AI-Enhanced Distributed Fiber Optic Sensors for Pipeline Monitoring

NATIONAL ENERGY TECHNOLOGY LABORATORY

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NETL Support Contractor



Digital Engineering Conference

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Authors

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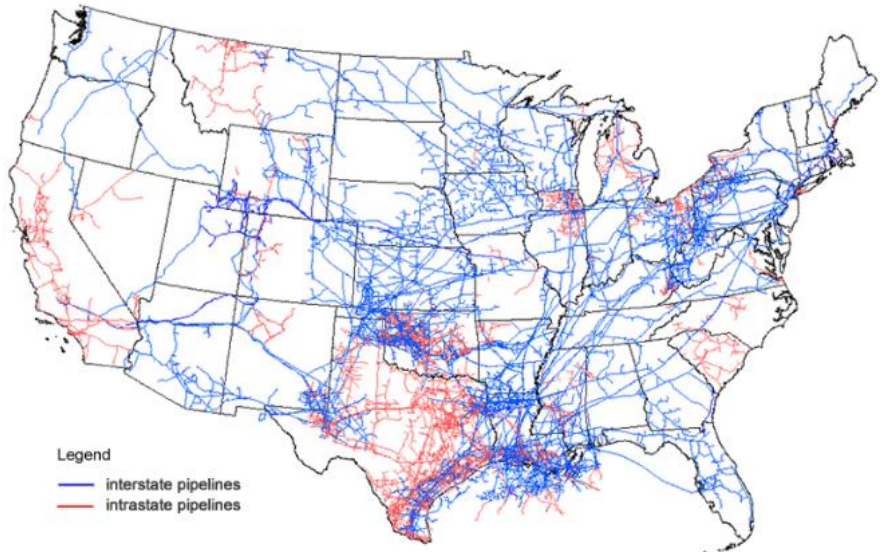
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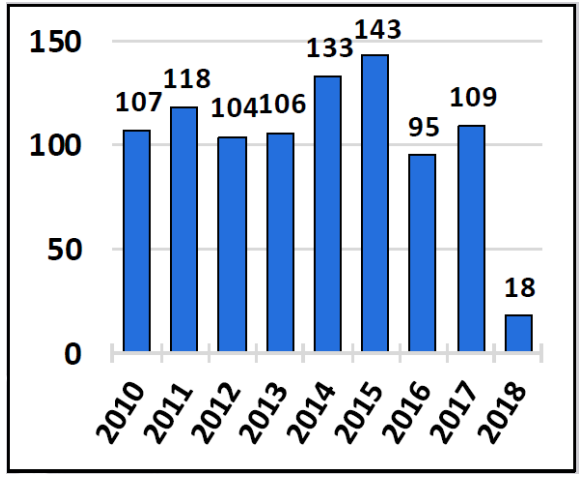
Outline

1. Introduction:
    - Natural gas pipeline monitoring challenges and needs
    - Distributed fiber optic sensing technology
2. Challenges and limitations of fiber optic sensor systems
3. Advanced data analytics: Physics-based modeling, data processing, and AI classification
4. Custom optical interrogation techniques and recent field-testing analysis and results
5. Conclusions and future research works

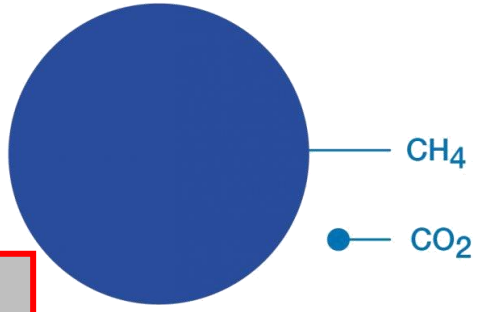
Reliability and Resiliency of Natural Gas Infrastructure



Number of natural gas transmission pipeline incidents (2010-2018)



Key methane facts



Atmospheric lifetime of **12 years**

Causes 1+ million premature deaths per year

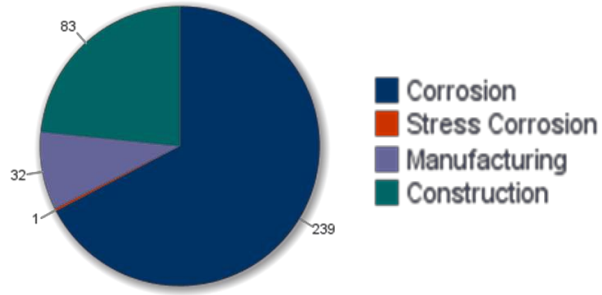
as a driver of tropospheric ozone formation

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Minimize Environmental Impact from CH_4 Emission

>400,000 miles of gas transmission pipelines, and every inch is susceptible to ruptures, and leaks which threatens the safety of our communities, and poses a serious environmental risk

Gas Transmission Leak Sources



Real-time monitoring and leak detection/mitigation for the natural gas infrastructure is increasingly important. At NETL, new sensing technologies are being developed to address these needs.

Conventional Monitoring Technologies

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Pipeline Explosion Caused by Cracks/Corrosion



http://wvpublic.org/post/ntsb-determines-cause-december-2012-sissonville-pipeline-explosion#stream/0

Primary Emphasis: Detecting Presence of Leaks and Failures

- Internal leak detection systems: measured flow rates and computational models
- Periodic in-line inspections
- Monitoring of local geohazards (ground movements and seismic events)
- External inspections, including aerial surveys
- Optical fiber-based leak detection systems: indirect measurement (temperature, strain, acoustic)

