The Stakeholder Webinar is being recorded

Your audio and video is muted by default

Use the “Questions” feature to ask questions

Use the “Chat” feature to let us know if you have technical difficulties.

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Questions will be addressed at the end of each presentation (time permitting)

ML-AI Symposium 3.0

IDAHO NATIONAL LABORATORY

NS&T ML-AI

Big Data, Machine Learning, Artificial Intelligence

Welcome to the ML-AI Symposium 3.0

October 16th, 2020

Dr. Curtis Smith, Director

Nuclear Safety and Regulatory Research Division (NSRR)

Idaho National Laboratory

Idaho National Laboratory

Dr. Curtis Smith, Director
Nuclear Safety and Regulatory Research Division
Idaho National Laboratory

Machine Learning & Artificial Intelligence Symposium 3.0

Friday, October 16, 2020

Idaho National Laboratory

Moving from Symposium 1.0 to 2.0 to 3.0

- In April, INL sponsored a symposium on Artificial Intelligence (AI) and Machine Learning (ML) approaches and activities related to science and engineering
  - The “1.0 Symposium” focused on internal-to-INL activities and capabilities
  - Eleven speakers discussed a variety of current topics and future applications
  - Over 200 INL staff participated in the symposium
- For Symposium 2.0 we engagement with industry and universities
  - It was noted that AI/ML will be a key technology moving forward as we continue our R&D
- Today, for Symposium 3.0, we will be focusing on nuclear-related applications using AI/ML

11:05	Analysis of Containment Images for Concrete Degradation	Thiago Seuaciuc-Osorion
11:20	Distributed Fiber Sensor Enabled Big Data Analytics for Pipeline Monitoring	Kevin Chen
11:35	Machine Learning for Autonomous Drone Operation	Ahmad Al Rashdan
11:45	Analysis of Work Order Data for Cross-Utility Trends	Dave Olack
11:55	Design of Risk-Informed Autonomous Operation for Advanced Reactors	Hyun Gook Kang
12:05	SMART Piping & Instrumentation Drawing Recognition	Carol Smidts
12:15	Applications of Natural Language Processing in Reliability Engineering	Nicholas Zwiryk
12:25	Uncertainty Quantification with Scientific Machine Learning	Xu Wu
12:35	Federated Transfer Learning for Circulating Water Pump Motor Health Prediction	Koushik Manjunatha
12:45	Failures in Artificial Intelligence and Machine Learning - Insights and Mitigations	Charmaine Sample
12:55	Learning for Concrete Damage Diagnosis using Vibration Testing	Sankaran Mahadevan

Presenters and Topics

Idaho National Laboratory

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Analysis of Containment Images for Concrete Degradation

Thiago Seuaciuc-Osorio
Sr. Technical Leader

INL ML/AI Symposium 3.0
October 16, 2020

Remote Visual Inspections with Unmanned Aerial Systems

- Benefits during data collection
  - Saves time
  - Reduces costs
  - Increases safety
  - Provides better inspection data record
- Increased burden on analysis
  - Large quantity of monotonous images or videos

Can machine vision models help with analysis?

Data & Scope

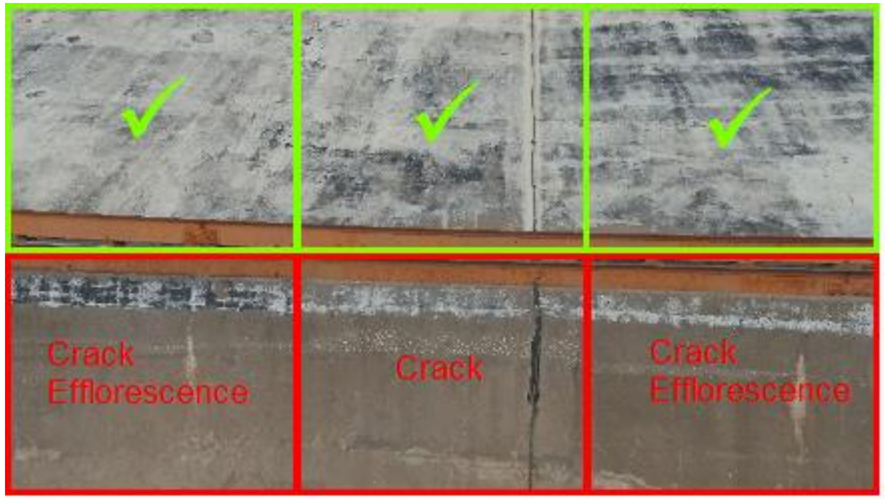
- Data from 2 containment buildings (~2,500 images)
  - One complete inspection
  - One partial inspection (demo)
- No standards for data collection yet
  - Varying resolutions
  - Varying distances & fields of view
- Five damage types
  - May not have enough examples of all types
- Labeled with polygon masks
- Sequential images
  - Multiple views of same physical defect
  - Prone to data leakage

Object	Count	Share
Efflorescence	5,377	39%
Crack	3,248	24%
Background	2,202	16%
Tendon Cap	751	6%
Grease Stain	722	5%
Spall	721	5%
Corrosion	518	4%
Pattern Cracking	71	1%
Abraison	6	0%
Honeycomb	2	0%

Approaches

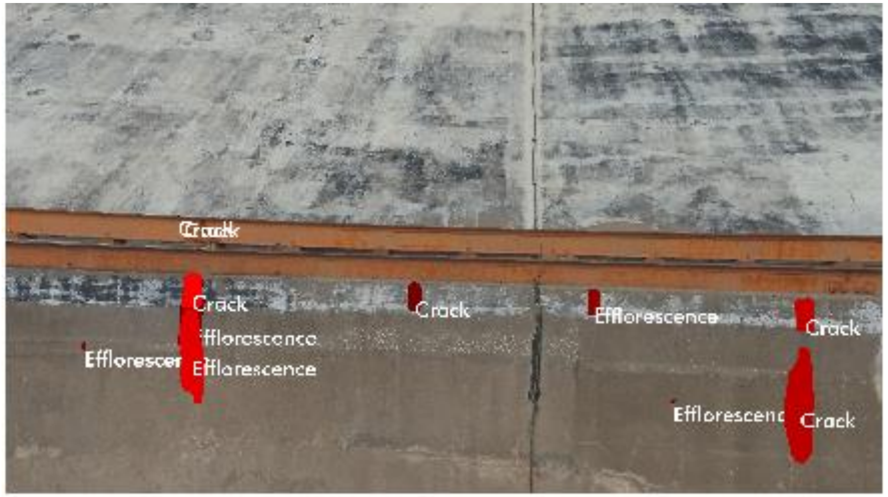
Classification

- Presence/absence of each damage type in an image *tile*
- Lighter, faster



Defect Localization

- Provides a mask to localize the object in the image
- Heavier, slower



Preliminary Results

Classification (tile level)

	P	N	TP	TN	FP	FN	Recall	Precision	FCR
Corrosion	75	4509	61	3863	646	14	0.81	0.09	0.14
Crack	383	4201	294	2227	1974	89	0.77	0.13	0.47
Efflorescence	292	4292	239	4160	132	53	0.82	0.64	0.03
Grease Stain	282	4302	179	4003	299	103	0.63	0.37	0.07
Spall	124	4460	90	3299	1161	34	0.73	0.07	0.26

Defect Localization (instance level)

	Population	TP	FP	FN	Recall	Precision	F1
Corrosion	21	18	32	3	0.86	0.36	0.51
Crack	138	123	125	15	0.89	0.50	0.64
Efflorescence	208	192	127	16	0.92	0.60	0.73
Grease Stain	60	49	106	11	0.82	0.32	0.46
Spall	35	0	0	35	0	-	-

* Classification and localization results above are not on the same test data

- CAUTION: Work-in-progress!
  - First-cut models
  - Assessment underway
- Recall biased results
  - This may be a recall-biased application
  - False call rate (FCR) typically low despite low precision
- Most notable challenges:
  - Cracks, spalls

Going Forward

- Obtain more field datasets
  - Better testing & performance assessment
- Synthetic images
  - Focused on less common damage types of interest
- Model optimization
  - Parameter tuning
  - Different classification models (or network depth) for different damage classes
  - Chain classification & localization models

Together...Shaping the Future of Electricity

Kevin P Chen
University of Pittsburgh

Andrei M Gribok
Idaho National Laboratory

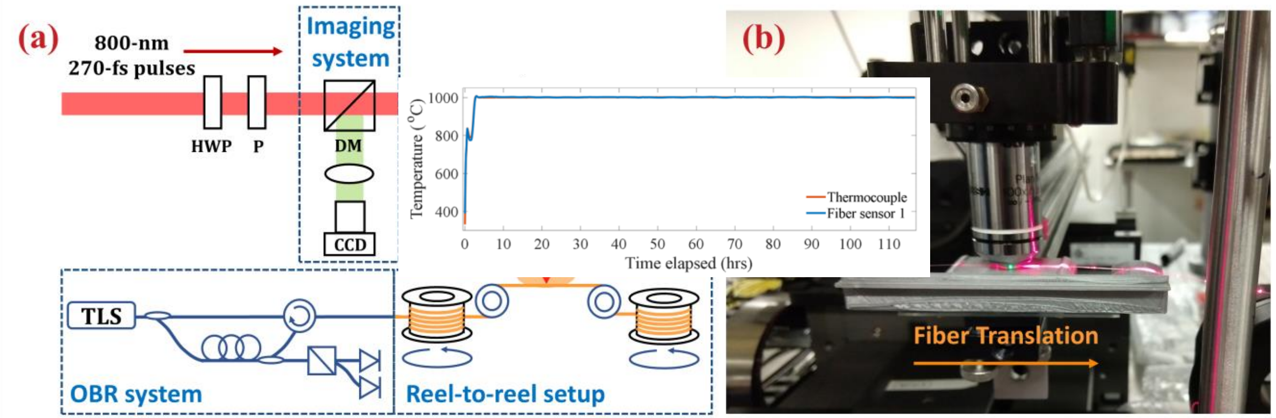
Distributed Fiber Sensor Enabled Big Data Analytics for Pipeline Monitoring

Machine Learning & Artificial Intelligence Symposium

October 16, 2020

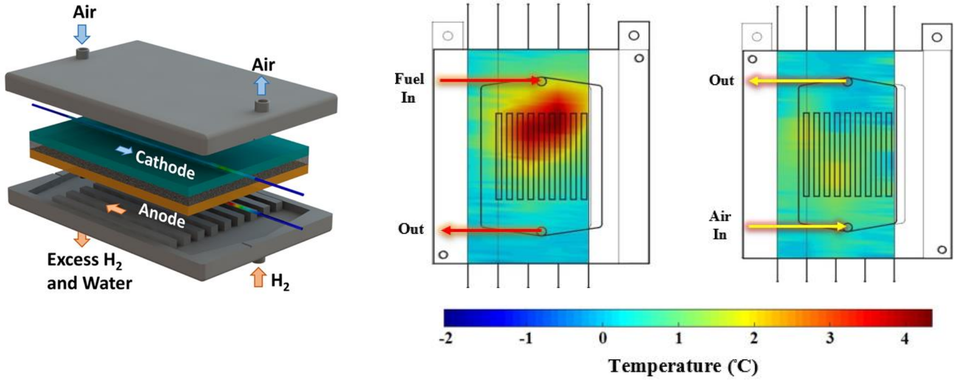
Fiber Sensor Enabled Big Data Analytics

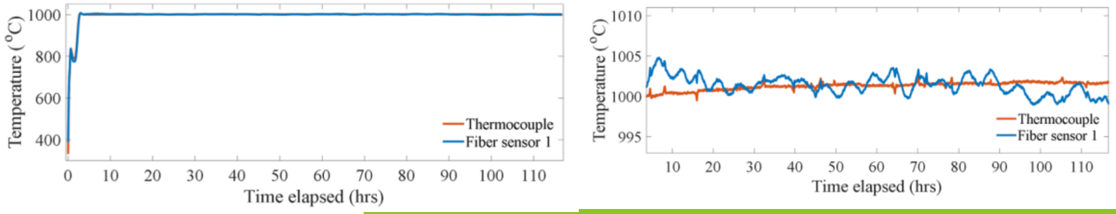
Reel-to-Reel Fabrication of Radiation-Harden Fiber Sensors



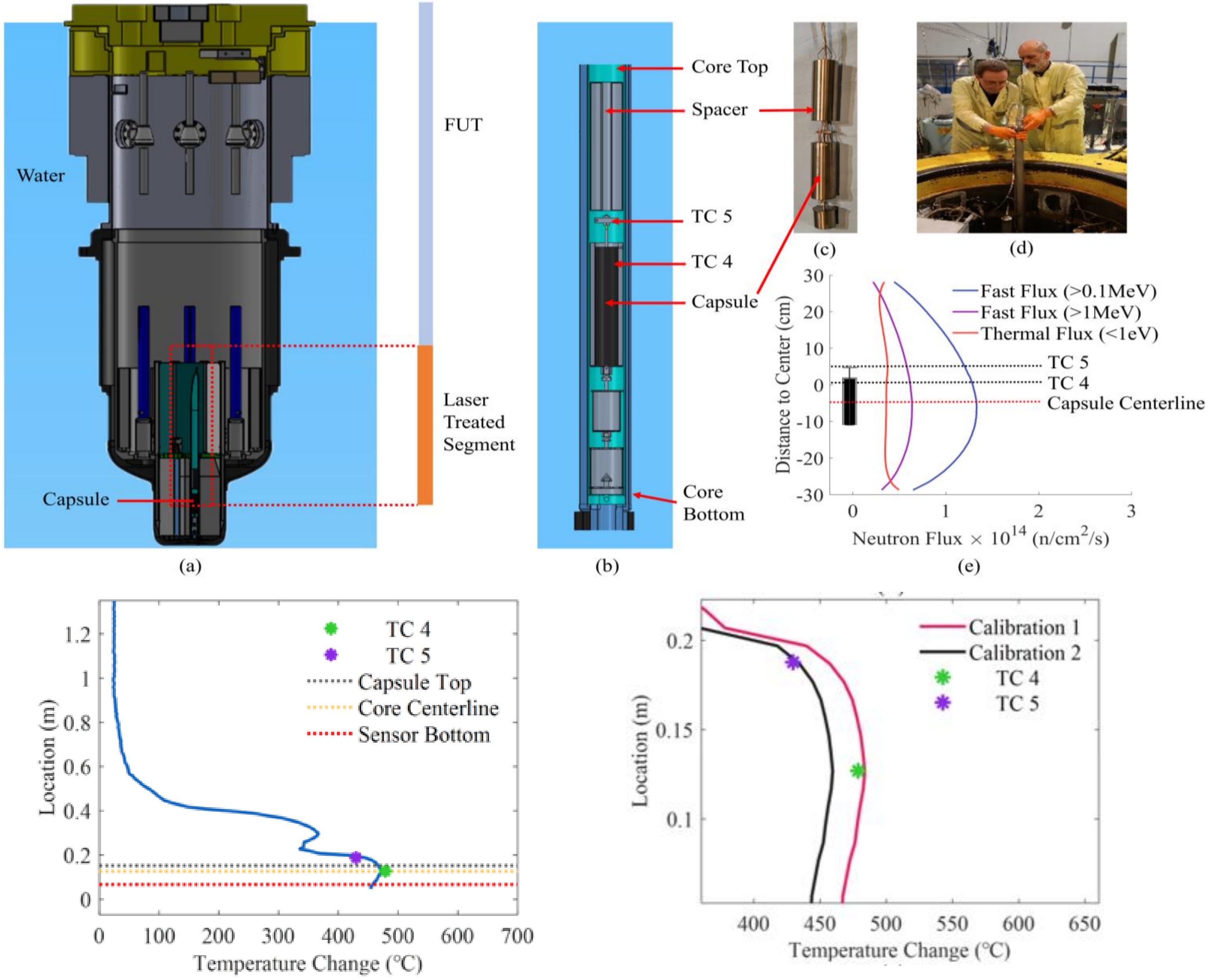
- Femtosecond/UV lasers sensor fabrication
- Highly flexible for all fibers (silica/sapphire)
- Reel-to-reel fabrication through fiber jackets
- Over 1000 sensors can be continuously fabricated
- Extreme temperature and radiation stable
- Hydrogen stable
- Cross-cutting applications for all energy sectors

Solid-Oxide Fuel Cells





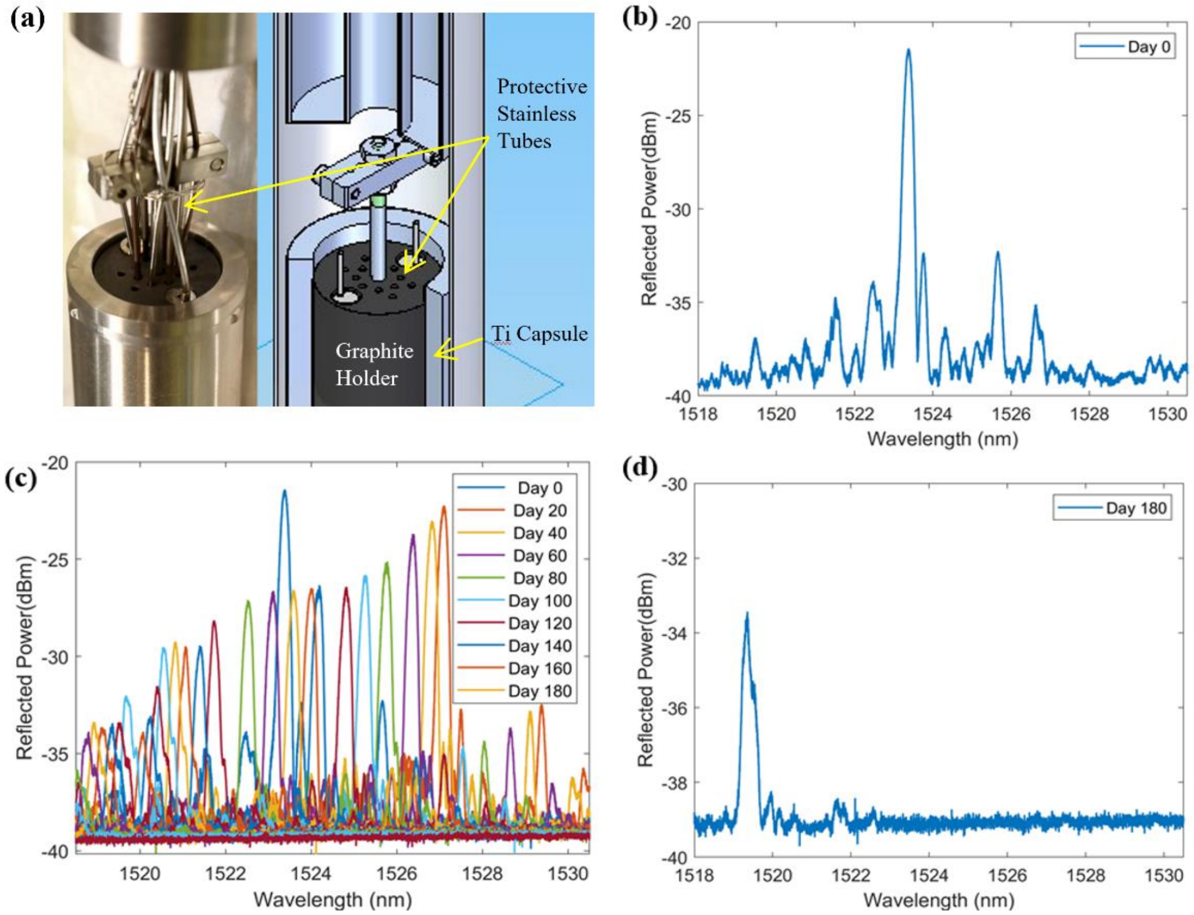
Fiber Sensor Applications in Nuclear Energy



- **High spatial resolution measurements**
- **Withstand extreme radiations**
  - **1.4×10^{14} fast neutron/s/cm^2**
  - **300 days exposure**
  - **Temperature 650^{o}C**
- **Perform temperature profile measurement in MITR**
  - **1-cm spatial resolution**
  - **1.6 meter T profile**
- **Perform transient T measurements**

