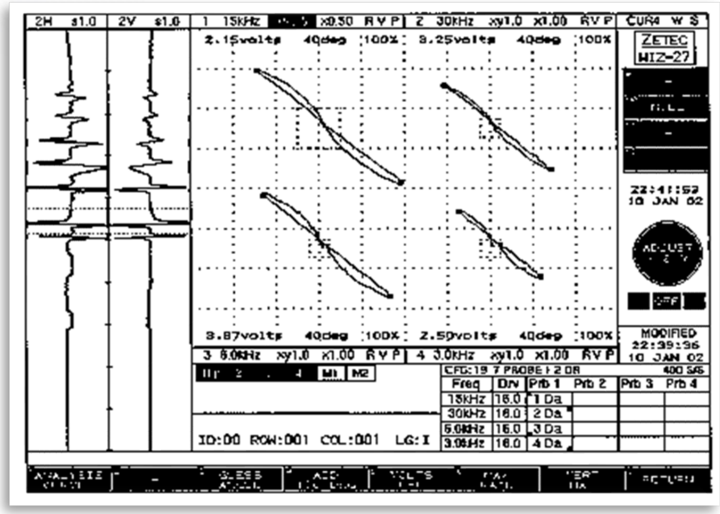


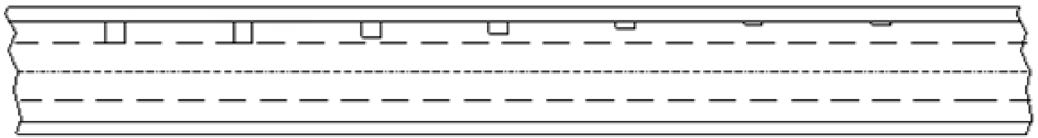
Fig. 2 ECT signals at 30, 15, 6, 3 kHz

- ECT can detect various defects that occur in fuel rods as well as clads by using multiple frequencies
- The reliability of ECT signal analysis is highly dependent on the operator,
  thus proper signal analysis method is needed to secure the high reliability of the test result
- The reliability of defect inspection results by ECT can be improved via deep learning technique

02 Experiment

Specimen & eddy current inspection

» Al1060 dummy concentrically extruded rod was used for the standard rod



- Seven types of notch defects were fabricated by electro-discharge machining
- Notch depths were 100%, 80%, 60% 40%, 20%, 17%, and 13% of the cladding thickness (0.79 mm)

» Zetec MIZ-27ET and the probe designed for reactor fuel rod inspection

- The inspection frequencies were 30 kHz, 15 kHz, 6 kHz, and 3 kHz
- For each frequency, the two-channel signals were collected at 12 in/s with an excitation voltage of 16 V and a sampling rate of 400 S/s
- The phase angle was set to 40 degrees at the 100% notch defect signal
- The measurement was conducted 98 times

Neural network: ResNet18-1D

A variant of ResNet18-1D

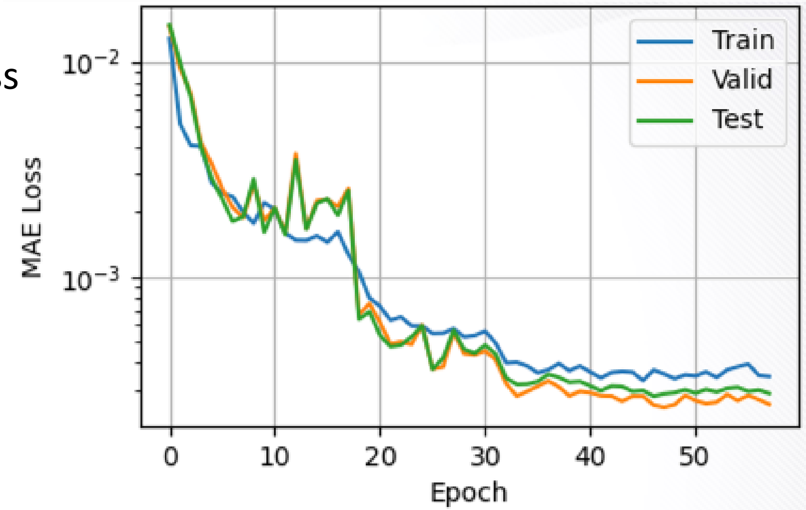
- ResNet: an architecture for CNN with skip connections
- The input to a layer is added to the output of the layer with the skip connection, which helps to avoid gradient vanishing as well as to train deeper networks
- Since ResNet18 is designed for image data, 2D operations of ResNet18 should be replaced with 1D operations for signal data
- The inputs were signals with a length of 150
- The output was a floating value for the defect depth

Layer Name	Output Shape	ResNet18-1D
	B x C x 150	input
conv1	B x 64 x 75	[1 x 7 conv, 64, stride 2]
max pooling	B x 64 x 38	[1 x 3 max pool, stride 2], skip connection
conv2_x	B x 64 x 38	[1 x 3 conv, 64, stride 1] x 2, skip connection, [1 x 3 conv, 64, stride 1] x 2
conv3_x	B x 128 x 19	[1 x 3 conv, 128, stride 2], [1 x 3 conv, 128, stride 1], skip connection, [1 x 3 conv, 128, stride 1] x 2
conv4_x	B x 256 x 10	[1 x 3 conv, 256, stride 2], [1 x 3 conv, 256, stride 1], skip connection, [1 x 3 conv, 256, stride 1] x 2
conv5_x	B x 512 x 5	[1 x 3 conv, 512, stride 2] x 2, skip connection, [1 x 3 conv, 512, stride 1] x 2
average pooling	B x 512 x 1	skip connection, [1 x 1 avg pool]
fully connected	B x 1	[512 x 1 fully connections]
		ouput