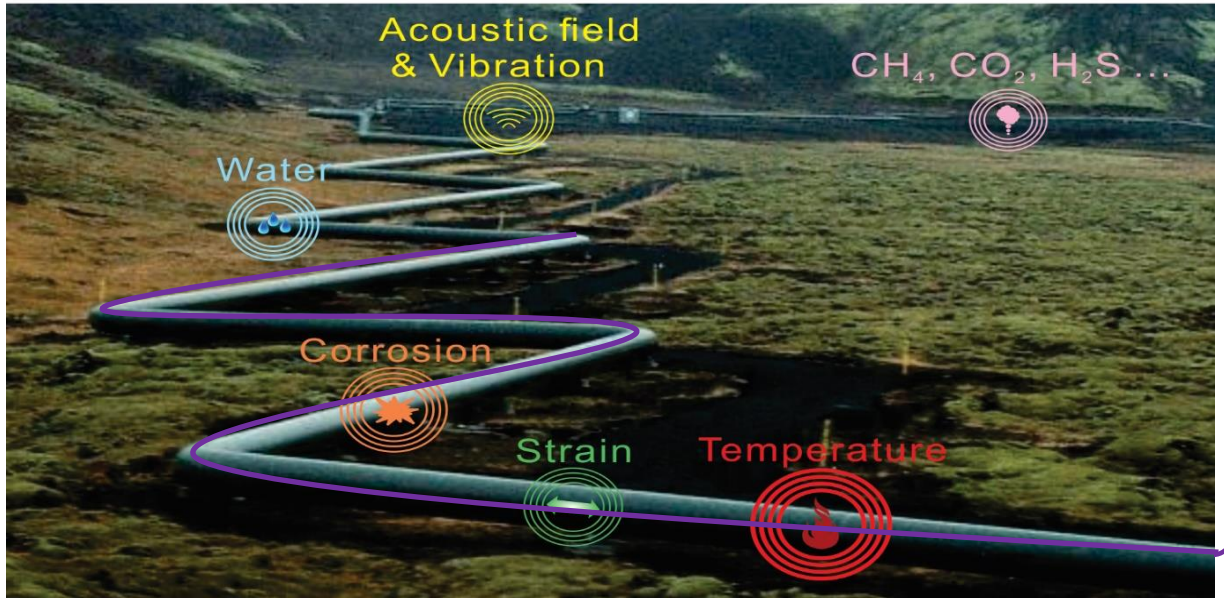
Opportunity to expand capability for incipient failure, defects, potential hazards, and operational efficiency

Conventional monitoring techniques identify leaks and events once they have occurred to enable faster responses, but are limited in capability to identify failures before they occur.

Approach: Distributed Optical Fiber Sensing Technology

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Pipeline Integrated with Distributed Optical Fiber >100 km



Fiber Interrogators



Remote Monitoring



- Detect leaks in real-time
- Safe and reliable pipelines
- Improved pipeline safety
- Improved confidence and assurance
- Lower maintenance costs



Operator

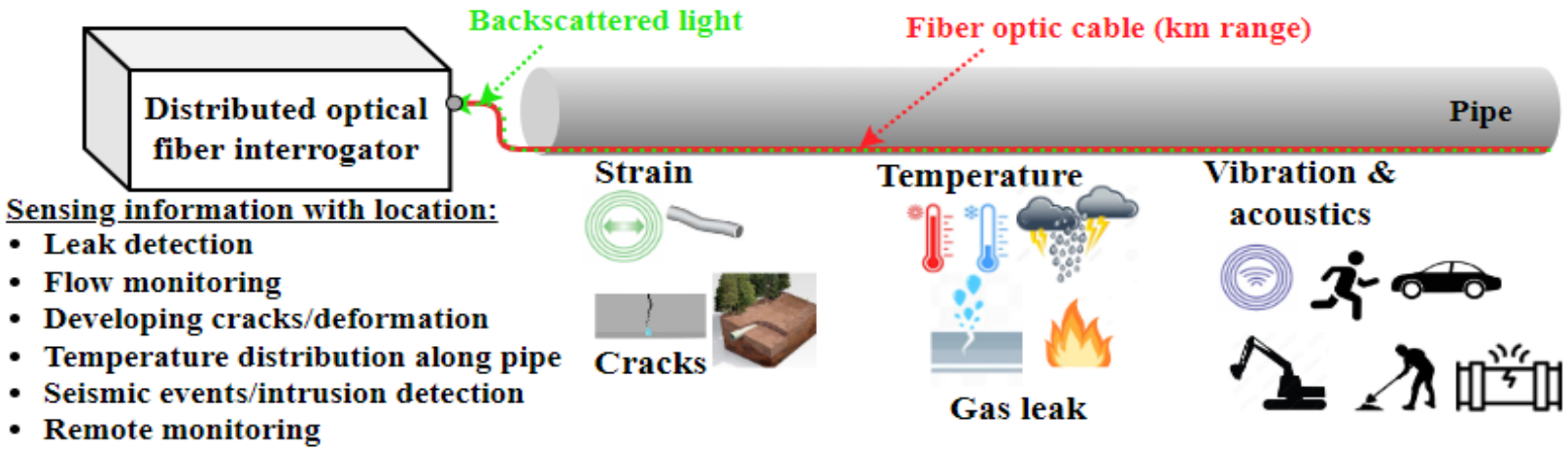
Increased Range Enhanced SNR → **Multi-Parameter Monitoring** → **Small Footprint** → **Reduced Cost**

Distributed optical fiber sensor platform to enable reliable and resilient pipelines

Target Metrics: >100 km interrogation, <5 m spatial resolution, cost ~$40-70 k (<$0.30/m)

Distributed Optical Fiber Interrogator Development

Pipeline Integrity Monitoring Based on Various Distributed Fiber Sensor Systems

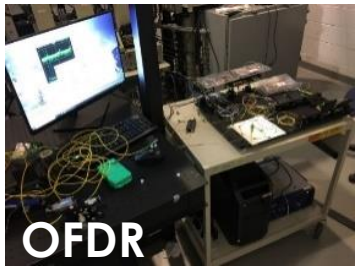


Sensing information with location:

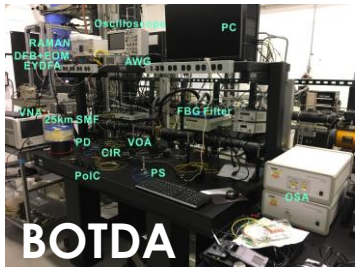
- Leak detection
- Flow monitoring
- Developing cracks/deformation
- Temperature distribution along pipe
- Seismic events/intrusion detection
- Remote monitoring

In-House NETL Distributed Optical Fiber Sensor Interrogators

Technology	Sensing Range	Spatial Resolution	Measurement Time	Target Parameter
Rayleigh Phase-OTDR	**Kilometers**	**Meters**	**Seconds**	**Acoustic/vibrations**
Brillouin- OTDA	**Tens of kilometer**	**Centimeter to meter**	**Minutes**	**Temperature and strain**
Rayleigh OFDR	Meter to kilometer	Millimeter to centimeter	Seconds	**Temperature and strain**