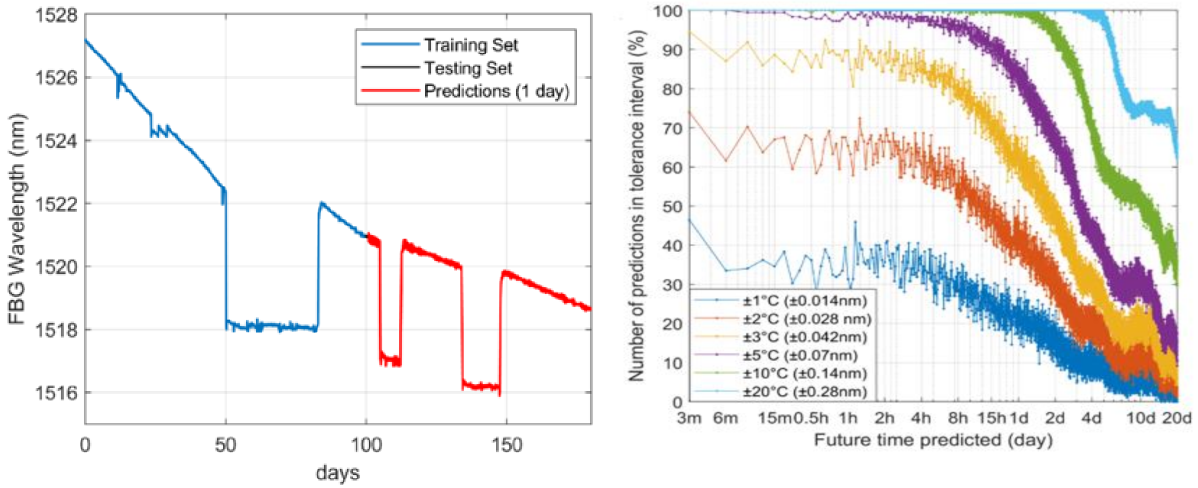
Why We need A.I. : Temporal Analysis

A.I. Data Analytics for Temporal Analysis of Fiber Sensors



Sensor Drift Prediction Using Bayesian Learner

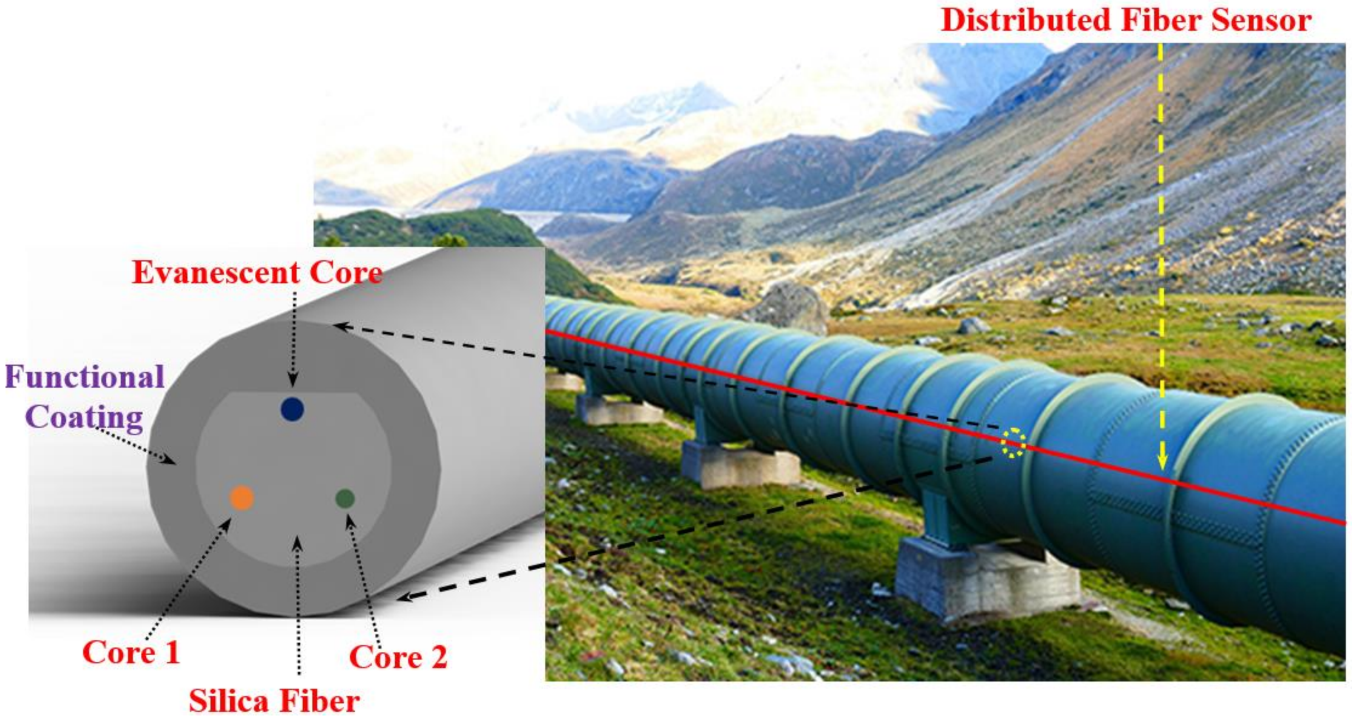
$$P\left(s(t)|X(t)\right) = \frac{P\left(s(t),X(t)\right)}{P\left(X(t)\right)} = \frac{P\left(X(t)|s(t)\right)\cdot P\left(s(t)\right)}{P\left(X(t)\right)}.$$



- **To address sensor drift**
- **To perform classification for reactor anomaly**
- **Successfully addressing sensor drift to 98.4%**
- **Trigging anomaly warning within 4^{o}C T changes**

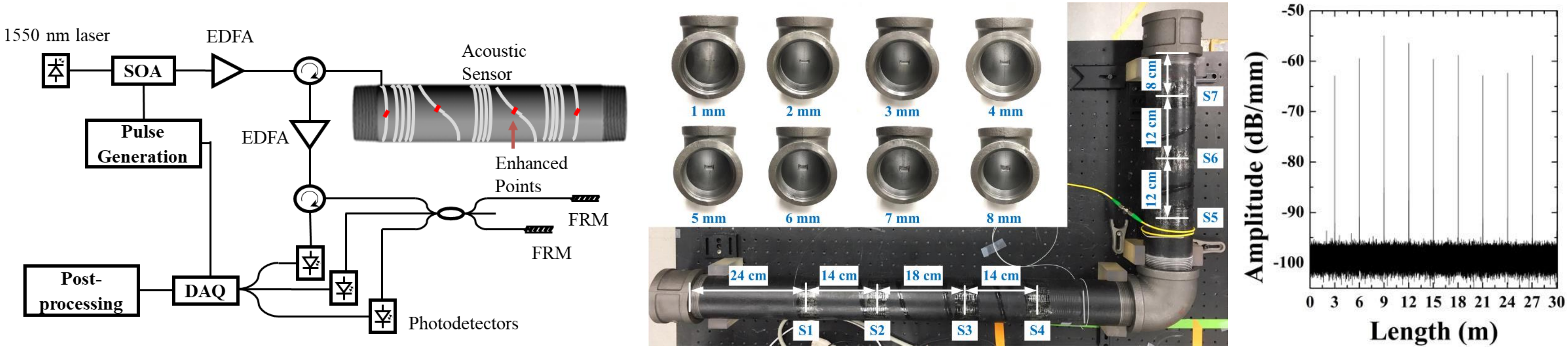
A.I. for Spatial/Temporal Data Analysis

Pipeline Defect and Intrusion Detection and Classifications



- Condition-Based Monitoring
- Large varieties of threats and pipeline defects
- Large varieties of pipe structures and configuration
- Requiring multitude measurements (T, strain, chemical)
- Requiring high spatial resolution information
- Requiring high temporal resolutions

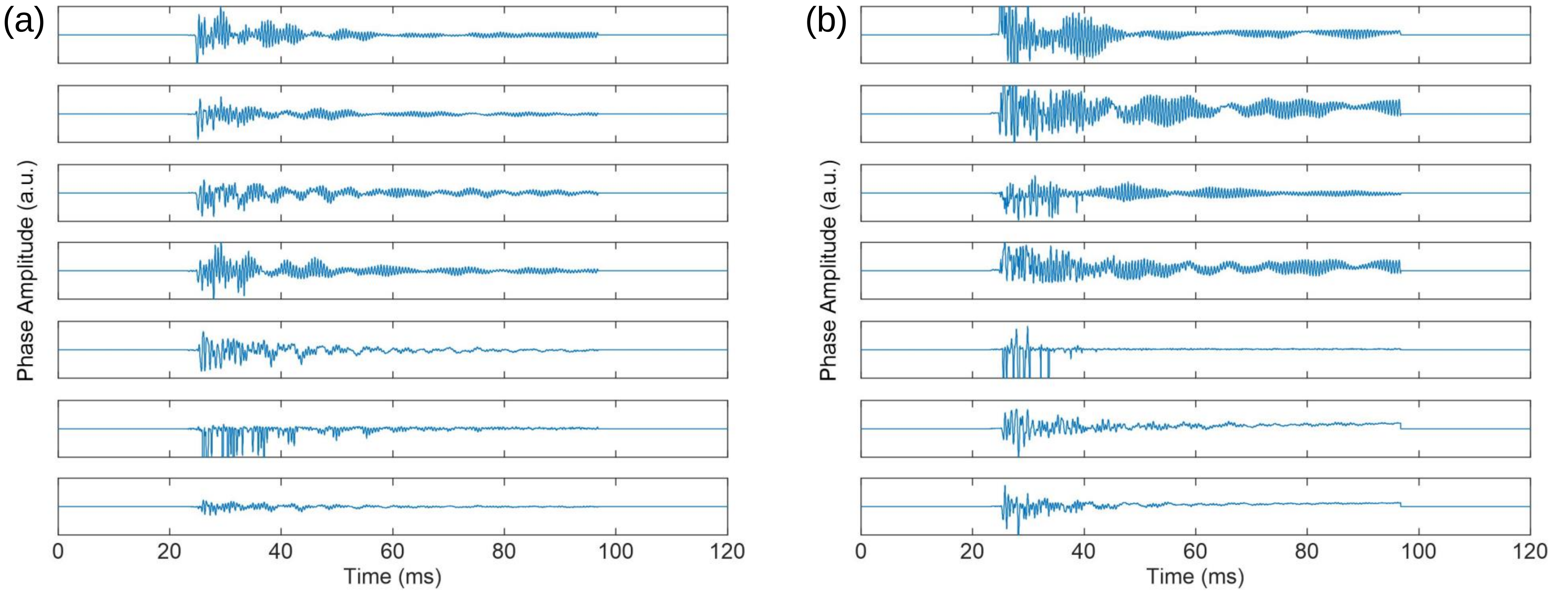
Distributed Fiber Sensor Enabled Big Data Analytics for Pipeline Monitoring



Distributed Acoustic Sensing (DAS) System with Rayleigh Enhancement

- ϕ-OTDR based DAS based on 3x3 demodulation scheme
- SNR enhancement by femtosecond laser enhanced Rayleigh backscattering (>35dB enhancement)
- Radiation-resilient and high-T stable
- Highly adaptable for complex structures & harsh environments (corrosion etc.)
- High spatial resolution measurements
- High bandwidth measurement (100 kHz)

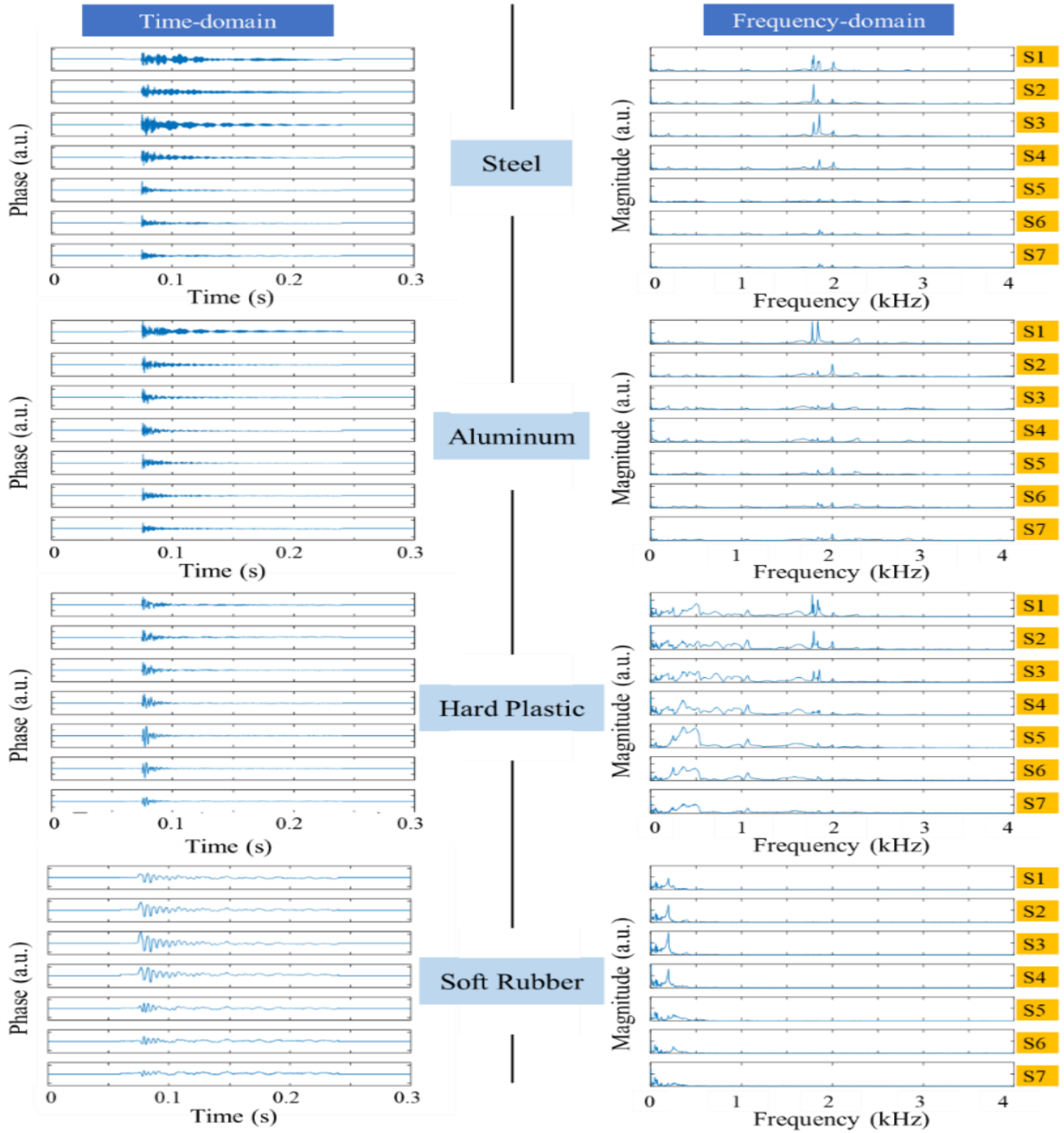
Distributed Fiber Sensor Enabled Big Data Analytics for Pipeline Monitoring



Time-domain acoustic phase signals measured by 7 sensors with (a) healthy, and (b) 8-mm defective elbows

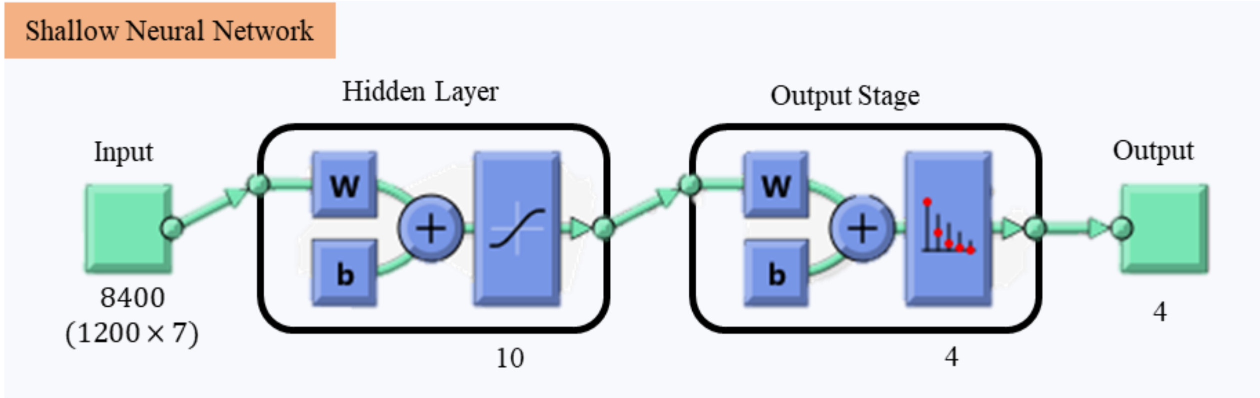
- Changes of phase signals due to elbow connectors with different defect depths (0 ~ 8 mm)
- Machine learning is efficient and effective to analyze minor variations in phase signals

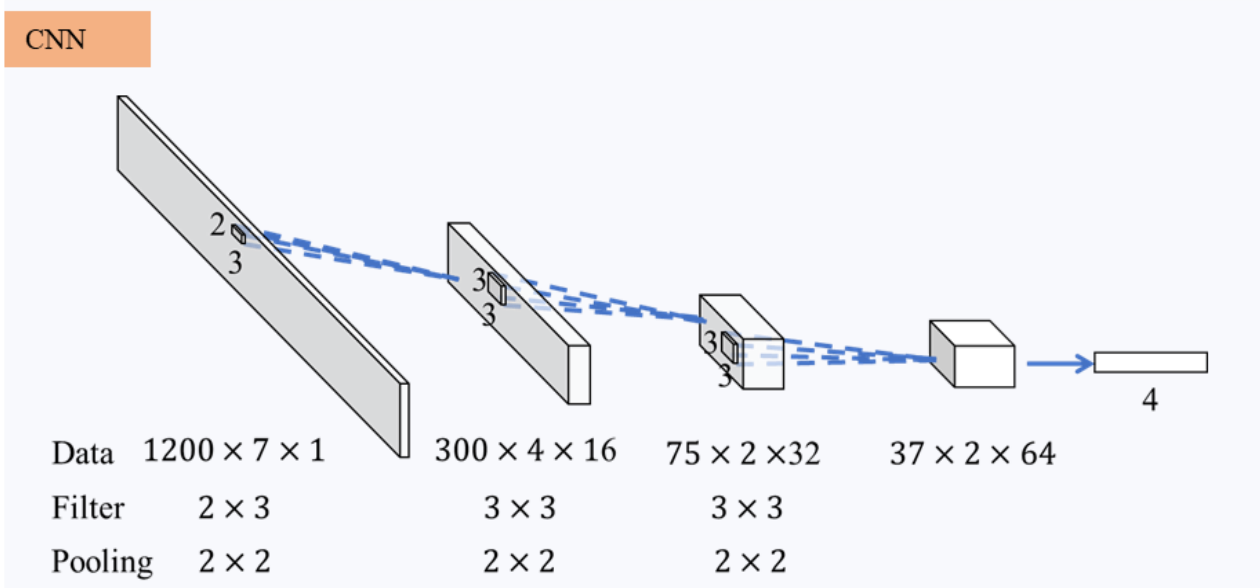
Identification of Extrinsic Acoustic Events



- 4 types of hammer heads to mimic different external impact events & destructive effects
  - Steel & aluminum (1.5 ~ 2 kHz)
  - Plastic (< 1 kHz, 1.5 ~ 2 kHz)
  - Rubber (< 1 kHz)
- Shallow & deep neural networks are trained to identify 4 external perturbation events
- Useful for monitoring the intrusion process & the severity of those types of damages