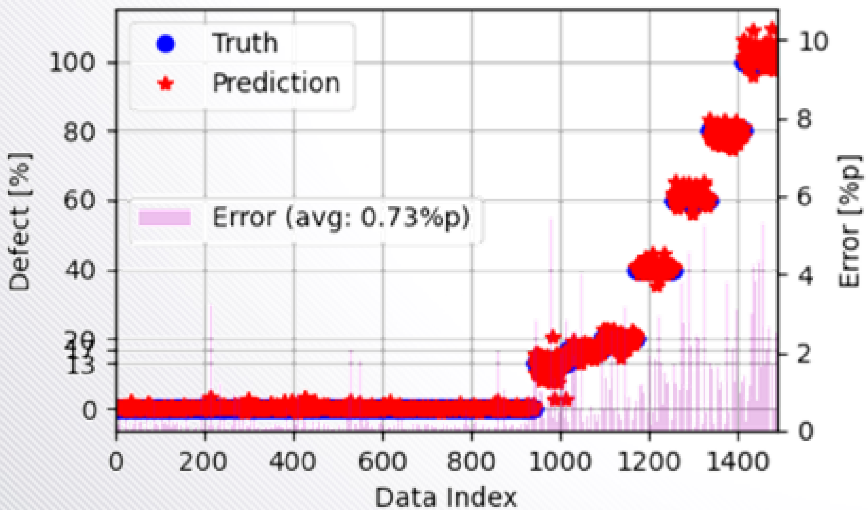
※ B: batch size, C: the number of channels

Training & testing

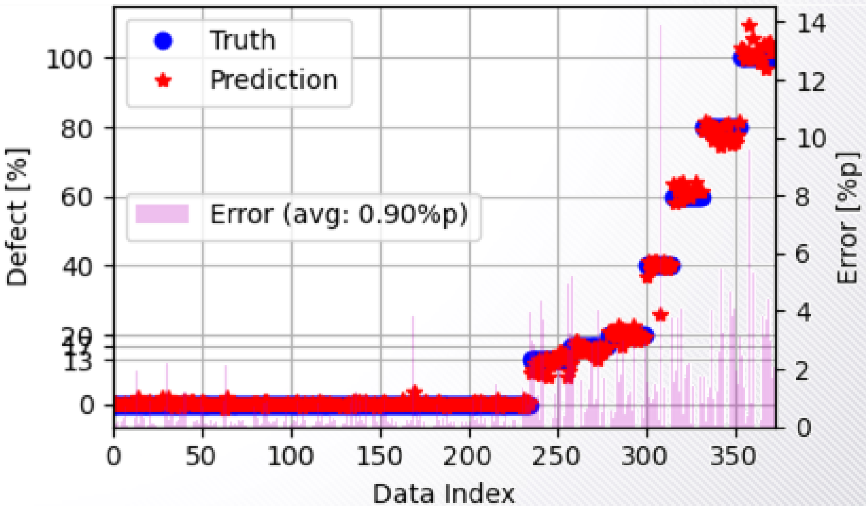
- MAE was adopted as the loss function and Adam optimizer was used to minimize the loss
- LR was 0.001 and it became halved when the validation loss was not updated for more than 5 times
- The training was stopped when the validation loss was not updated for more than 10 times



Train & Validation Datasets sorted by Defect Depth [%]



Test Datasets sorted by Defect Depth [%]



Favorable frequencies exist for defect depth estimation

» Errors according to batch size and input channel

Input Channel	Batch Size						Average
	32	64	128	256	512	1024	
1	1.07	1.17	1.32	1.65	2.42	3.56	1.86
2	1.05	1.01	1.13	1.29	2.05	3.03	1.59
3	1.02	1.02	1.15	1.47	2.40	4.24	1.88
4	1.61	1.80	1.86	2.08	2.71	4.03	2.35
5	0.67	0.75	0.88	1.11	1.90	2.43	1.29
6	2.20	2.56	3.00	3.36	4.16	5.26	3.42
7	0.59	0.61	0.70	1.05	1.81	2.07	1.14
8	0.70	0.76	0.80	1.03	2.13	2.94	1.39
All	1.02	1.20	1.35	2.02	2.54	5.59	2.29
Average	1.10	1.21	1.35	1.67	2.46	3.68	

- To compare the performance according to input channel (1, 2, 3, 4, 5, 6, 7, 8, and 1~8) and batch size (32, 64, 128, 256, 512, and 1024), training and testing were conducted 10 times per case
- Using channels 5 (6 kHz), 7 (3 kHz), and 8 (3 kHz), the averaged losses were lower than the others
- Using channel 7 (3 kHz) with a batch size of 32, the error was the lowest
- In terms of batch size, the performance degraded by batch size, especially 256 or higher
- It is important to choose the proper batch size, especially when training small datasets