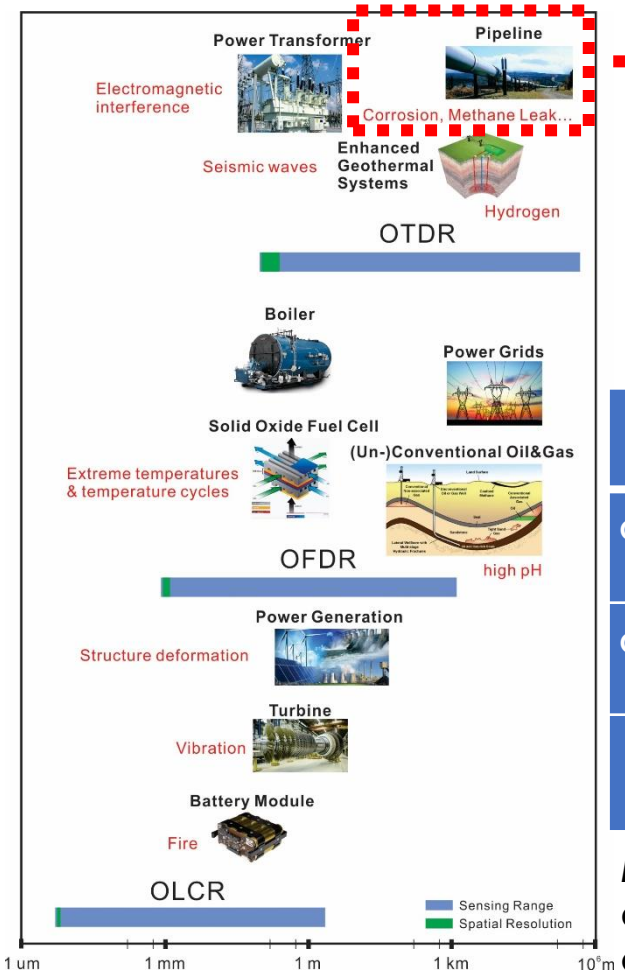




Multiple distributed/point optical fiber sensing platforms have been developed to enable structural health monitoring of natural gas pipeline.

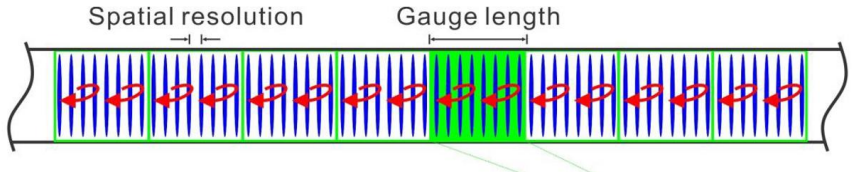
P. Lu, N. Lalam, M. Badar, B. Liu, B. T. Chorpening, M. P. Buric, et al., "Distributed optical fiber sensing: Review and perspective," *Applied Physics Reviews*, vol. 6, p. 041302, 2019.

Distributed Optical Fiber Interrogator Development

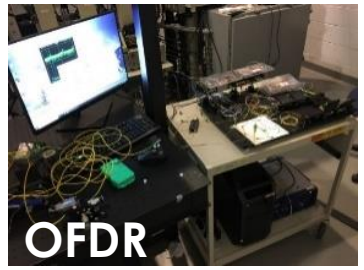


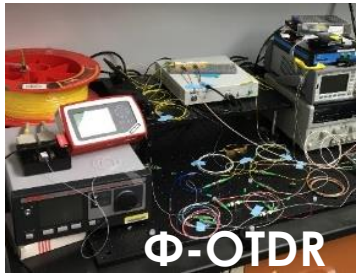
Challenges: Long-distance, **big data, low data processing speed**, **cross-sensitivity**, field deployment, capital cost, **event classification**

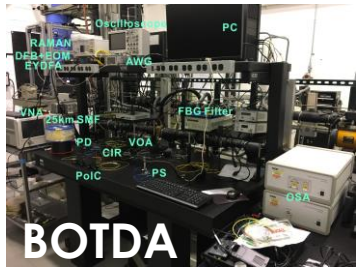
In-House NETL Distributed Optical Fiber Sensor Interrogators



Technology	Sensing Range	Spatial Resolution	Measurement Time	Fiber Type	Sensing Performance
Coherent Rayleigh OFDR	m – km	mm – cm	seconds	SMF	Temperature, strain, vibration, chemical sensing
Coherent Rayleigh OTDR	km	m	seconds	SMF	Acoustic wave, vibration
Brillouin OTDR/BOTDA	> 100 km	cm – m	minutes	SMF	Temperature, strain







Multiple distributed optical fiber sensing platforms have been developed to enable structural health monitoring of natural gas pipelines, particularly for corrosion onset and gas leak detection.

P. Lu, N. Lalam, M. Badar, B. Liu, B. T. Chorpening, M. P. Buric, et al., "Distributed optical fiber sensing: Review and perspective," *Applied Physics Reviews*, vol. 6, p. 041302, 2019.

Challenges and Objective

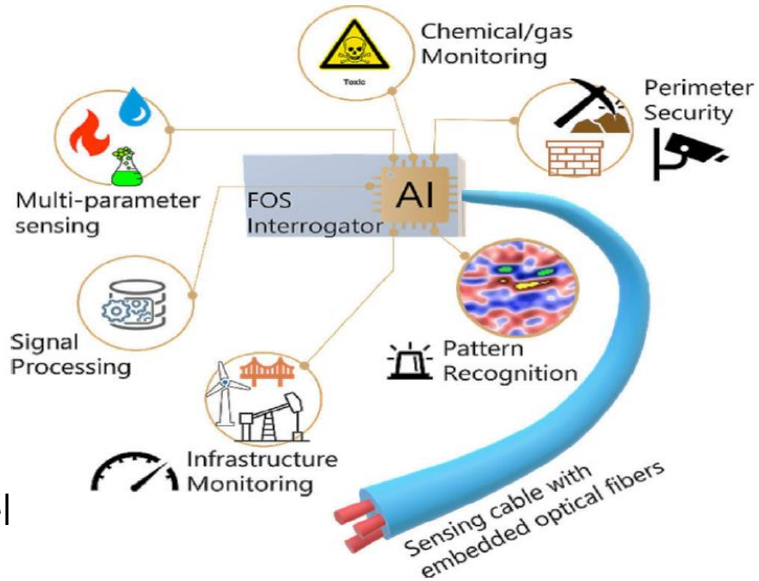
Challenges:

1. **Real-time DOFS monitoring generates large datasets, which takes time to process**
   - >10^5 datapoints per measurement - 100 MB per measurement, can get up to over 1 TB a day
   - Current DOFS data process time: ~10 min per measurement; increase with length and spatial resolution
2. **Low signal processing speed, and** complicated conditions of pipelines
   - High-quality, large-volume data are needed for **AI model training**; however, DOFS sensor data are limited in response to catastrophic failures.