Identification of Extrinsic Acoustic Events



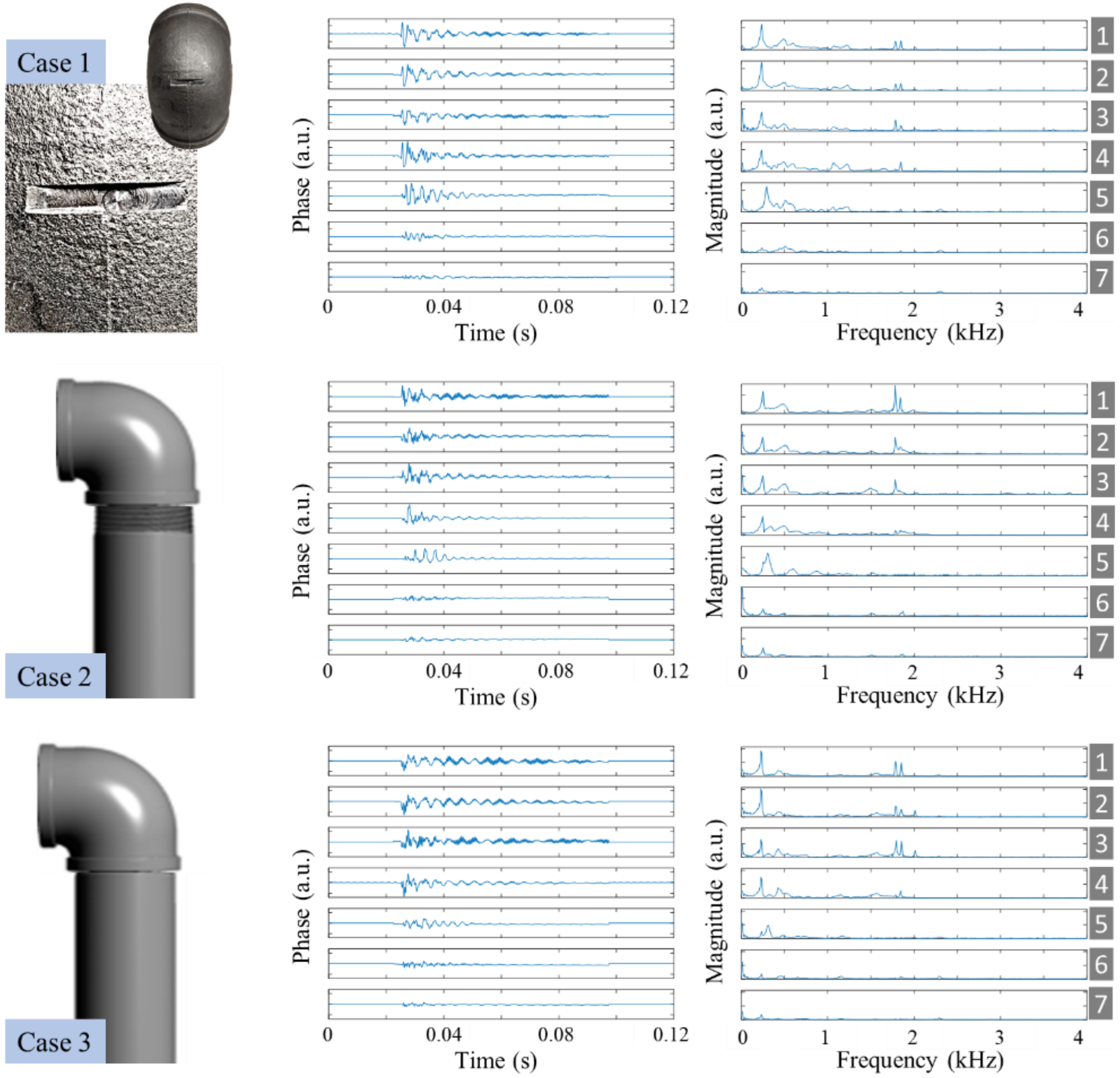


Classification result of 4 types of extrinsic acoustic sources

Material	Shallow Neural Network	CNN
Rubber	80% − 100%	85% − 100%
Plastic		
Aluminum		
Steel		

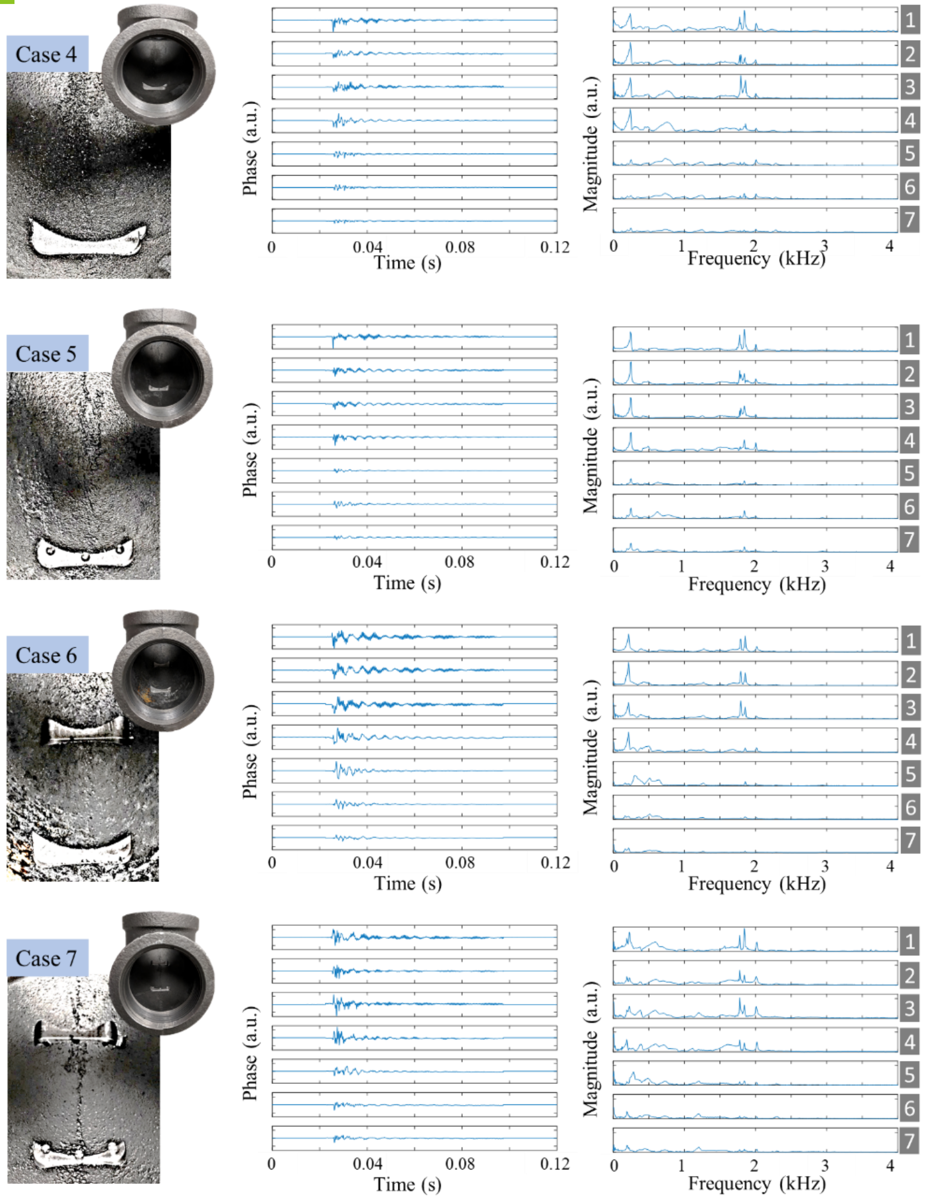
- Each classification runs 10 times to determine the uncertainty of data selection and obtain accuracy range
- Both can reach over 80% accuracy

Identification of Intrinsic Structural Corrosion (7 cases)



- Case 1: External corrosion, a trench on the outer wall
- Case 2: Galvanic corrosion, loose connection
- Case 3: Defect-free elbow connector

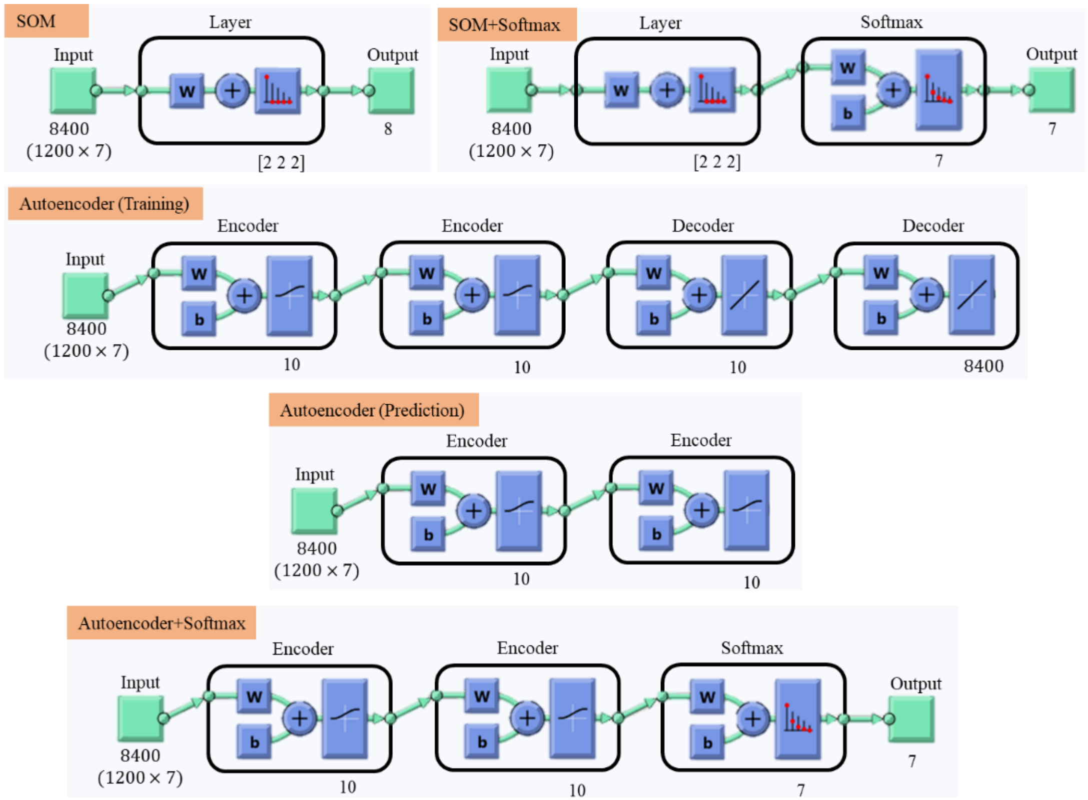
Identification of Intrinsic Structural Corrosion (7 cases)



- Case 4: 1 cutting groove
- Case 5: 1 cutting groove with 3 drilling holes
- Case 6: 2 cutting grooves
- Case 7: 2 cutting groove with 6 drilling holes

- Size information
  - Groove: 1.5 in. (L) × 0.25 in. (W) × 0.08 in. (H)
  - Hole: 0.125-in. diameter, 0.2-in. depth

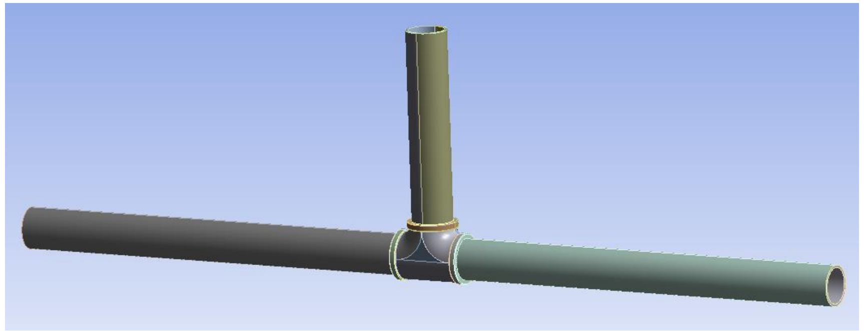
Identification of Intrinsic Structural Corrosion (7 cases)



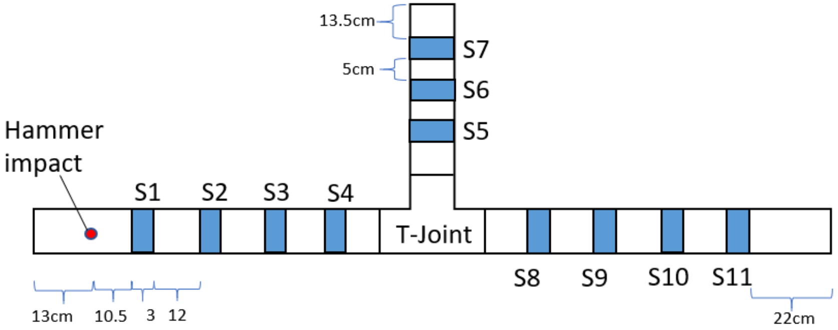
Scenario	Shallow	CNN	SOM	SOM +Softmax	Auto-encoder	Autoencoder+Softmax
Normal	97.1% – 100%	94.3% – 100%	71.4% – 83.3%	74.3% – 85.7%	73.8% – 84.5%	94.3% – 100%
Loose						
1 inner groove						
1 inner groove and 3 holes						
2 inner grooves						
2 inner grooves and 6 holes						
1 external trench						

- 94% accuracy is achieved by supervised learning compared to >71% by unsupervised learning
- Autoencoder+Softmax achieves over 94% accuracy

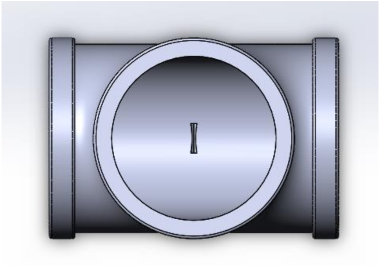
Hammer Impact DAS Response Simulation for Pipeline



(a) Pipeline assembly: Two long pipes and one short pipe joined with a T junction



(b) Sensors and hammer impact location



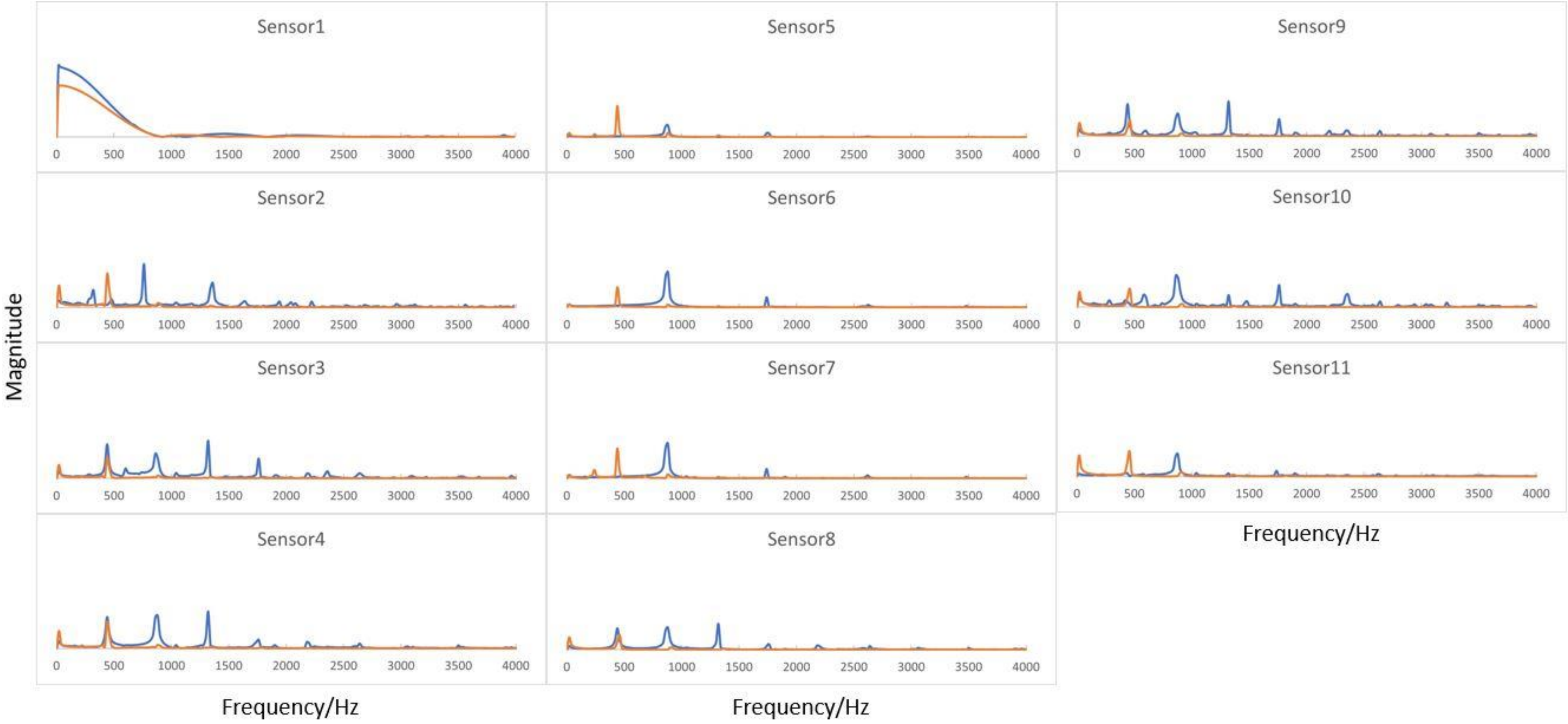
(c) Groove defect (1mm thickness)

Figure1: Pipeline assembly, loading and sensor configuration

- Method: Transient Structural Analysis using Finite Element Modeling
- Modal analysis was conducted to determine the natural frequencies of the model.
- An impact force of amplitude 1000 N and time duration 4 ms was applied to model a hammer impact.
- The structural response of the model was obtained using a transient structural analysis.

Hammer Impact DAS Response Simulation for Pipeline

(-----) indicates damaged response while (----) indicates healthy response.



Looking Ahead

- Develop new fibers for through jacket sensor writing (Patent pending)
- Develop and test fiber sensors to perform multitude measurements (DAS, Temperature, Flow)
- Develop fiber sensor with proper packaging for easy installation (Patent pending)
- Reduce cost of DAS/DTS interrogation systems based on modeling outcome

- Perform extensive FEA modeling to simulate acoustic response for all type of defects
- Machine learning using combined data of experiment and simulation
- Demonstrate pipeline testing in field

Ahmad Al Rashdan, Ph.D.
Instrumentation, Control, and Data Science, NST, INL

Machine Learning for Autonomous Drones Operations

Machine Learning & Artificial Intelligence Symposium

October 16, 2020

Idaho National Laboratory

Drones Uses in a Nuclear Power Plant

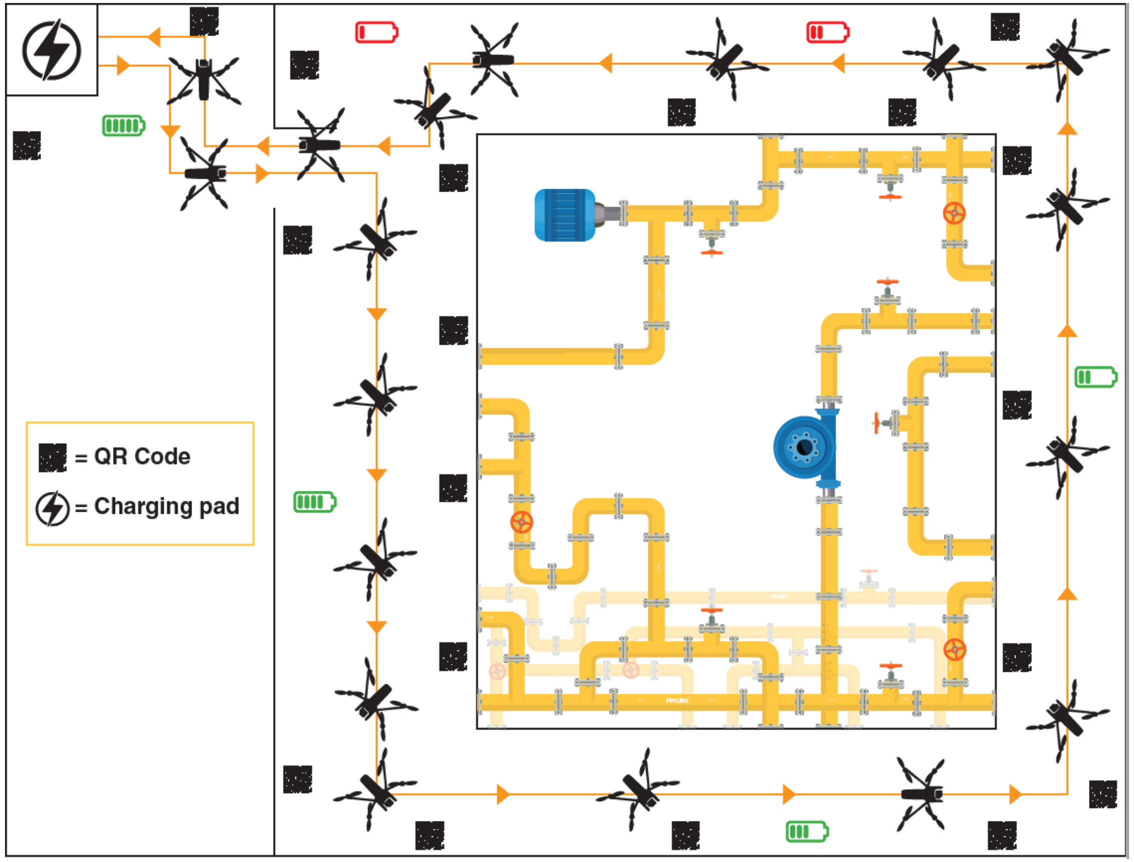
- Operator rounds
- Security rounds
- Radiation Monitoring
- Inspections
- Surveys
- Monitoring

Drones can:

- eliminate/reduce the human role and save cost.
- increase activities frequency
- increase fidelity (broader sensory perspective)
- access hazardous locations

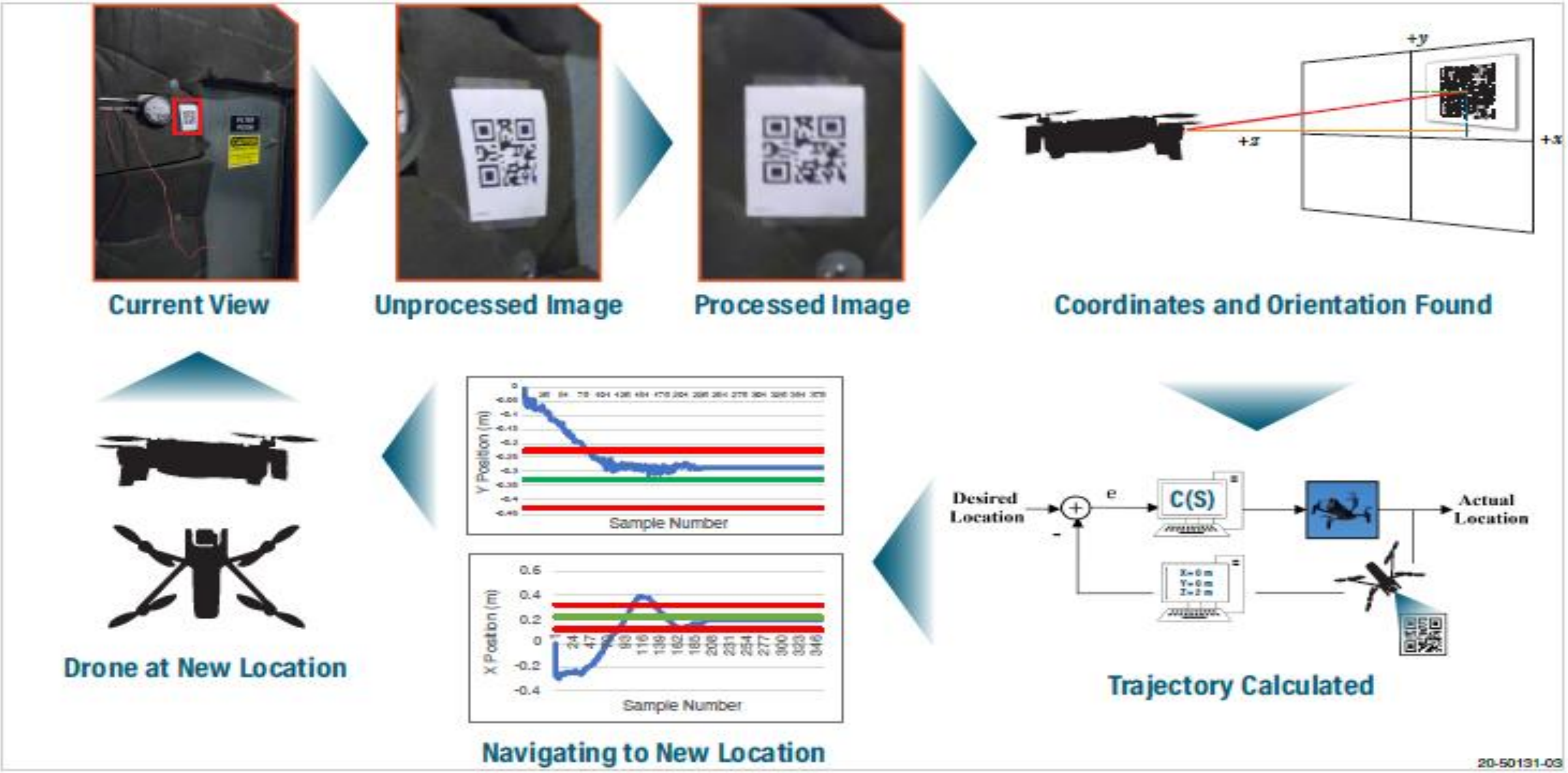
Drone Uses can Drive ML/AI Development

- ML/AI can enable drones to perform visual functions:
  - Classifying objects (e.g. gauges)
  - Recognizing events (e.g. fire, leak, etc.)
  - Identifying objects (people, ladder, etc.)
- ML/AI can enable drone to autonomously navigate in an environment.
  - Route Operable Unmanned Navigation of Drones (ROUNDS)



Route Operable Unmanned Navigation of Drones (ROUNDS)

Route Operable Unmanned Navigation of Drones (ROUNDS)



Current Status

Benefits

- Drone agnostic- Currently using OTS drone (low cost)
- No additional hardware needed for the drone
- QR codes are printed on A4 sheets- QR codes can be easily added for change of conditions
- Way points are fed through a mapping table or imbedded into the QR codes
- Very accurate (few inches accuracy)
- Utilize external computational resource for analysis

Analysis of Work Order Data for Cross-Utility Trends

Dave Olack, Principal Technical Leader
Nuclear Sector – Plant Engineering
Charlotte, NC

October 16, 2020

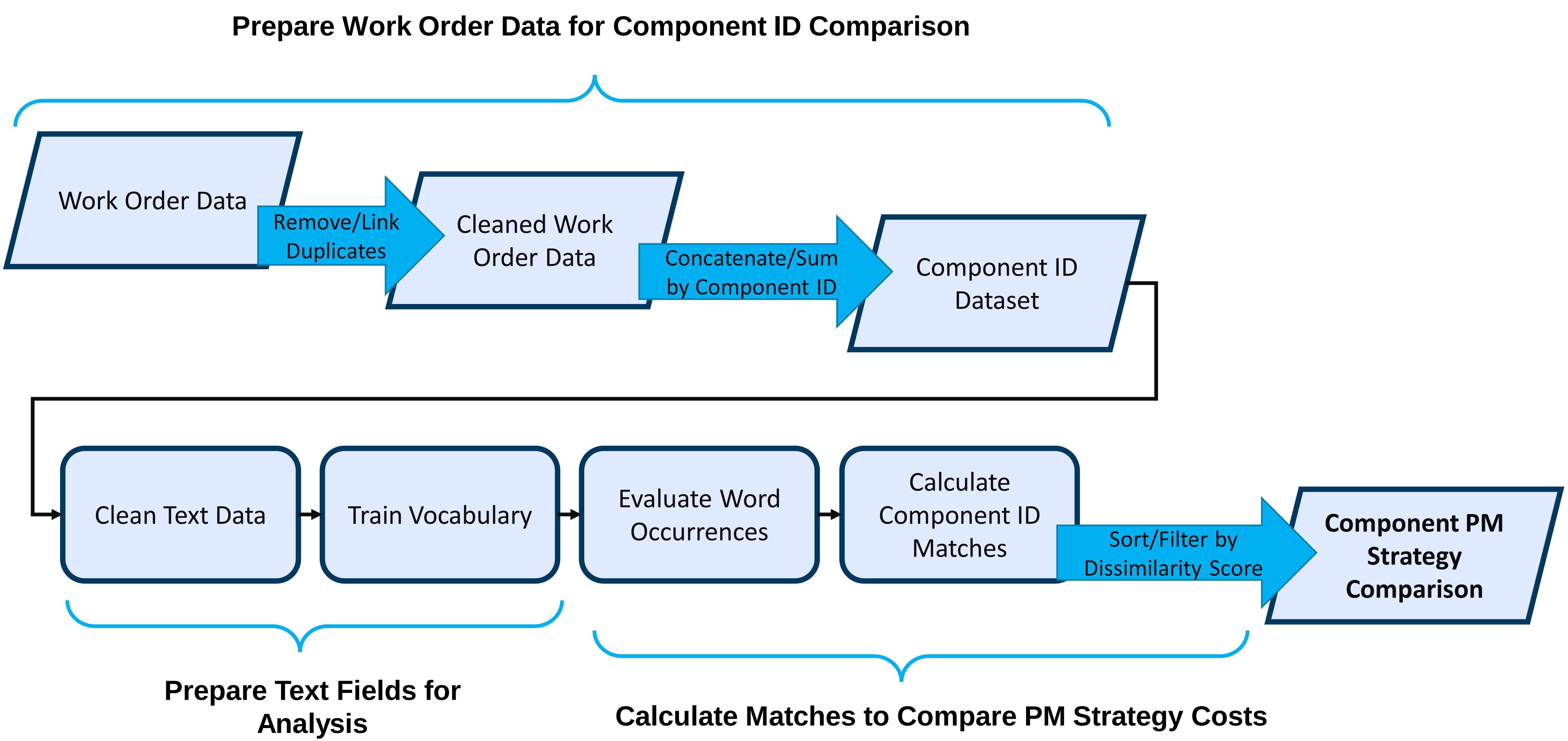
Background

- Commercial nuclear power utilities have large amounts of equipment maintenance records captured over many decades
- Due to a combination of advancements in computational capabilities and external market financial pressures on the nuclear power industry, EPRI has engaged in a project to analyze and more effectively utilize maintenance data in order to implement more cost-effective preventative maintenance (PM) strategies
- Some utilities have applied a combination of natural language processing (NLP) and an artificial neural network to evaluate similar plant process data to improve the administration and evaluation of programmatic data to reduce the required labor resources.

Project Objective

- Utilizing machine learning (ML) and data analytics (DA), determine to what extent these analysis tools can analyze large volumes of equipment data and provide insights leading to improving plant equipment reliability and/or reduce significant equipment related events
  - EPRI has collected approximately 18 million maintenance work order records from 10 utilities over the last few years
- Using NLP, compare the work order history of similar components across a number of different utilities and plants
  - Compare statistical annual costs of each matching (similar) component with existing PM strategy
- Evaluate the impact of different PM strategies based on total CM and PM costs (both labor and material)

PM Strategy Comparison Overview

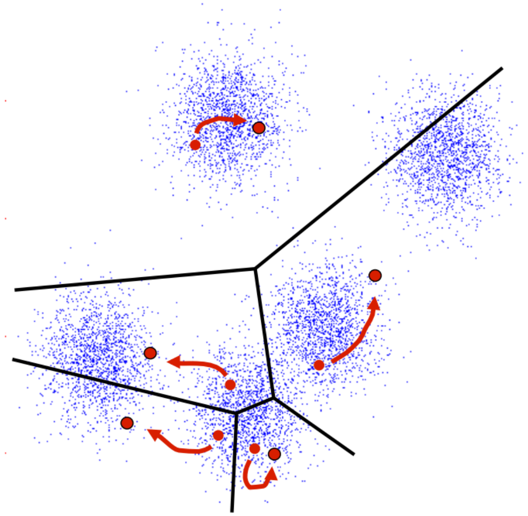


Challenges

- Data Quality
  - These records are in a variety of host database software programs
  - There is not a standard set of data fields utilized by all utilities
  - Due to the variation of original plant architect engineers, system and component IDs vary
  - Within the industry there is not a standard set of acronyms
  - High dollar value and negative values for select labor hours and material costs require further text field review for resolution

Data Analysis of the Project

- Progress to Date
  - Develop and test the computational architecture and algorithms to be used to perform the data analytics
  - Created K-mode clustering algorithms and applied to an example dataset to establish initial data clustering and to identify data centroids
  - Created an acronym translation matrix and applied to a sample set of the dataset
  - Processing of text data fields and incorporated results into clustering analysis
  - Correlation of text field phrases with actual labor hours and costs



Data Analysis of the Project

- Statistical Analysis of Work Orders
  - Developed K-mode clustering approach to identify similar work orders
  - Performed statistical assessment of clusters to identify trends in material and labor costs
- PM Strategy Comparison
  - Developed approach to identify similar equipment at different sites and utilities
  - Developing the ability to examine the impact of different PM strategies on the overall maintenance costs

Annualized Material Costs and Labor Hours

Component ID	Site	Component Description	PM Hours	CM Hours	All Hours	PM Costs	CM Costs	All Costs
01-FP-P-2-PUMP		diesel driven fire protection pump	19.30	179.00	198.30	38.80	5,436.30	5,475.10
01-FP-P-10-PUMP		warehouse diesel fire pump	15.20	31.90	47.10	0.00	629.90	629.90
M2P82P		fire pump	17.70	5.10	22.90	28.80	0.00	28.80
0FP03PB-PMPA-03PB-P30-<		pump diesel driven fire pump	64.30	47.00	111.30	1,017.80	5,091.80	6,109.50
01-FP-P-1-PUMP		motor driven fire pump	3.80	15.80	19.50	0.50	132.40	132.90

Queried Component ID

PM Strategies for each selected Component ID

PUMP-01 PM Strategy

PMID	PMFREQ	PMDESC	PMHRSAVG	PMCSTAVG
RE500071	364	Pump Packing Inspection and Adjustment (Annual PM)	7.84	0
RE500401	364	SERVICE BATTERY CHARGER	5.96	0
RE500067	728	Oil CNG in Diesel Driven FP (Angle Drive) & lube U-Joint that connects AD to ENG	8.36	77.99

Alternative Pump 02 PM Strategy

PMID	PMFREQ	PMDESC	PMHRSAVG	PMCSTAVG
RE500178	182	LUBRICATE BEARINGS eWP	3.09	0
RE500070	364	Perform Annual Pump Maintenance - Packing Inspection and Adjustment	8.22	0

Next Steps

- Continue with text processing and apply to additional component types
- Quantify impact of different PM strategies on overall cost (PM Cost + CM Cost)
- Progress the analysis with additional utility datasets

Together…Shaping the Future of Electricity

Hyun Gook KANG

Rensselaer Polytechnic Institute

Balanced and Harmonized Automation of Nuclear Application using Data Analytics and AI

Machine Learning & Artificial Intelligence Symposium

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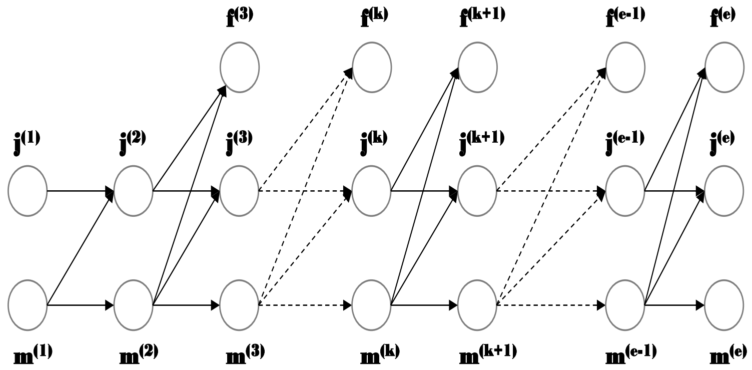
Nuclear Plant Automation

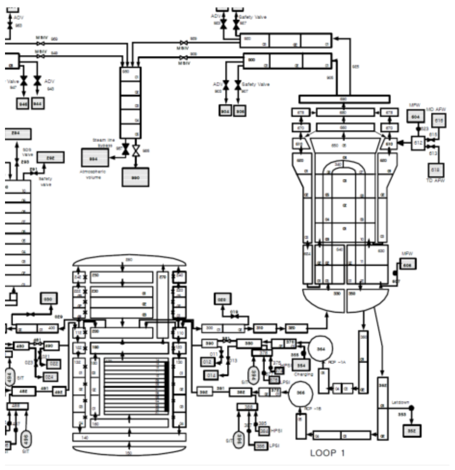


- Team: M. Golay (MIT), S. Cetiner, P. Ramuhalli (ORNL)
- Complex and dynamic plant response in broader scenarios must be captured
  - Problem area becomes very large
  - AI/ML with data analytic can be mobilized, but it is a black box approach
- Human operators (in control room or remote) must be considered
  - A white box approach is needed for better collaboration
  - The outcome of AI/ML must be verifiable, so physical meaning plays a key role
- The balanced and harmonized automation
  - How to express current plant status, target status, and operational strategy?
    - High precision in large problem in dynamic situation
    - Link with advanced sensors, monitoring algorithms, experts knowledge
  - Controllable size of AI applications which are connected by physical knowledge
  - Cells in the system space motivated by Markov CCM*
    - Movement through cell space → dynamic modeling, operational strategy
    - Current cell identification → connection with available information and expert knowledge
    - Relationship among cells → controllable problem size
    - Tagging with physical meaning → collaboration with human

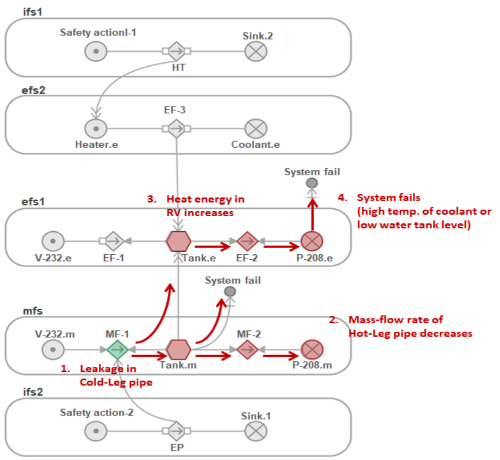
* Tunc Aldemir. "Computer-assisted Markov failure modeling of process control systems." *IEEE Transactions on reliability* 36.1 (1987): 133-144.

Integrated Artificial Reasoning

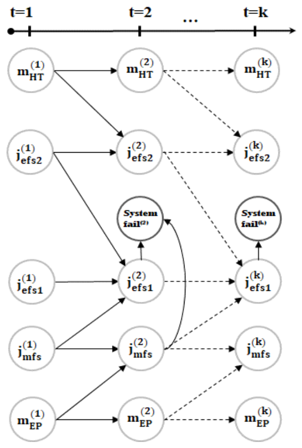
System P&ID



Functional Modeling (MFM)



Dynamic Bayesian Network

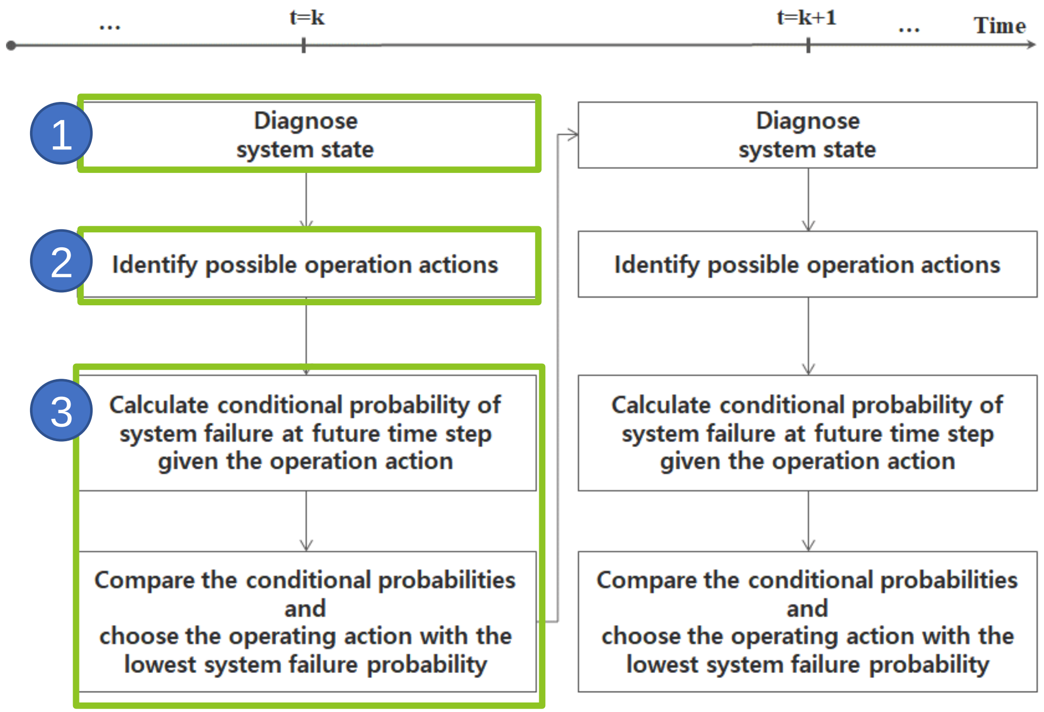


- Functional modeling represents system knowledge and dependency information
  - Connection between the nodes was identified by MFM (the arrows in Bayesian net)
  - No unnecessary joint probability calculations in Bayesian net
- The states of nodes were determined by unsupervised ML based on plant simulation results
  - The role of data analytics is limited to state discretization: defining the possible states in each node.
  - Computational cost was reduced comparing to equal width discretization (EWD)*

* Junyung Kim, Asad Ullah Amin Shah, and Hyun Gook Kang. "Dynamic risk assessment with Bayesian network and clustering analysis." *Reliability Engineering & System Safety* (2020): 106959.