Objective:

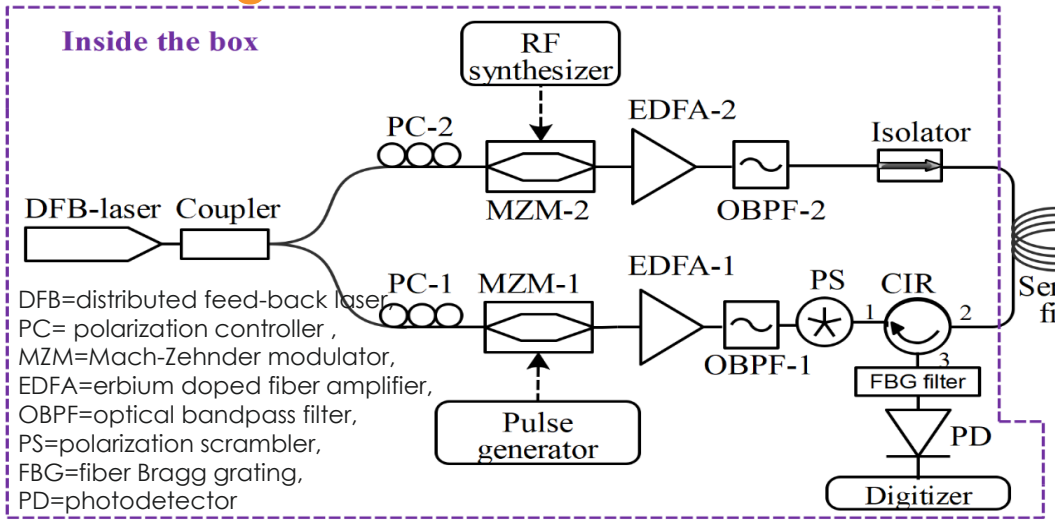
To develop advanced data analytic techniques and methods based on AI/ML for identification of signatures and patterns representative of hazards, defects, and operational parameters of the natural gas pipeline network

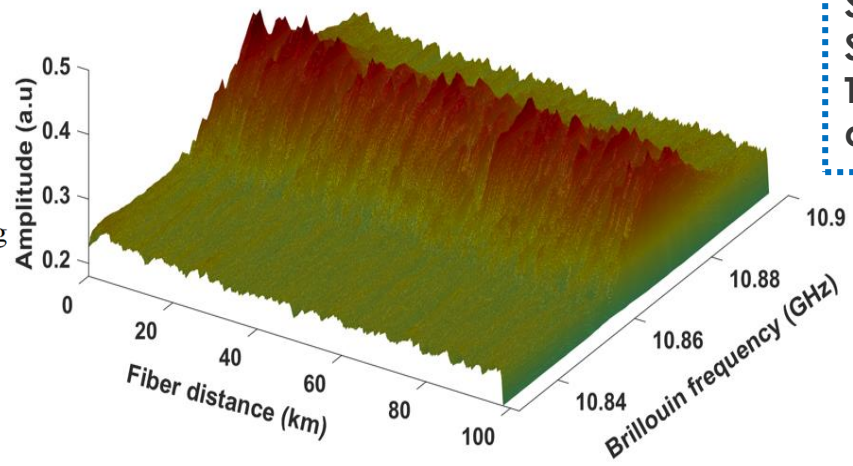
1. Accelerate data processing for DOFS measurements
2. Translate large sensor datasets to concrete actionable information.
3. Data generation using simulation or hybrid methods to accelerate AI model training



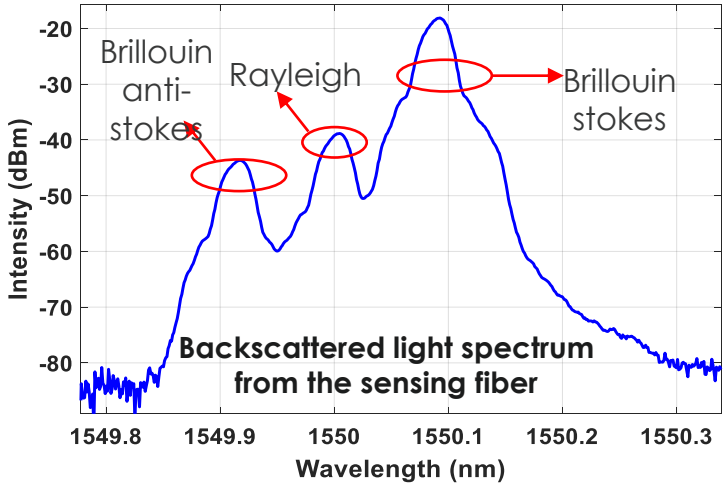
Brillouin Optical Time Domain Analysis (BOTDA)