Automated Reasoning Algorithm for Decision Support

General Flow of Decision Making Support



1. **System state is defined by integrated artificial reasoning.**

2. **Operators may have multiple options**

3. **Outcome of mitigation strategies can be quantified by the conditional probabilities**

$$\Pr(\text{System}^{(k+n)} = \text{FAIL} \mid \text{Strategy } 1, \text{System}^{(k)} = \text{'A'})$$

$$\Pr(\text{System}^{(k+n)} = \text{FAIL} \mid \text{Strategy } 2, \text{System}^{(k)} = \text{'A'})$$

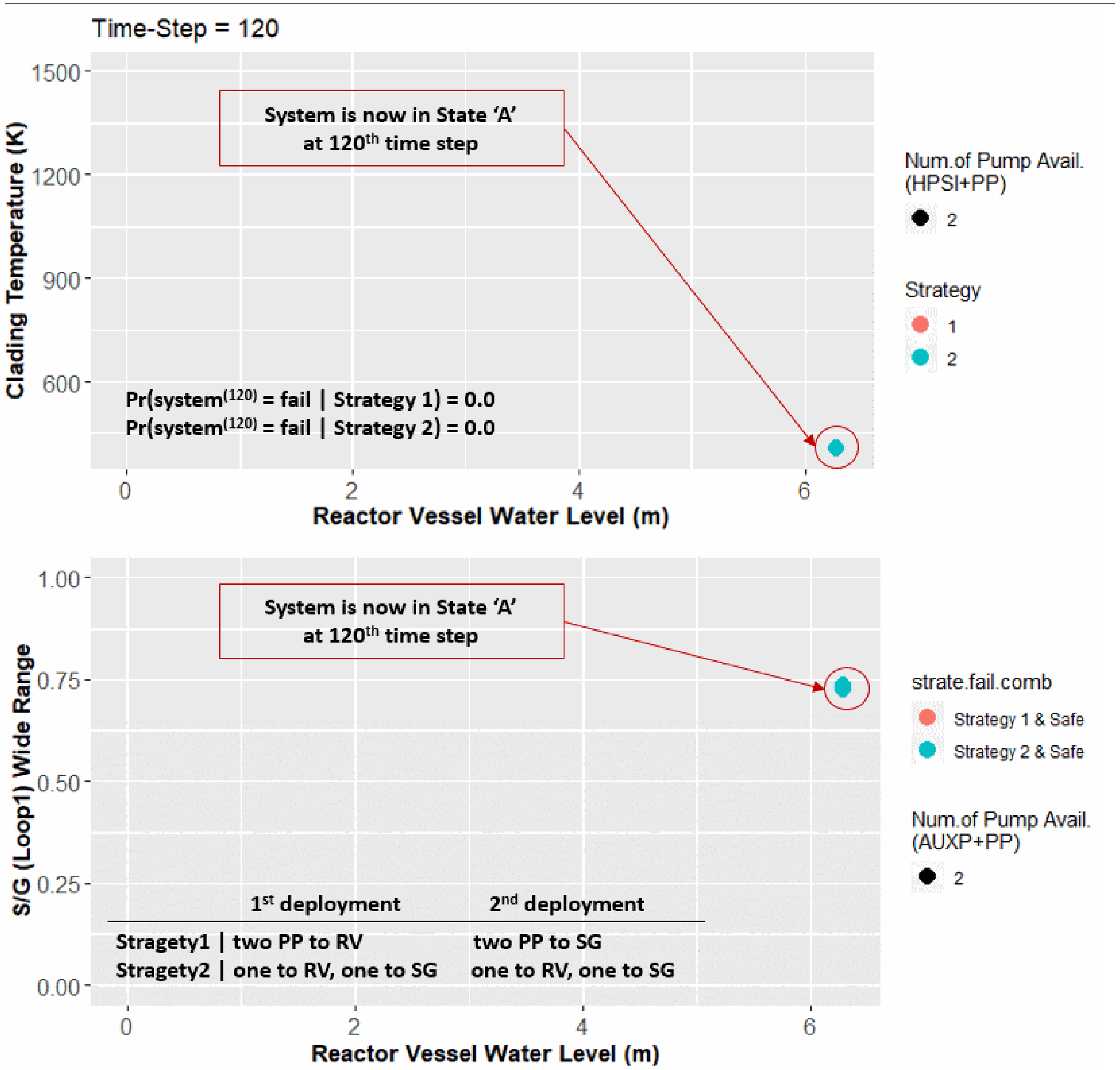
$$\Pr(\text{System}^{(k+n)} = \text{FAIL} \mid \text{Strategy } i, \text{System}^{(k)} = \text{'A'})$$

$$\vdots$$

Example: FLEX Strategy Decision Making

Arrangement of Portable Pumps Deployment

- Combined accident: LOCA * LOOP
  - Break size, battery time, EDG duration are unknown*
  - RELAP simulations + MFM model → Dynamic Bayesian network
- Operator decision making 1hr after accident
  - Four pumps are available and two can be deployed at one time**
  - Larger break requires direct RV refilling, while smaller break needs Aggressive cool-down
  - Two options
    - Strategy 1: Refilling reactor vessel in priority
      First two pumps deployed to RV and next two to SG
    - Strategy 2: Refilling RV and Aggressive cool-down
      In each deployment, one to RV + the other to SG
- Integrated approach
  - Physical simulation results, physical inference reasoning, and ML are integrated into Dynamic Bayesian network
  - Joint probabilities for all connected states and nodes are calculated
- Conditional probability evaluates the options
  - $\Pr(\text{System}^{(end)} = \text{FAIL} \mid \text{Strategy } 1, \text{System}^{(120)} = 'A') = 0.2963$
  - $\Pr(\text{System}^{(end)} = \text{FAIL} \mid \text{Strategy } 2, \text{System}^{(120)} = 'A') = 0.1111$



Note: * Break size 1 (m^2) ∈ {0.0006, 0.0012, 0.0018} ; Break size 2 (m^2) ∈ {0.0005, 0.0007, 0.0009} ;
Battery time (hr.) ∈ {3, 4, 5}, EDG working time (hr.) ∈ {3, 4, 5}
**Portable pump arrangement time: first deployment (hr.) ∈ {4, 5, 6} ; second deployment (hr.) = 1.5 hr after 1st deployment

Looking Ahead

- Integrated artificial reasoning method is important
  - Many possible sources of information can be merged for the best decision making
  - Mathematical expression serves as the basis of verification and validation
  - Well organized analysis provides dependency information which reduces computational cost
- Connection between AI/ML outcomes with Physical meaning is challenging
  - It is inevitable for the collaboration with human and for the utilization of prior knowledge
  - A systematic method to back-track the cluster’s physical meaning is under development
- Automation should be verifiable
  - For enhanced traceability and physical inference, the system state needs to be carefully defined and identified. This state concept will be the start point of verification
  - Automated decision making algorithm will have better applicability when it is balanced with human operator’s power of verification
- Understandable AI
  - This is one of possible approaches to achieve the understandable AI

Machine Learning & Artificial Intelligence Symposium

October 16, 2020

The Ohio State University

Smart Piping & Instrumentation Diagram Drawing Recognition

Carol Smidts

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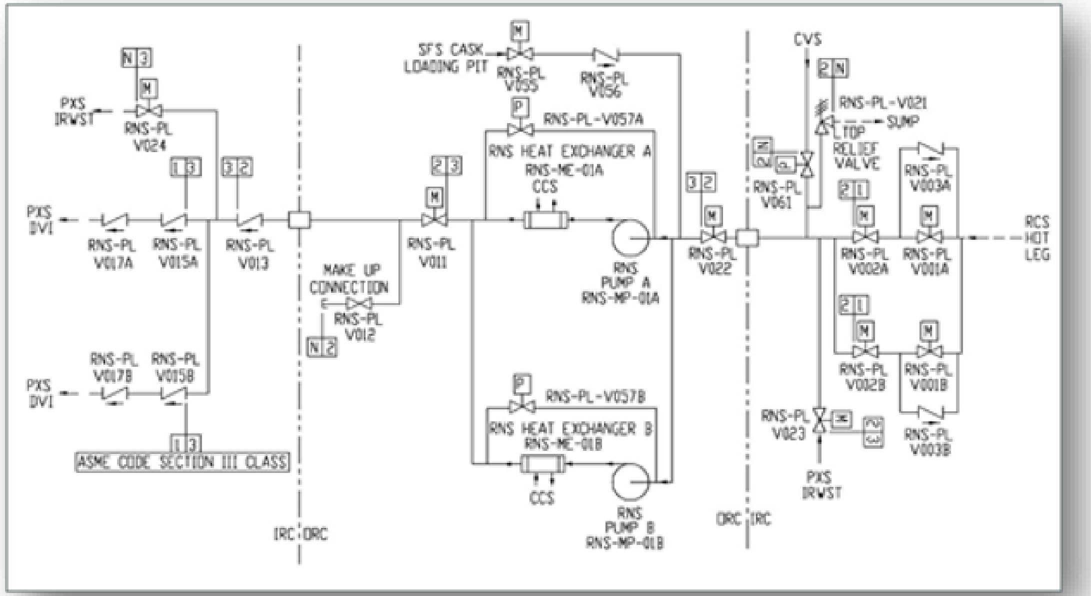
The Ohio State University

Topic Introduction

- Piping and Instrumentation diagrams (P&ID) are one of the most commonly used drawings to describe components and the relationships between components in nuclear power plants.
- They are inputs to safety analysis and analysis related to O&M.
- Manually extracting information from P&IDs is time consuming, and error prone.
- Our research aims to use advances in neural networks to automatically extract all relevant information from P&IDs.

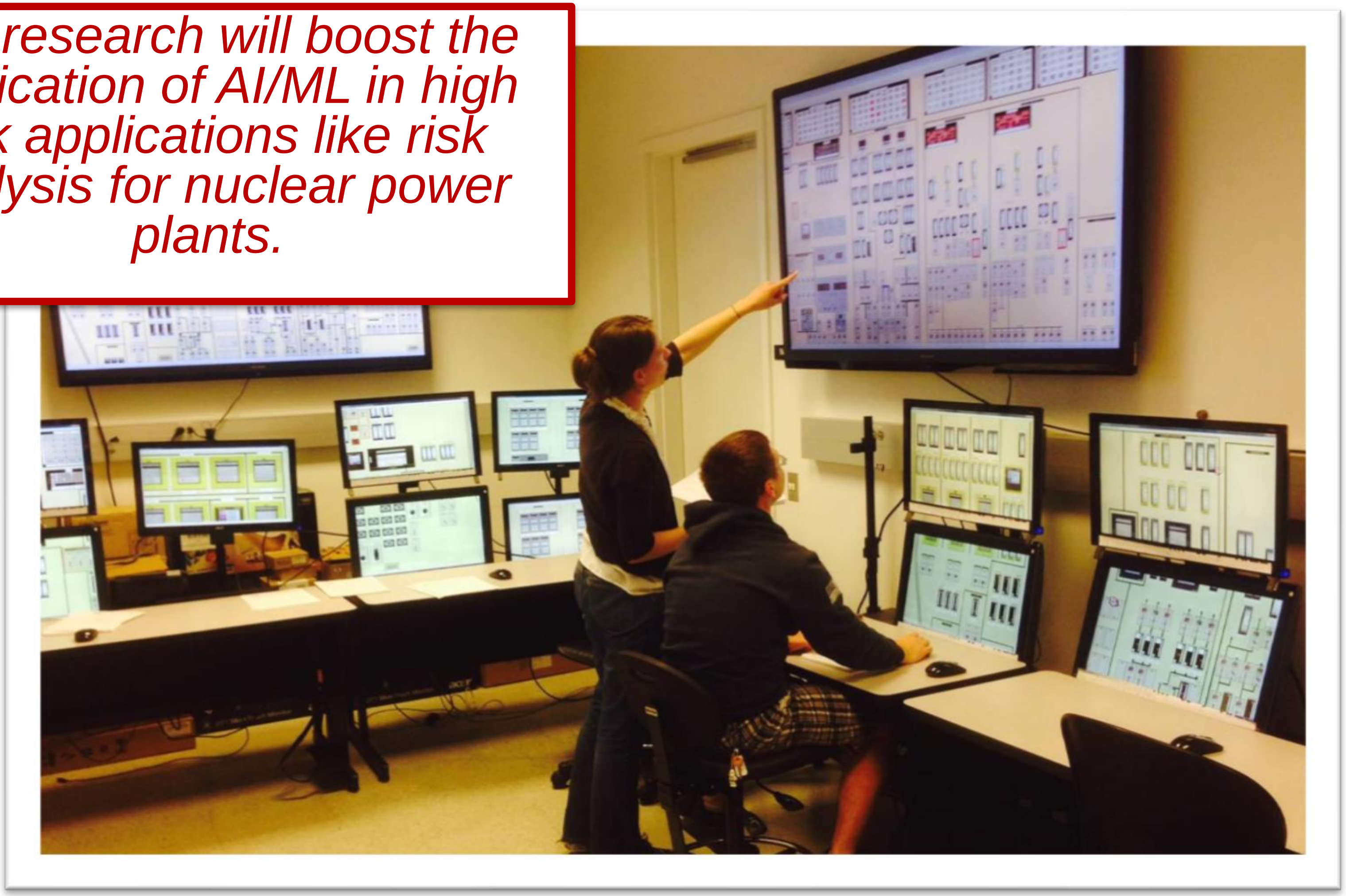


P&ID for Residual Heat Removal System*

*Westinghouse Electric Company LLC, 2011. AP1000 Design Control Document No. APP-GW-GL-700, Rev. 19

Why it is relevant to ML/AI Future

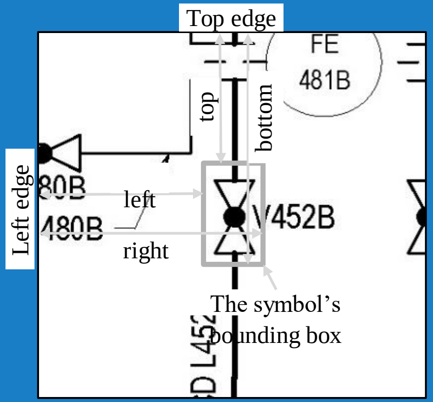
The research will boost the application of AI/ML in high risk applications like risk analysis for nuclear power plants.



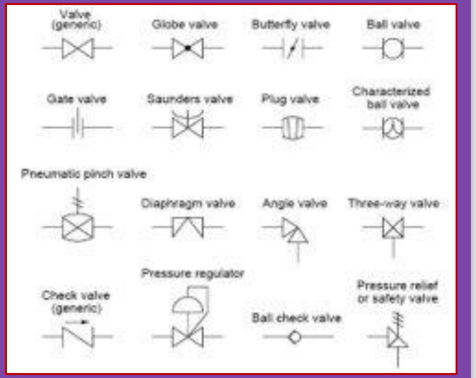
(OSU's Nuclear Power Plant Simulator running the GSE Systems GPWR)

Challenges*

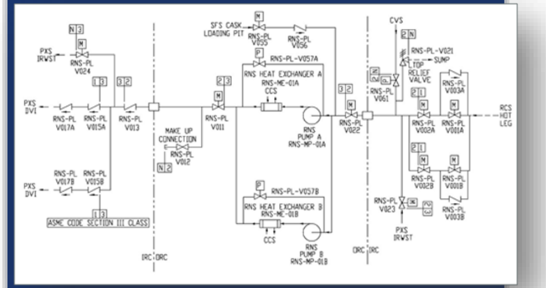
Little Training Data



Diverse Symbols



Small Objects



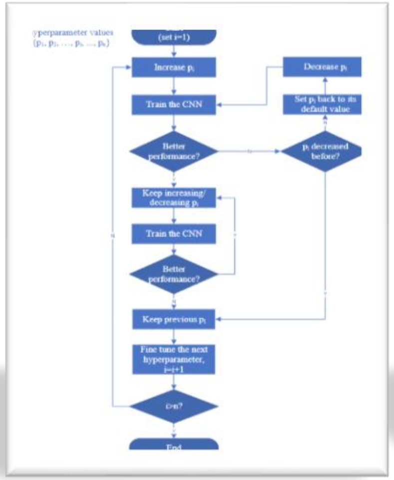
*Gao, Wei, Yunfei Zhao, and Carol Smidts. "Component detection in piping and instrumentation diagrams of nuclear power plants based on neural networks." *Progress in Nuclear Energy* 128 (2020): 103491.

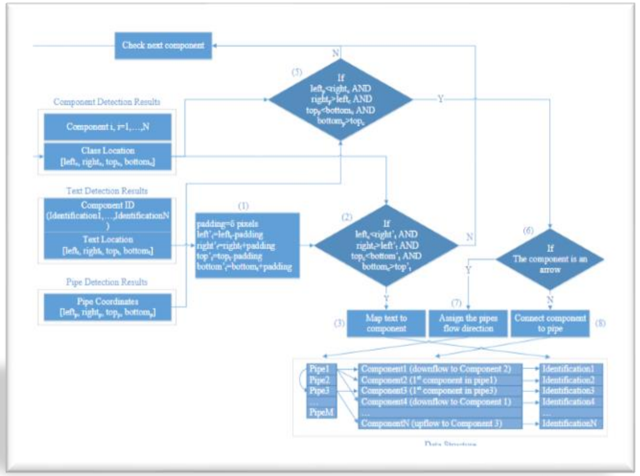
Methodology*

Data Preparation
- Data Source: DCD
- Data Grouping
- Label Images
- Data Augmentation
- Split Datasets

Detection
- Faster RCNN
- Hyperparameters Configuration
- Component Detection
- Text Detection

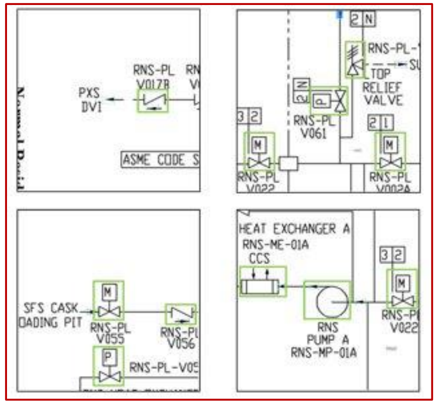
Association
- Map Text to Component
- Connect Components to Pipes



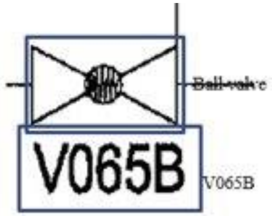


*Gao, Wei, Yunfei Zhao, and Carol Smidts. "Component detection in piping and instrumentation diagrams of nuclear power plants based on neural networks." *Progress in Nuclear Energy* 128 (2020): 103491.

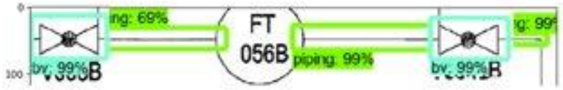
Illustration*



Cropping scheme*



Matching text to component*



Matching component to pipe*

Hyperparameters	Value Range	Value	Description
keep_aspect_ratio	Yes/No	Yes	Whether to let the resizer maintain the aspect ratio of the input image
min_dimension	>33	1400	Minimum dimension (in pixels) after resizing
max_dimension	>33	1400	Maximum dimension (in pixels) after resizing
first_stage_features_stride	8/16	8	Sliding strides (in pixels) of the RPN
height_stride	[2,16]	8	Vertical distance (in pixels) between 2 anchor boxes' center points
width_stride	[2,16]	8	horizontal distance (in pixels) between 2 anchor boxes' center points

Hyperparameters to tune*

*Gao, Wei, Yunfei Zhao, and Carol Smidts. "Component detection in piping and instrumentation diagrams of nuclear power plants based on neural networks." *Progress in Nuclear Energy* 128 (2020): 103491.

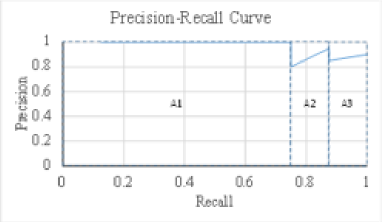
Results*

•Defining Groups.

	Group 1	Group 2	Group 3
Aspect Ratio	$[0.2,5]$	$[0.2,5]$	$(0,0.2)$ or $(5,+\infty)$
Scaling Factor	$(0,1.5)$	$[1.5,+\infty)$	$(0,+\infty)$

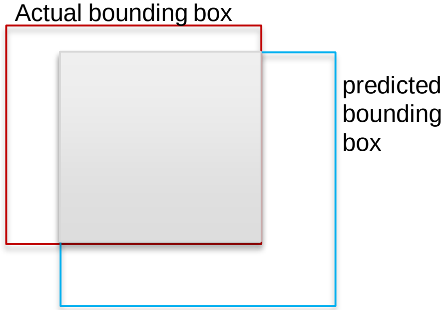
Metric:

AP(Average Precision) = A1+A2+A3



0.5IoU

TP, if intersection/union >=0.5



Mapping	ratio
Text to components	117/120
Component to pipe	315/315

Group no.	AP(%)
2	95%
3	92%

Test Results for Group 1

Class #	Class Name	AP (%)
1	Butterfly Valve (normally open)	100
2	Butterfly Valve (normally closed)	100
3	ball valve (normally open)	99.6
4	ball valve (normally closed)	100
5	check valve	100
6	flow control valve (normally open)	100
7	flow control valve (normally closed)	100
8	heat exchanger	99.8

Class #	Class Name	AP (%)
9	manual valve	100
10	motor pump	90.6
11	motor valve (normally open)	83.3
12	motor valve (normally closed)	100
13	orifice	88.1
14	pneumatic valve (normally open)	100
15	pneumatic valve (normally closed)	100
16	relief valve (normally open)	100

Class #	Class Name	AP (%)
17	relief valve (normally closed)	100
18	squib valve	100
19	solenoid valve (normally open)	100
20	Solenoid valve (normally closed)	100
21	tank	100
22	up_arrow	94.1
23	right_arrow	93.3
24	down_arrow	96.2
25	left_arrow	90.0

*Gao, Wei, Yunfei Zhao, and Carol Smidts. "Component detection in piping and instrumentation diagrams of nuclear power plants based on neural networks." *Progress in Nuclear Energy* 128 (2020): 103491.

Results* (cont'd)

Comparisons of the training time using different settings

	Initial Configuration	New Configuration	Configuration Ratio (%)	Initial TrainingTime (hours)	New TrainingTime (hours)	Relative TimeReduction (%)	InitialAP(%)	New AP(%)	AP Difference (%)
Hardware configuration	NVIDIA 2080Ti	NVIDIA RTX Titan	-	116 (for pipes)	-	20	92	-	-
Optimization algorithm	Momentum	Adam	-	116 (for pipes)	25 (for pipes)	78	92	91	-1.07
Batch size	1 (256×256)	16 (256×256)	1600	6	2hrs 50mins	47	67	66	-1.49
The dimension of the training images	1400×1400	1000×1000	51	116 (for pipes)	34 (for pipes)	70	92	84	-8.70
		256×256	3	116 (for pipes)	6 (for pipes)	95	92	66	-28.26
The number of training images	90% of the total images	50% of the total images	56	54 (for common symbols)	30 (for common symbols)	44	95	90	-5.26

The amount of time needed for traditional manual analysis is about 600 hours.
The total training time of the three detectors is about 200 hours.

*Gao, Wei, Yunfei Zhao, and Carol Smidts. "Component detection in piping and instrumentation diagrams of nuclear power plants based on neural networks." *Progress in Nuclear Energy* 128 (2020): 103491.

Contributions

- Previous work on P&ID information extraction in non-nuclear industry
- Work precedes deep learning
- No existing benchmark
- Not enough information to reproduce results
- Most recent work (FCN with Probabilistic Hough Transform 95%, 65% whereas our approach in average reaches 98%, 92%)
- No linking of information
- Our work systematically explores CNN applications and hyperparameter selection
- Our work defines a robust P&ID specific training data preparation and augmentation approach
- Our work links available information and can be used to automatically create safety analysis or other models.

Looking Ahead

- Combine the detection results of all patches
- Reduce detection error that comes from incomplete symbols resulting from cropping
- Use presumed component relationships to increase performance
- Extend to other nuclear plants and possibly to other industries that use the same standards
- Further optimize the training time while maintaining performance
- Requires an understanding of hyperparameters and their relation to performance
- Automatically generate the fault tree structure from the detected components and their relationships

Acknowledgement

- This research is being performed using funding received from the DOE Office of Nuclear Energy's Nuclear Energy University Program.

Thank you.

Questions?

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Applications of NLP in Reliability Engineering

Nicholas Zwiryk – Data Scientist

PKMJ Technical Services

Background

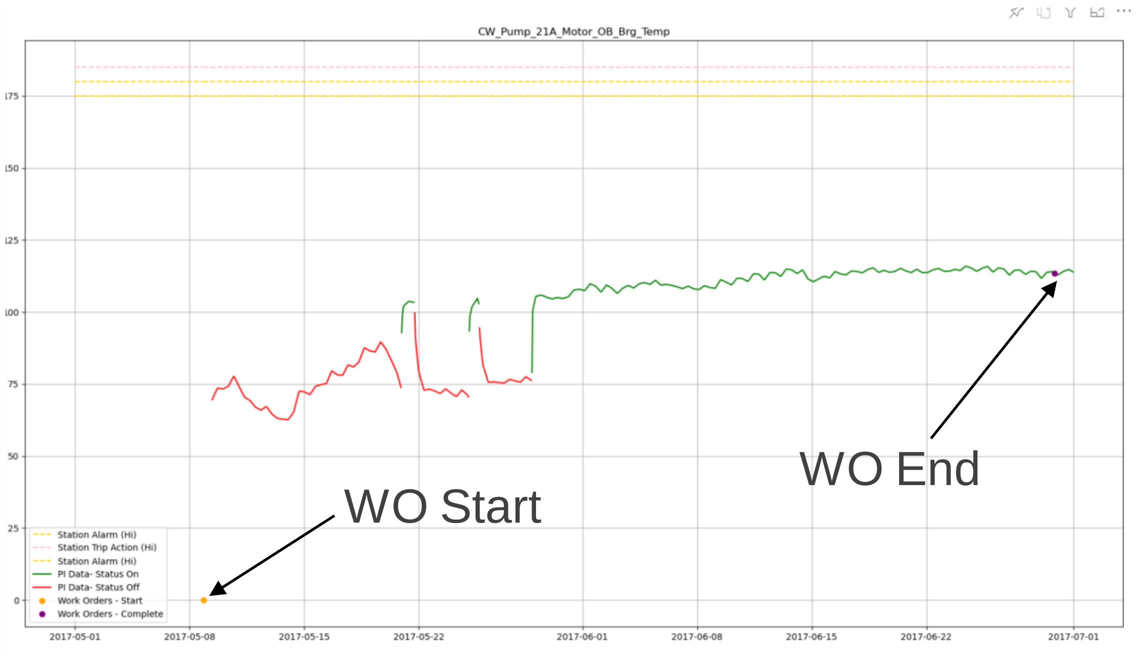
- **Objective:** Improve reliability and streamline maintenance for Circulating Water Pump & Motor sets
  - Critical to plant operation – helps to remove heat from system via river water
  - Large, expensive assets that the plant requires to safely operate
  - Rigorously maintained by plant engineers
- **Method:** Estimate number of events related to equipment degrading
  - Application with traditional reliability engineering methods
  - Ideally, this approach could be applied to other equipment and sites across the nuclear industry - not all equipment monitored by sensors
- **Datasets:** Maintenance records (work orders) & sensor data
  - Work orders contained description field – free form text

Why ML/AI?

- NLP able to extract valuable insights from previously unusable/unwieldy data
  - Incredibly difficult with traditional text analysis tools
  - Corroborates or challenges other data
  - Accuracy comparable to that of SME
- **Allows us to..**
  - More accurately estimate equipment degradation events
    - Goes beyond site work order labels and failure databases
  - Develop a rich history of equipment performance and maintenance
    - Not dependent on sensor data – can be used on any equipment with maintenance history
  - Validate work order part consumption data vs. work order description
    - E.g. work describes parts being used – but no stock is tied to work order (or vice versa)

NLP & Reliability Engineering

- Mixture of NLP and subject matter expert (SME) examination
- Utilizing NLP, classifiers were designed that would attempt to determine key facts and observations from the work order description
- Overlay this information with sensor data to observe performance trends and the maintenance response
  - To our understanding, this approach is novel
- Cross-validate extracted work order information with sensor data
  - Leverage SMEs to provide engineering knowledge and operating experience
  - Lends insights into interactions between operations and maintenance



Desc: “21A CW Motor Otbd Bearing Temp Fail wc”

PKMJ Technical Services
Engineering and Software Solutions

Challenges

- Free form text with many technical abbreviations and keywords
  - "CALIBRATE DIV 2 CORE SPRAY PUMP DISCHARGE FLOW SWITCH PER NE-6.6-EQMS.080"
  - "SODIUM HYPOCHLORITE DOSING PUMP 1 LEAK FROM DISCHARGE PIPE"
  - "23B IMPELLER TOUCHES CASING,REPLACE PUMP"
- Inconsistent, complex – but valuable – content
- Sample stratification difficult
  - Relying on site provided labels which may have bias
- SME annotation requires clear communication across disciplines
  - Strive for consistency
  - Objective as possible

Future Work

- Incorporate data from newly installed vibration sensors
- Support ongoing reliability engineering analytics
  - Survivability analysis, condition-based maintenance
- Analyze maintenance data traditions vs. sensor data
  - Equipment state vs. work order data response
- Utilize SMEs to identify sensor trends and corresponding modes of equipment failure
  - Use this information to automatically generate work packages
  - Analyze past work order part usage to correlate failure modes and parts issued for repair
- Apply to other equipment sets and sites

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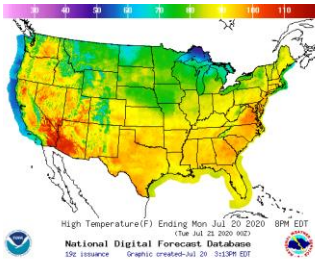
Uncertainty Quantification with Scientific Machine Learning

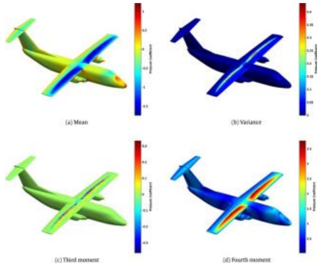
Machine Learning & Artificial Intelligence Symposium

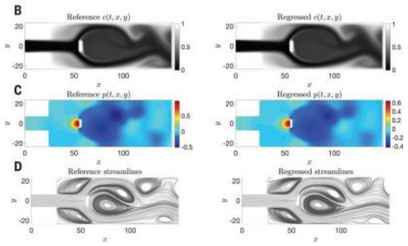
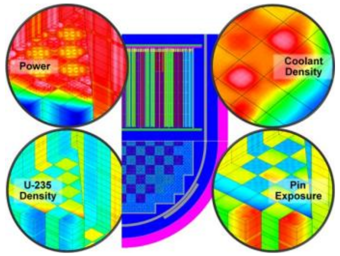
October 16, 2020

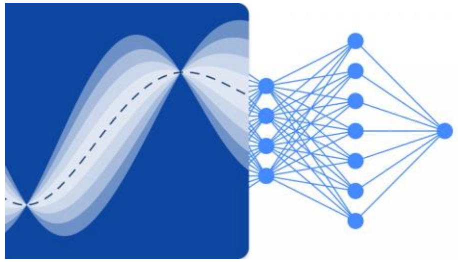
The importance of Uncertainty Quantification (UQ), sources of uncertainties

- Although M&S has made tremendous progress in many areas[1], there are always discrepancies between ideal in silico designed systems and real-world manufactured ones. Therefore, uncertainties must be quantified along with simulation to facilitate optimal design and decision making.
- UQ systematically treats various sources of uncertainties and propagates them through a computational model to produce predictions of Quantities-of-Interest (QoIs) with quantified uncertainty.
- **Sources of uncertainties**:
  1. Parameter uncertainty: due to ignorance in the exact values of input parameters or inherent variations
  2. Numerical uncertainty: due to numerical approximation errors, such as spatial/temporal discretizations
  3. Model uncertainty: due to simplifications in the model, such as missing/incomplete and inaccurate underlying physics. Also called model bias/error/discrepancy/inadequacy, or model form uncertainty.
  4. Experimental/data uncertainty: due to measurement noise
  5. Code/interpolation uncertainty: due to emulation (surrogate modeling) of expensive computer models





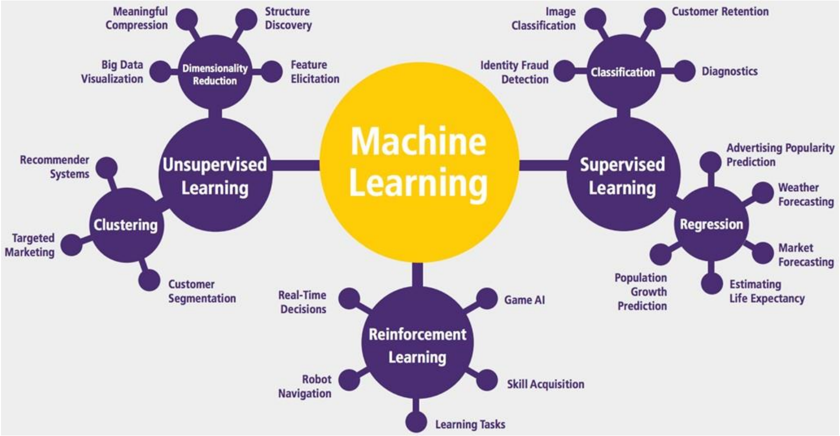



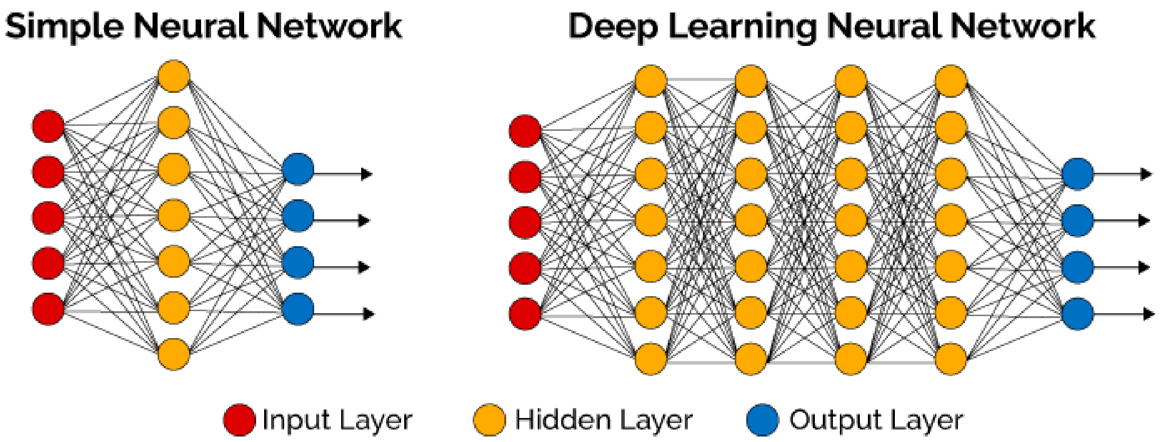


[1] Sources of figures, from left to right: (1) https://graphical.weather.gov/, (2) van den Bos et al. (2017). Non-intrusive uncertainty quantification using reduced cubature rules. Journal of Computational Physics, 332, 418-445. (3) https://www.sciencemag.org/news/2020/02/scientists-are-racing-model-next-moves-coronavirus-thats-still-hard-predict, (4) Raissi, M. et al. (2020). Hidden fluid mechanics: Learning velocity and pressure fields from flow visualizations. Science, 367(6481), 1026-1030., (5) https://www.ornl.gov/project/vera-cs-high-fidelity-lwr-core-simulator-casl, (6) https://www.inovex.de/blog/uncertainty-quantification-deep-learning/. The copyright belongs to the original author.

Use Machine Learning (ML) and Deep Learning (DL) for scientific computing and UQ

- Supervised Learning algorithms are more likely to be used since in M&S we generally have labeled QoIs.
- Unsupervised Learning algorithms can also be very helpful, especially dimensionality reduction together with UQ.
- ML/DL algorithms generally require large amount of training data and high-performance platforms (e.g., GPUs).
- They are typically used as a certain form of black-box surrogates or Reduced Order Models (ROMs). In certain cases, Physics-Informed ML/DL (PIML/PIDL) can be used to incorporate physical knowledge that comes from sources such as physical principles, constraints, expert feedback, initial/boundary conditions, etc.
- Code uncertainties (i.e., prediction uncertainties in ML/DL models) can be laborious to obtain. Using methods such as Monte Carlo Dropout[2], Deep Ensembles[3], Bayesian Neural Network[4], etc.





[2] Gal, Y., & Ghahramani, Z. (2016, June). Dropout as a bayesian approximation: Representing model uncertainty in deep learning. In international conference on machine learning (pp. 1050-1059).

[3] Lakshminarayanan, B., Pritzel, A., & Blundell, C. (2017). Simple and scalable predictive uncertainty estimation using deep ensembles. In Advances in neural information processing systems (pp. 6402-6413).

[4] Neal, R. M. (2012). Bayesian learning for neural networks. Springer Science & Business Media.

A new course: NE 795 Special Topics in Nuclear Engineering - Scientific Machine Learning

- AI/ML has been very successful in areas such as computer vision, natural language processing, etc. But its application in scientific computing is relatively new, especially in Nuclear Engineering (NE).
- Scientific Machine Learning (SciML) consists of computational technologies that can be trained with scientific data to augment or automate human skills.
- This course aims at augmenting the applications of AI/ML in NE scientific computing problems, and preparing the students for transformative solutions across various DOE missions. For example:
  1. Data-driven closure model development;
  2. Data-driven material discovery and qualification;
  3. Digital twins for integrated energy systems, SMRs and micro-reactors;
  4. AI-based autonomous operation and control for advanced nuclear reactors;
  5. AI-based diagnosis, prognosis and predictive maintenance;
  6. and many more. . .

1. Part 1: Fundamentals of Machine Learning
   - Perceptrons, Sigmoid Neurons and ANNs
   - Classifying Handwritten Digits and Gradient Descent
   - Backpropagation
   - Cross-entropy, Softmax and Negative Log-likelihood Cost
   - Overfitting and Regularization
   - Bias, Variance, Hyperparameters and Weight Initialization
   - Vanishing Gradient, Activation Functions and SGD Variations
   - Generalized Linear Regression, Subset Selection and Shrinkage
   - Gaussian Process Regression
   - Dimensionality Reduction with PCA
2. Part 2: Uncertainty and Sensitivity Analysis
   - Forward UQ
   - Inverse UQ
   - Prediction Uncertainty in ML/DL Models
   - SA Methods
   - Data-driven SA
3. Part 3: Advanced Topics
   - Physics-Informed Machine Learning (PIML)
   - Machine Learning in Nuclear Thermal Hydraulics
   - Bayesian Neural Networks (BNNs) and Variation Inference (VIs)
   - Convolutional Neural Networks (CovNets)
   - Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM)
   - Generative Adversarial Networks (GANs)
   - Variational Autoencoders (VAEs)

Computer projects from NE 795 - Scientific Machine Learning

1. Development of a Predictive Maintenance Framework using Bayesian Neural Networks
   – Andy Rivas and Kingsley Ogujiuba
2. Using an Artificial Neural Network to Speed Up Direct Numerical Simulation (DNS)
   – Anna Iskhakova
3. Demonstration of Advantages of Physics-Integrated Machine Learning for Fluid Mechanics Problems
   – Arsen Iskhakov
4. Implementation of Long-Short Term Memory (LSTM) for Turbulence Study of Single-phase Low Prandtl Fluid
   – Cheng-Kai Tai
5. Predict T/H parameters for Various Points in the BWR Stability Graph for the Hottest Assembly in Peach Bottom Unit 2 Reactor
   – Devshibhai Ziyad
6. Meta-Feature Landmarking for Efficient Model Selection in Ensembles
   – Edward Chen
7. Quantification of Uncertainty Introduced by Deep Neural Networks
   – Jess Williams
8. Application of Neural Networks for Predictions of the Axial Flux Profile in the SAFARI-1 Research Reactor
   – Lesego Moloko
9. Using Machine Learning Potential to Obtain Phonon Dispersion Curve
   – Yuqing Huang
10. Solving Ordinary Differential Equations by Deep Neural Networks
   – Ziyu Xie