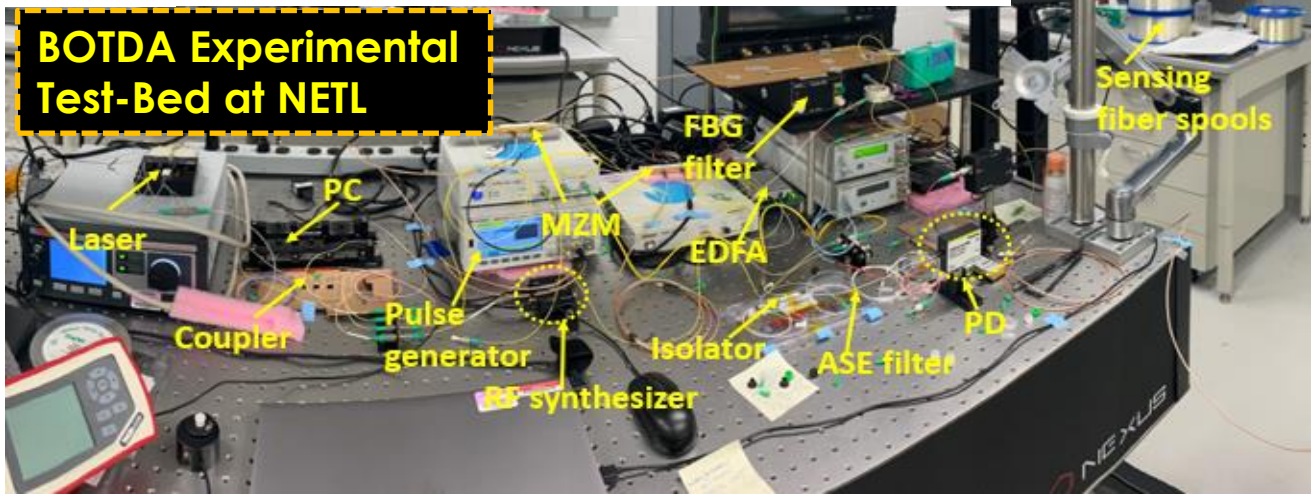
Ultra-Long Distance BOTDA for Strain/Temperature Measurement





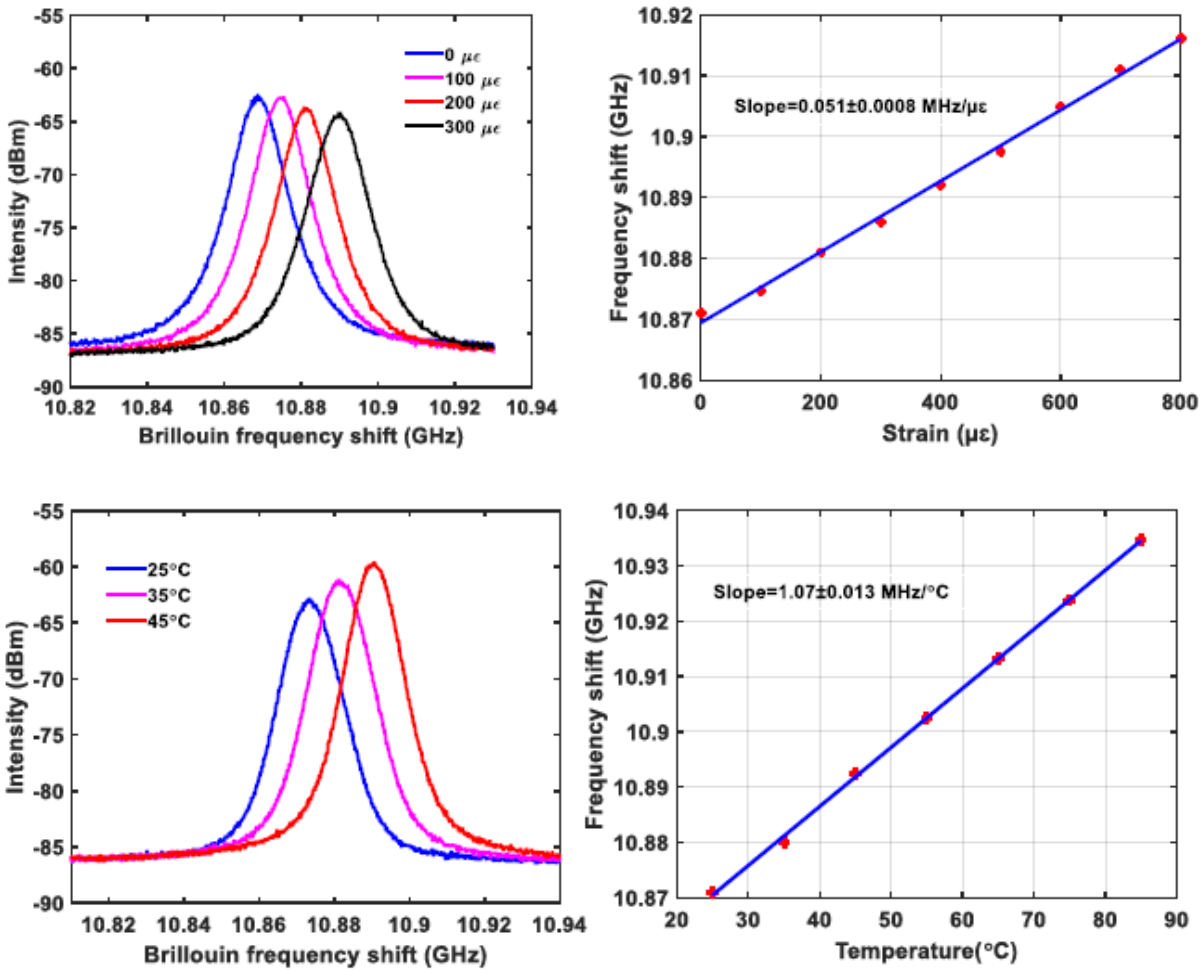
Sensing range = >100 km
Spatial resolution = < 5m
Target parameters: strain, and temperature



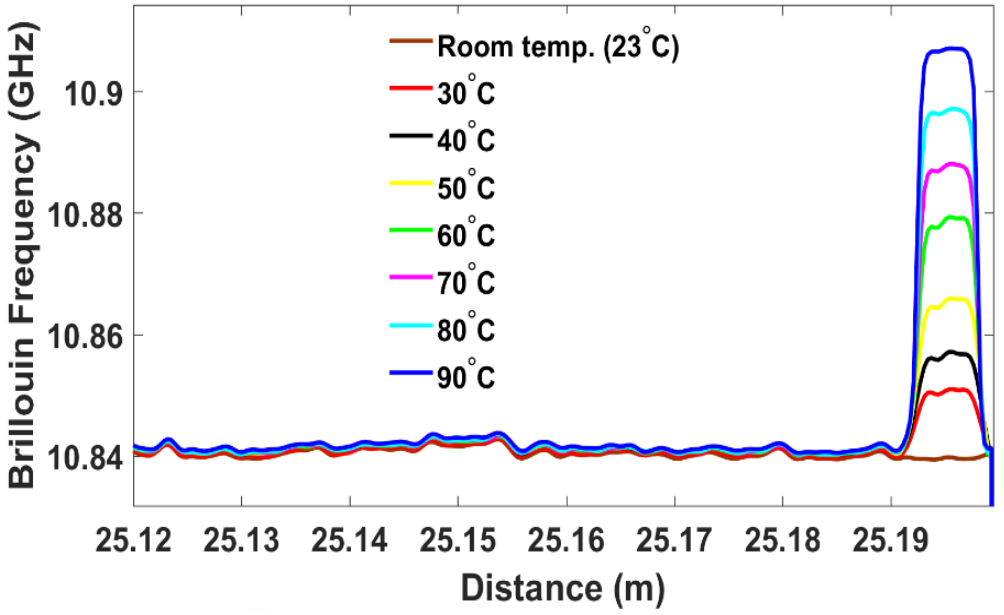


N. Lalam, P. Lu, A. Venketeswaran, M. Buric, and P. Ohodnicki, "Raman-assisted BOTDA performance improvement with the differential pulse-width pair technique and an artificial neural network based fitting algorithm," in *SPIE Defense + Commercial Sensing*, Online, 2020.

Temperature and Strain Effects on Brillouin Gain Spectrum (BGS)



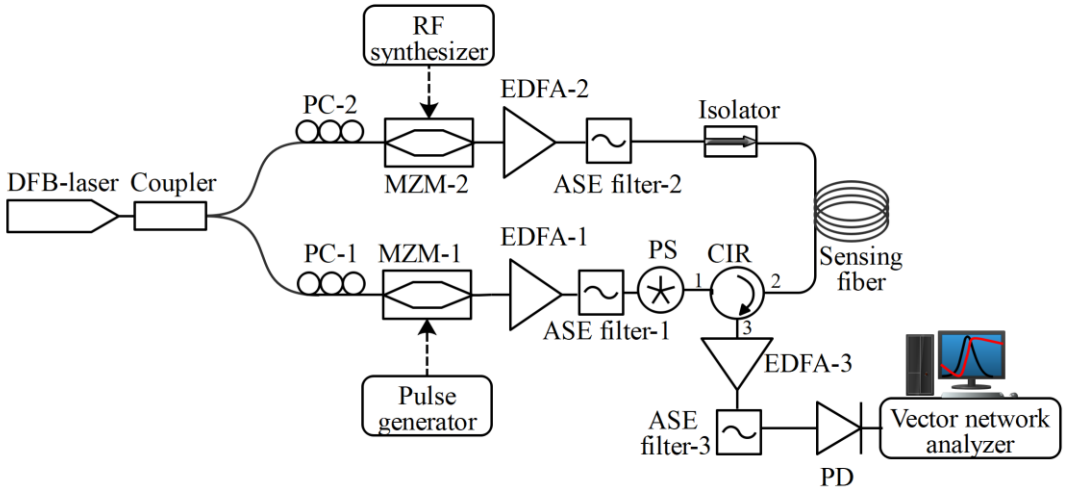
- Distributed strain measurement reveals developing pipeline cracks and alert before the structural failure occurs.
- Gas leak-induced temperature change can be alerted in real-time up to 150 km range.

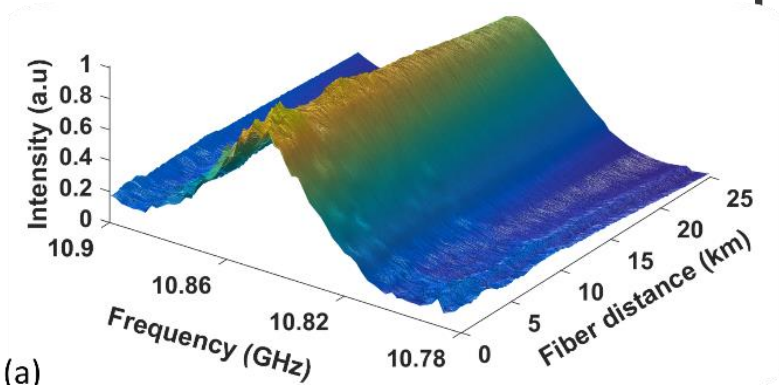


N. Lalam, W. P. Ng, X. Dai, Q. Wu and Y. Q Fu, "Performance Improvement of Brillouin Ring Laser based BOTDR System Employing a Wavelength Diversity Technique," *IEEE/OSA Journal of Lightwave Technology*, vol. 36, pp. 1084 - 1090, 2017.

Vector BOTDA System

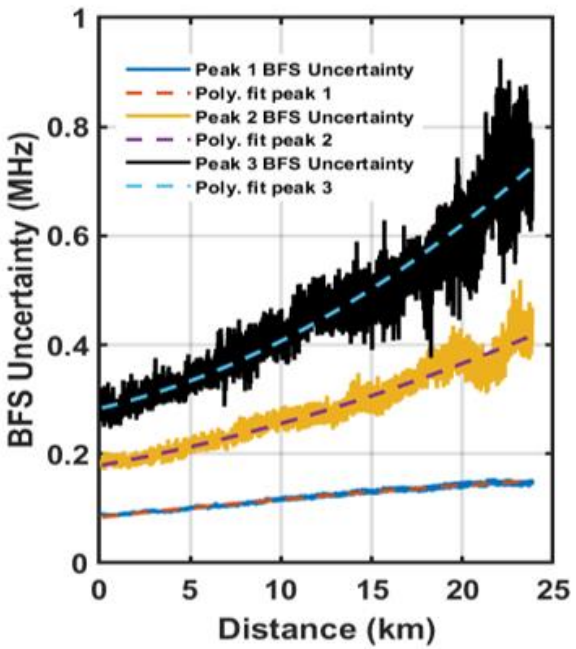
Vector BOTDA Interrogator Developed at NETL