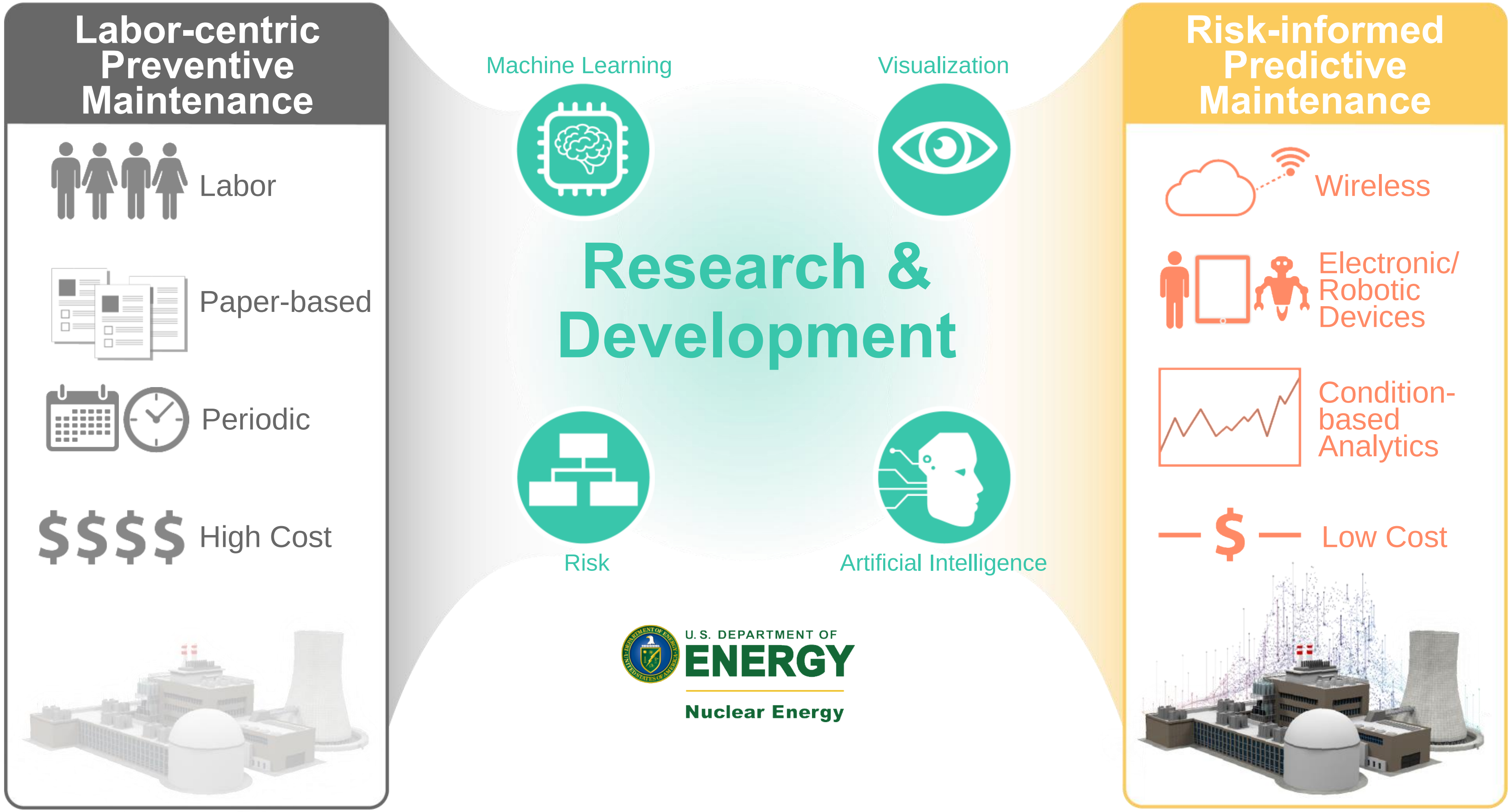
Koushik A. Manjunatha, Ph.D
Instrumentation, Controls, and Data Science

Federated Transfer Learning for Circulating Water Pump Motor Health Prediction

Machine Learning & Artificial Intelligence Symposium

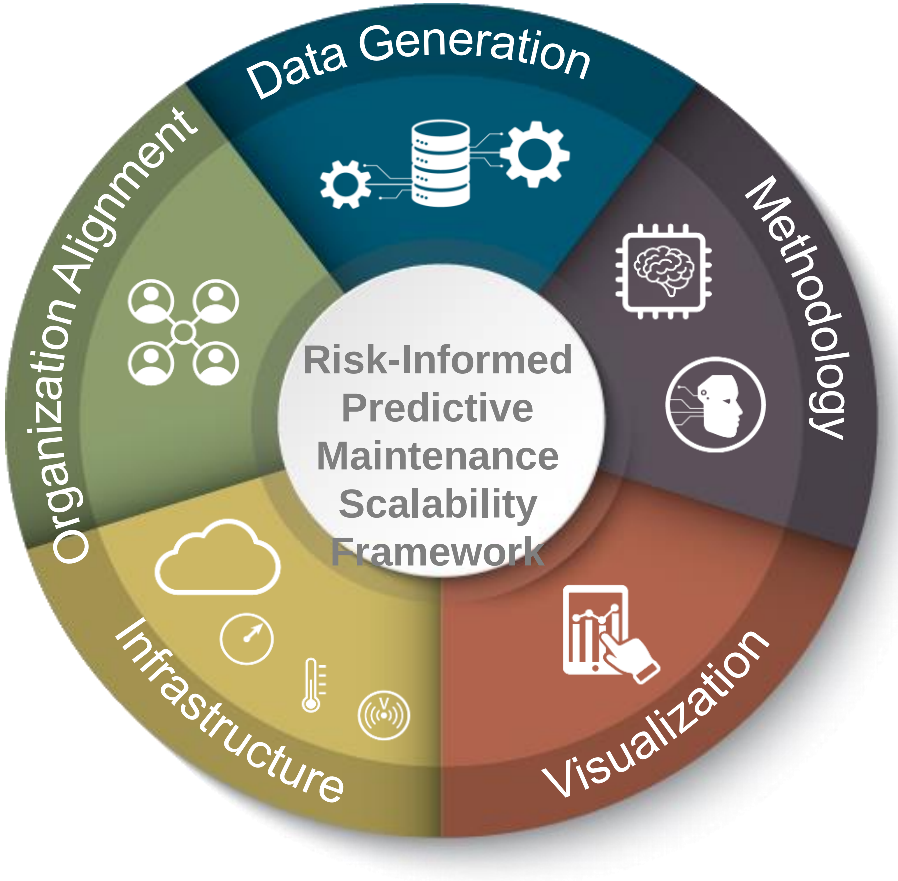
October 16, 2020

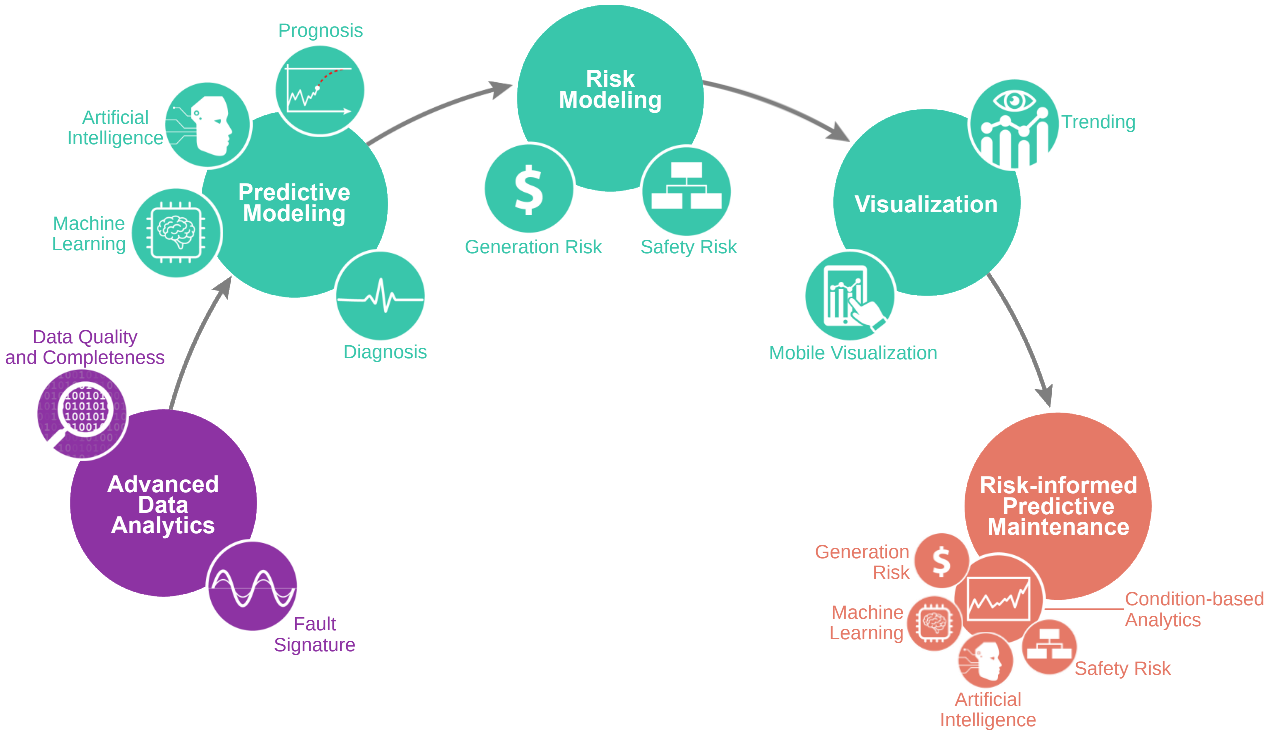
Risk Informed Predictive Maintenance Strategy*



* Agarwal, V et al., Deployable Predictive Maintenance Strategy based on Models Developed to Monitor Circulating Water System at the Salem Nuclear Power Plant (INL/LTD-1955637). Idaho National Laboratory, September 2019.

Scalability of Risk Informed Predictive Maintenance Strategy*





Scalability is defined as expanding capabilities of a target entity to meet current and future application-specific requirements

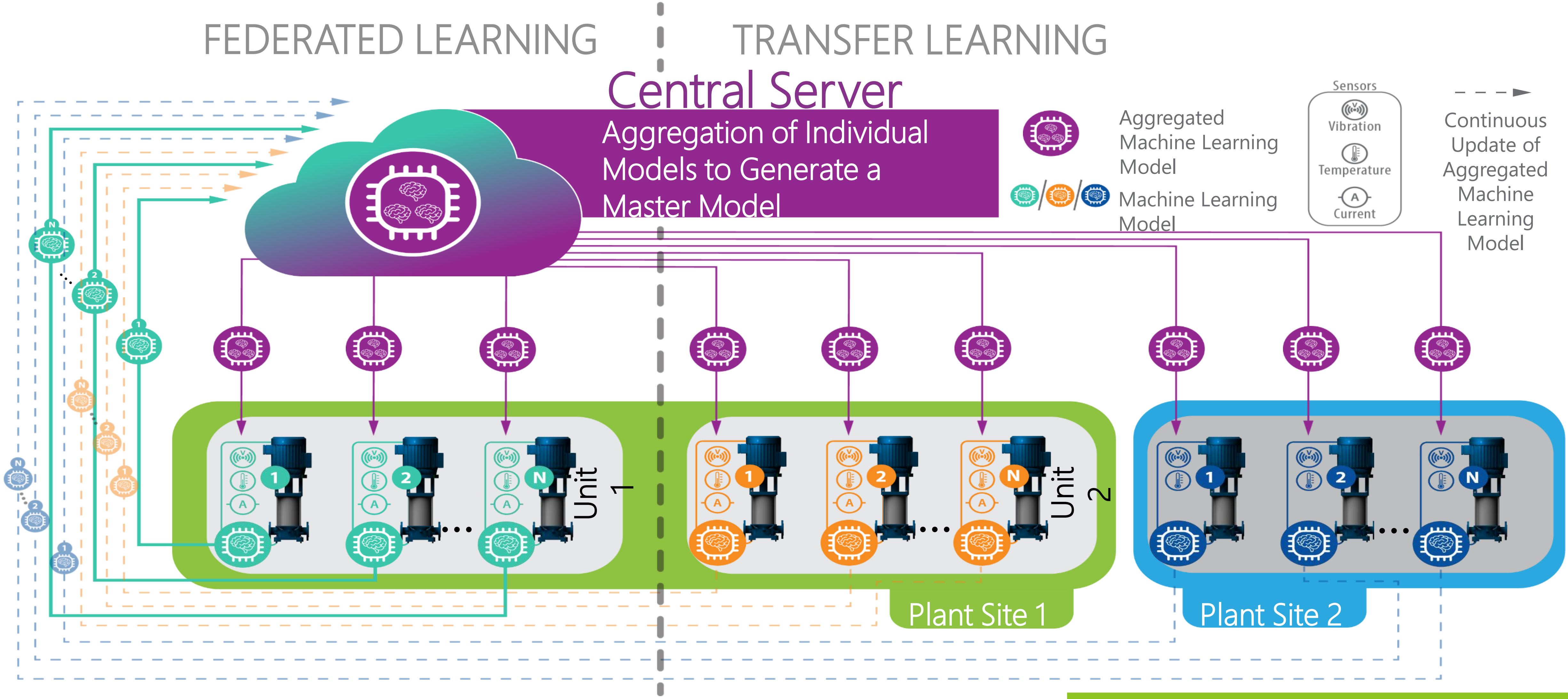
* Agarwal,V., Manjunatha, K., Gribok, A., Mortenson,T., Ulrich,T., Boring, R., and Harry, P. Scalability of a Risk-Informed Predictive Maintenance Strategy (INL/LTD-20-58848). Idaho National Laboratory, June 2020.

Significance and Impact of this Research

- Predictive maintenance are traditionally developed at component-level or at most at system-level

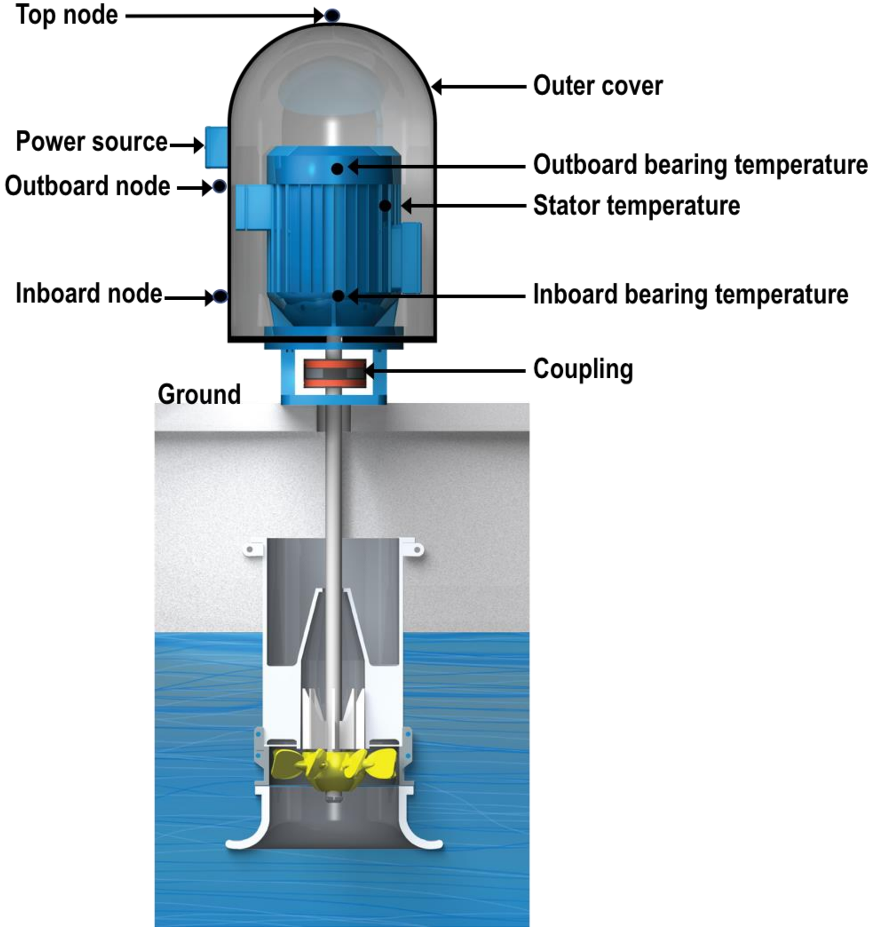
- Technology developed must be scalable across,
  - plant systems and
  - nuclear fleet

Federated Transfer Learning (FTL) Approach*



* Agarwal,V., Manjunatha, K., Gribok, A., Mortenson,T., Ulrich,T., Boring, R., and Harry, P. Scalability of a Risk-Informed Predictive Maintenance Strategy (INL/LTD-20-58848). Idaho National Laboratory, June 2020.

Circulating Water Pump (CWP) Data Types



A schematic representation of a CWS motor and pump with temperature measurement locations

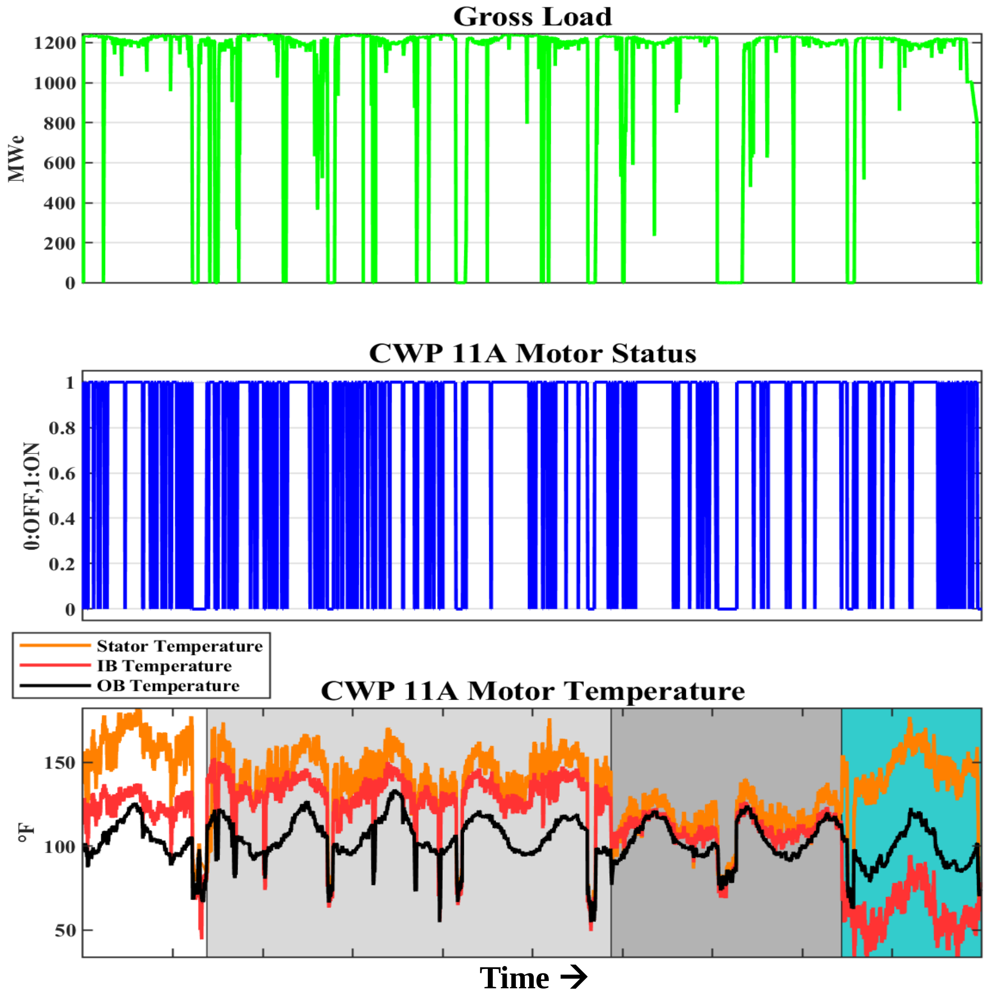
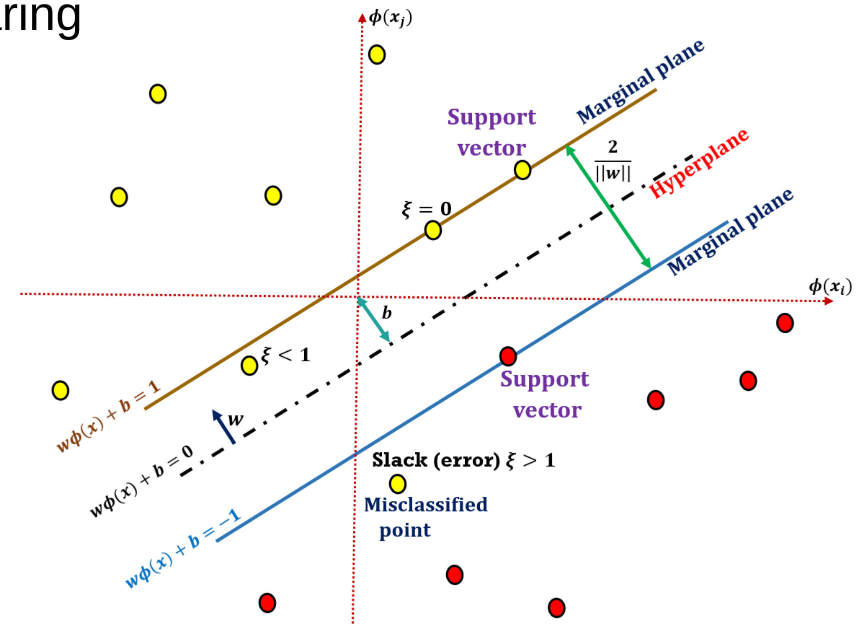


Figure: Salem Unit 1 Pump 11A

FTL: Support Vector Machine, (SVM)

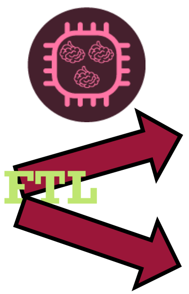
- ***Labels***: Motor status information (OFF = Under Maintenance, ON = Operating)
- ***Features***: Motor temperatures- Stator, Inboard bearing, and outboard bearing
- SVM to classify CWP as:
  - Healthy (Operating) or Unhealthy (Under Maintenance)
- Support Vectors from each SVM model are combined and shared



SVM model and parameters

SVM: Plant 1

CWP	Prediction Accuracy
Pump 11	94.3%
Pump 12	94.0%
Pump 13	92.6%



SVM Federated Learning: Plant 1

CWP	Prediction Accuracy
Pump 11	96.3%
Pump 12	96.9%
Pump 13	94.4%

SVM Transfer Learning: Plant 2

CWP	Prediction Accuracy
Pump 21	89.93%
Pump 22	90.23%
Pump 23	84.67%

Looking Ahead

- Enhance FTL modeling for other data types
  - Vibration
  - Motor current

- Develop FTL framework with other machine learning approaches
  - Logistic regression
  - eXtreem Gradient Boosting (XGBoost)

- Apply FTL to different applications
  - Secure wireless communication

Acknowledgements

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  - Vivek Agarwal
  - Andrei V. Gribok
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  - Thomas Ulrich
  - Ronald L. Boring

- Collaborator
  - Public Service Enterprise Group (PSEG) Nuclear, LLC

LWRS LIGHT WATER REACTOR SUSTAINABILITY

Dr. Char Sample

Chief Scientist – Cybercore Division

October 2020

Failures in AI and ML

Insights and Mitigations

INL Idaho National Laboratory

Introduction & Background

AI – technology that performs tasks which mimic human intelligence [1].

Machine learning (ML)

- Powers AI
- Algorithms capable of generalizing lessons learned from a limited data set to allow for abstraction of lessons to a larger environment [2].

- Disruptive technology

Problem

AI/ML introduces problems of a breadth and nature that are difficult for humans to envision.

- Traditional security problems
- AI/ML unique problems
- Rapidity

Specific Problem

Problem 1: Data corruption [3]

- Description: This group of attacks includes data poisoning, data perturbations, environmental corruptions, side effects, common corruption.
- Effects
  - Misclassifications
  - Grouping changes

Specific Problem

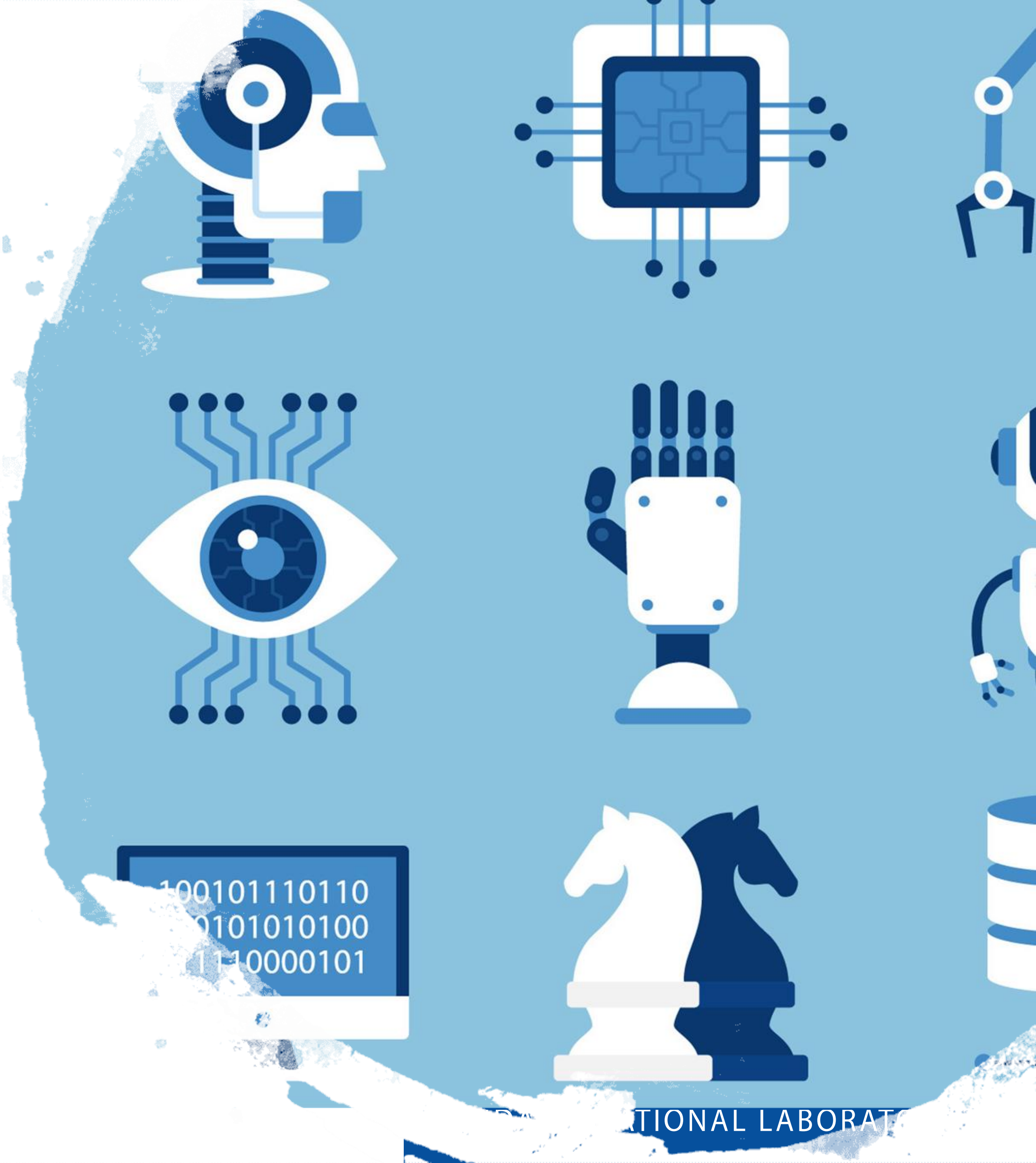
Problem 2: System corruption [3]

- Description: Reprogramming ML, malicious ML provider recovering training data, reward hacking, backdoor ML, software dependencies exploitation, AI supply chain attacks
- Effects:
  - Misclassification
  - Improper groupings
  - Data loss

Specific Problem

Problem 3: Model corruption [3]

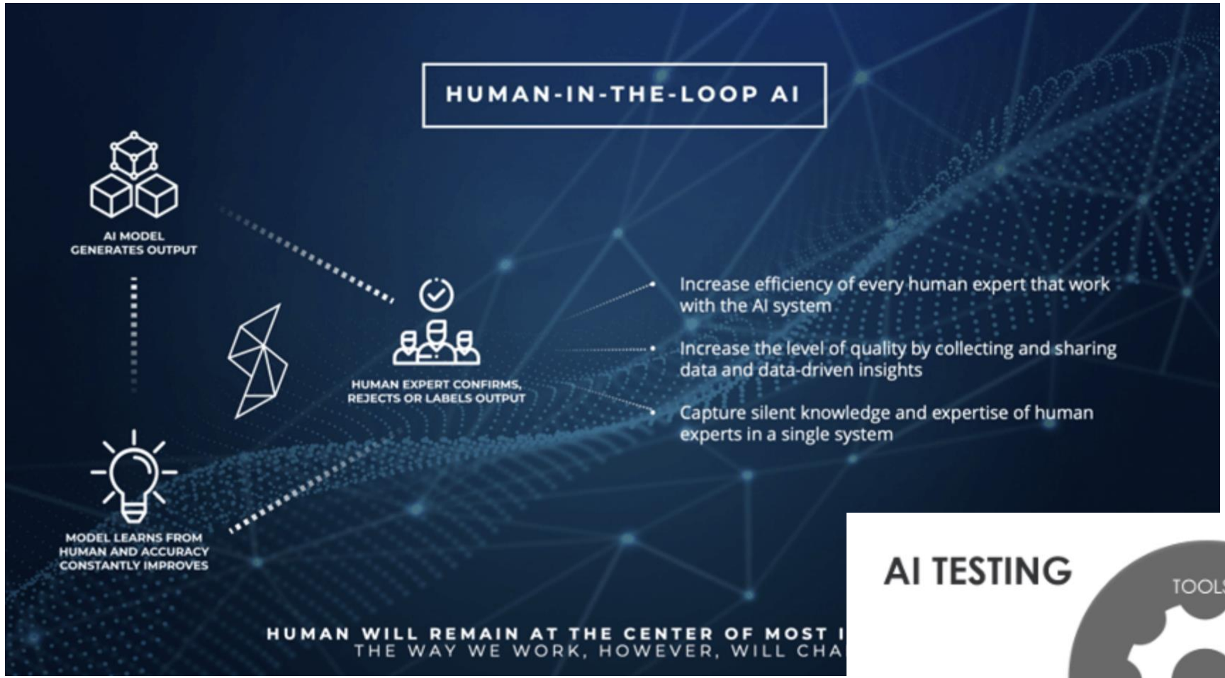
- Description: Membership inference, model stealing, model inversion, distributional shifts
- Effects:
  - Data loss
  - Algorithm manipulation
  - Algorithm anticipation
  - Data grouping manipulation



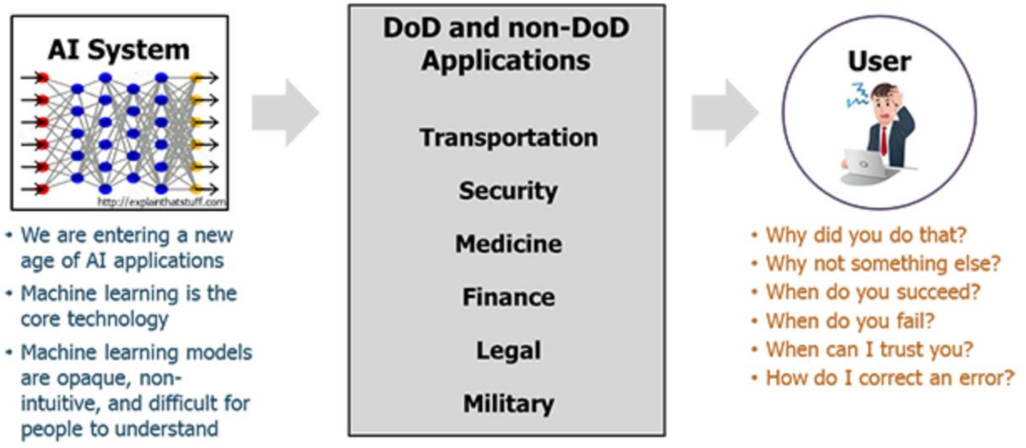
Specific Problem

- **Problem 4: Known unknowns and unknown unknowns [3], [4]**
  - Description: Natural adversarial examples, overfitted models, incomplete testing, MUAI,
  - Effects:
    - Algorithms prioritization schemes are inappropriate or inaccurate
    - Algorithms behave in unanticipated, unintended manner
    - Algorithm confusion

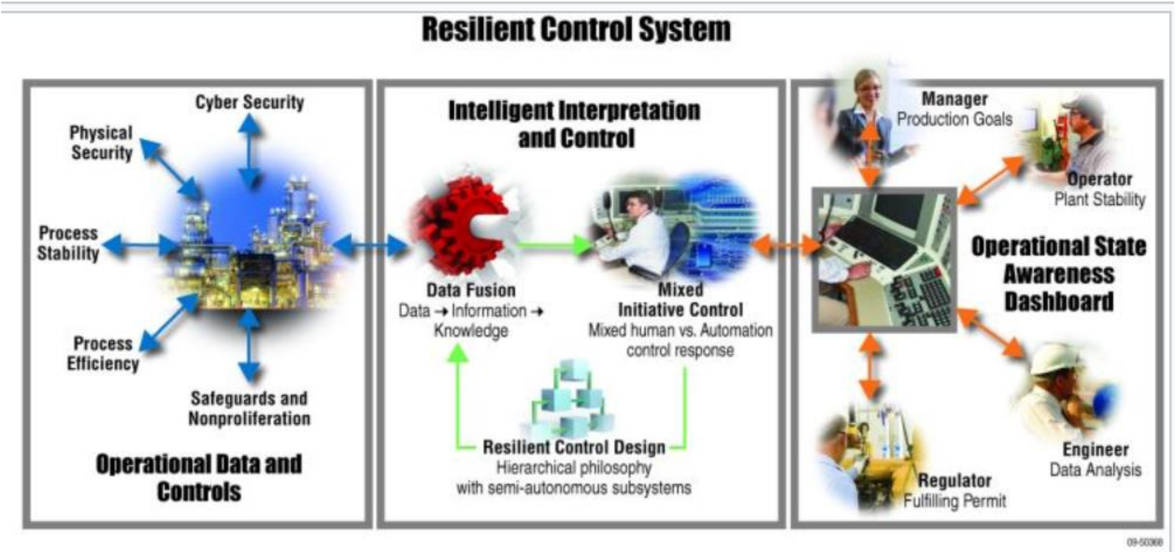
Proposed General Solutions - Traditional



Proposed General Solutions - Newer



[5]



Recommended Course of Action

Way forward

- Better coupling of policy makers, researchers, domain SMEs, engineers, users etc. to investigate, prevent and mitigate MUAI
- Research and engineers should take serious dual-use AI
- Develop best practices for AI uses
- Resilient data and systems
- Include cybersecurity representation on AI/ML initiatives.

Conclusions

- AI disruption will transform many of the workflows in our current lives.
- AI disruption will introduce unforeseeable problems.
- Humans will need to remain in the loop for the foreseeable future.
- Significant research into operational security will need to be undertaken.

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Questions & Answers

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Machine Learning for Concrete Damage Diagnosis using Vibration and Thermal Testing

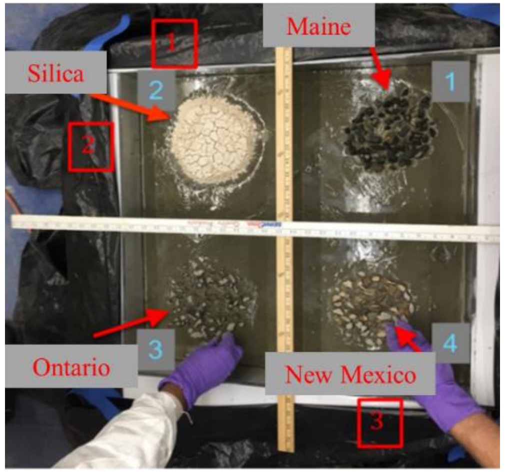
Machine Learning & Artificial Intelligence Symposium

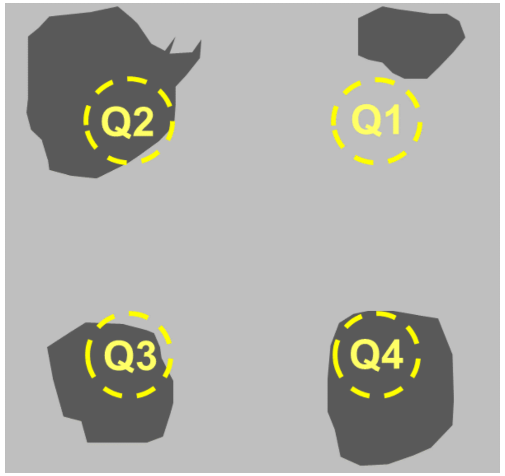
October 16, 2020

Idaho National Laboratory

Concrete Damage Diagnosis & Prognosis

- NPP Relicensing ➔ Secondary containment structures ➔ Concrete
- Concrete damage diagnosis and prognosis ➔ support relicensing
- Existing work in concrete ASR diagnosis: Damage detection only
- Our focus ➔ Damage localization and quantification
- Non-destructive testing
  - Dual excitation vibration (vibro-acoustic modulation, VAM)
  - Thermography (infra-red thermal camera)
- Experimental specimens
  - Induced alkali-silica reaction (ASR) ➔ Cracking
  - ML methods successfully constructed damage map
  - Validation:
    - Core samples (petrography, spectroscopy)
    - Destructive testing





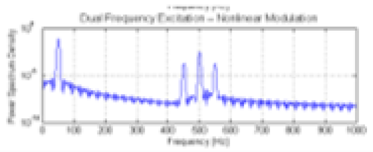
Why it is relevant to ML/AI Future

- ML/AI Approaches
  - Physics-informed learning
  - Transfer learning
- ML/AI Methods
  - Deep neural network
  - Convolutional neural network
  - Bayesian neural networks
- Benefits
  - Automation
  - Speed
  - Training cost
  - Uncertainty quantification
  - Decision support

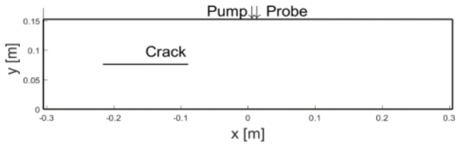
- Structural health monitoring
  - Concrete structures NDE
  - Heterogeneous materials
- Broader impact
  - Big data analytics (NASA)
    - Batch learning
  - Digital twin (U.S. Air Force, ABS, Mitsubishi)
  - Other applications in my group at VU
    - Additive manufacturing (NIST)
    - Air transportation safety (NASA)
    - Rotorcraft control (U.S. Army)
    - Patient care (NIH)
    - Power grid management (DOE)

Topic Details and Discussion

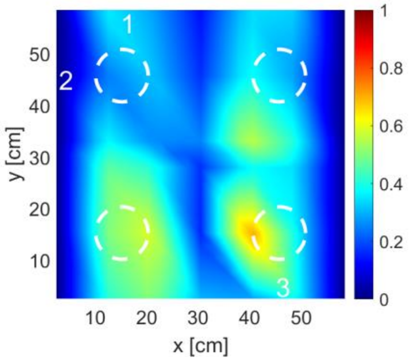
Dual excitation vibration testing (VAM)

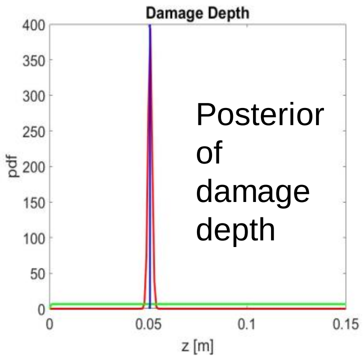


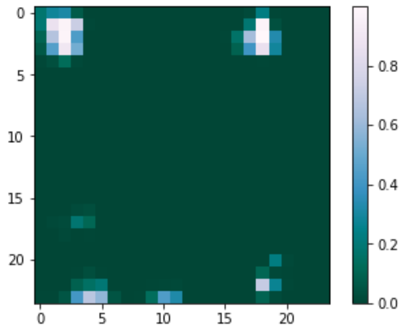
- Side-bands in frequency response
- Sum of side-band intensity (SBSum)
- SBSum value indicates damage likelihood
- Test inputs: excitation frequencies, amplitudes, and locations



- Training Data: 2D FEA model
- Two types of DNN models trained
  - Damage classification of sensor location
  - SBSum prediction at sensor location
- Output: Damage map, damage depth; Bayesian estimation (diagnosis uncertainty) using Monte Carlo dropout







Infra-red thermography

- Heating at bottom, observe top surface temperature evolution
- Traditional filtering techniques not useful

- Training Data: 3D FEA heat transfer model
- Two types of CNN models trained with transfer learning from Imagenet
  - VGG-19 convolution core
  - Inception/Resnet convolution cores
- Output for each element
  - Damage classification (yes/no)
  - Damage shape
  - Bayesian estimation (diagnosis uncertainty)
- Accuracy of result 85% to 95%

Looking Ahead

- Further work
  - Mechanical NDE (VAM)
    - Automation
    - Multi-fidelity training (Additional 3D FEA runs)
    - Distributed damage
    - Reinforced concrete
    - Non-contact sensing (e.g. laser Doppler velocimetry)
  - Thermal NDE (Infrared thermography)
    - Passive heating of specimen
    - Thermal video-based NDE
    - Reinforced concrete
  - Information fusion from thermal and mechanical NDE
  - Uncertainty quantification for decision support

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Sankaran Mahadevan, Professor, Vanderbilt U.
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Questions?

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