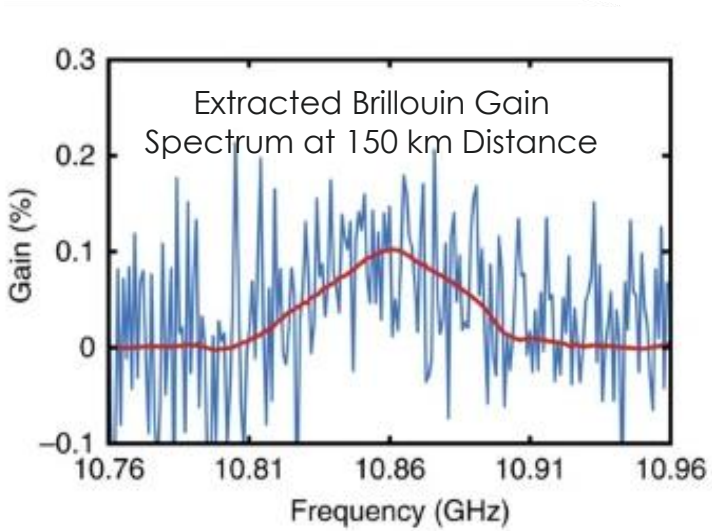




Vector BOTDA is useful for long-range distributed strain and temperature sensing

- Vector-BOTDA system employing distributed Raman amplification has been demonstrated for >100 km sensing distance
- Simultaneous measurements of both gain and phase spectrums gives high strain and/or temperature measurement accuracy



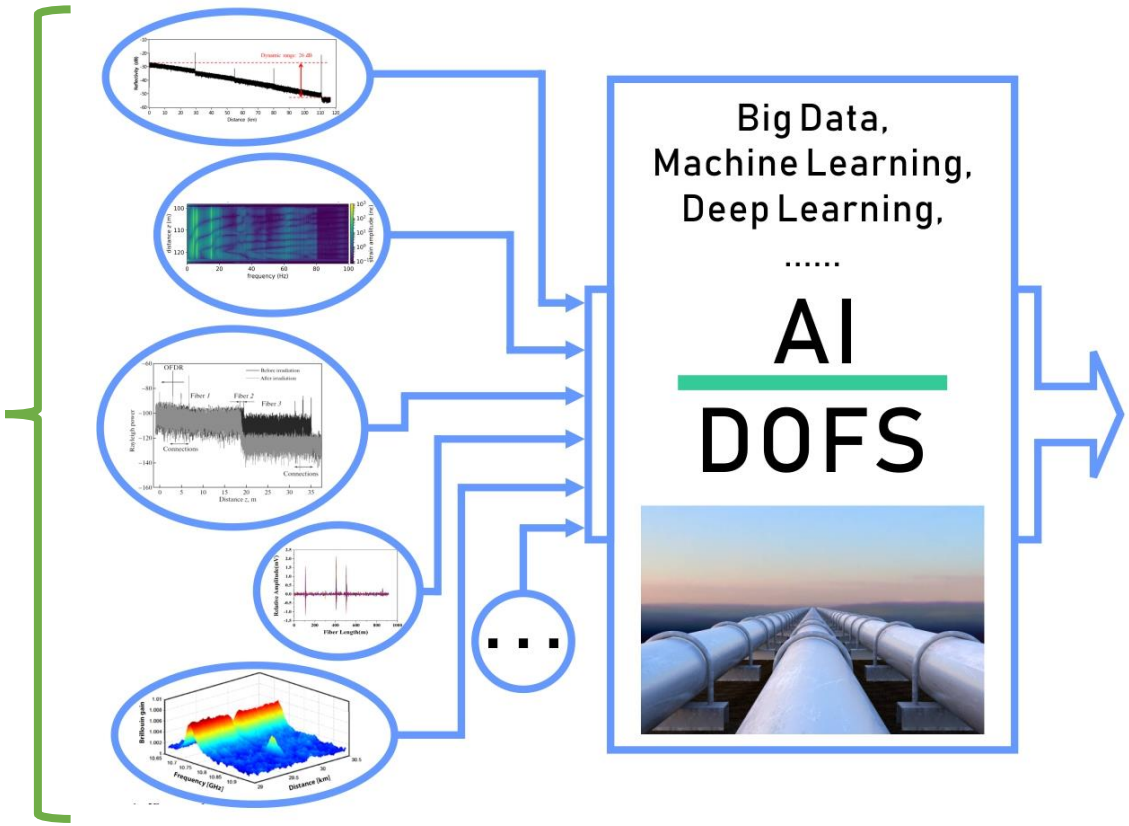


P. Lu, N. Lalam, B. Liu, M. Buric, and P. Ohodnicki, "Vector Brillouin optical time-domain analysis with Raman amplification and optical pulse coding," in *SPIE Photonics West*, San Francisco, California, 2019, p. 1092512.

AI-Enhanced Distributed Optical Fiber Sensors

Fiber optic-based distributed OFS technology integrated with advanced analytics including pattern and feature recognition can convert large data sets to actionable information.

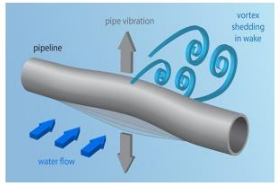
Distributed Fiber Optic Sensor Data
(Distributed Temperature, Strain, Acoustic, etc.)




Fire

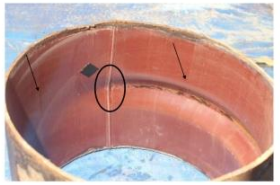

Gas Leak


Earthquake



Vibration


Lamination


Deformation


Cracking


Gouge


Corrosion

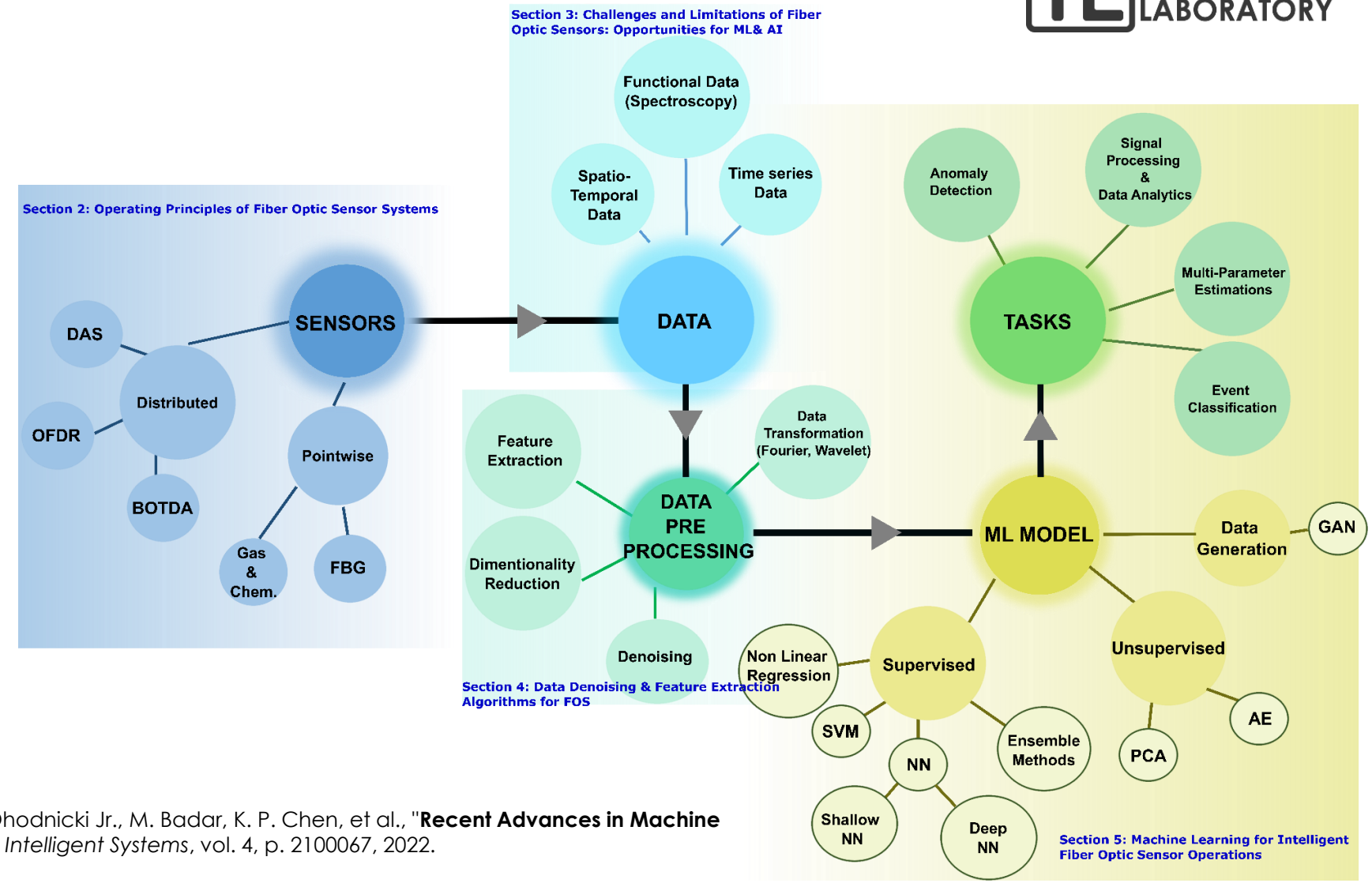
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Recent Advances in Machine Learning (ML) for FOS

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Challenges and Limitations of FOS: Opportunities for ML and AI

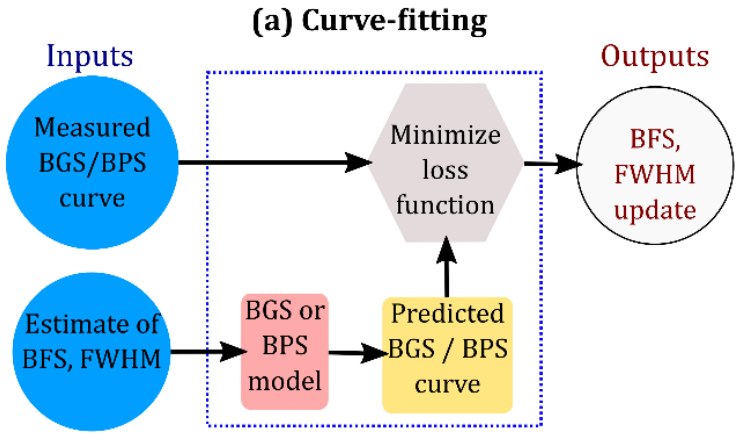
- Data availability
- Big data
- Sources of noise
- Cross-sensitivity challenges
- Nonlinear dynamic sensor data patterns

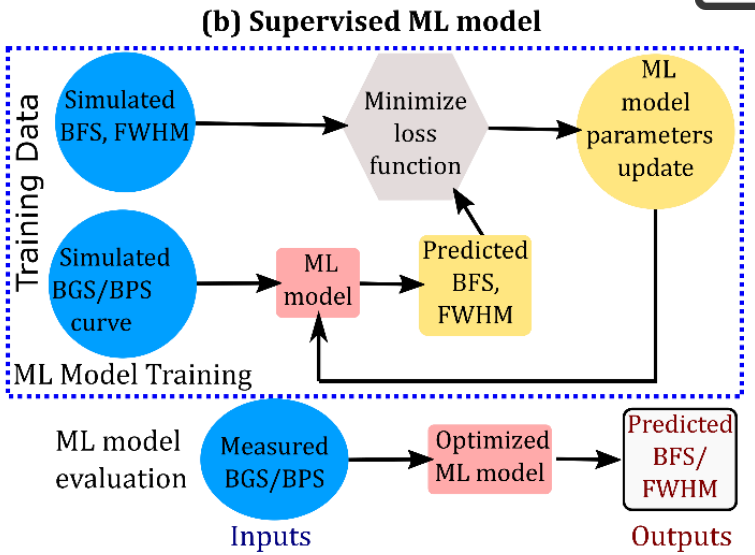


A. Venketeswaran, N. Lalam, J. Wuenschell, P. Lu, P. R. Ohodnicki Jr., M. Badar, K. P. Chen, et al., "**Recent Advances in Machine Learning for Fiber Optic Sensor Applications**," *Advanced Intelligent Systems*, vol. 4, p. 2100067, 2022.

Advanced Data Analytics for Distributed OFS

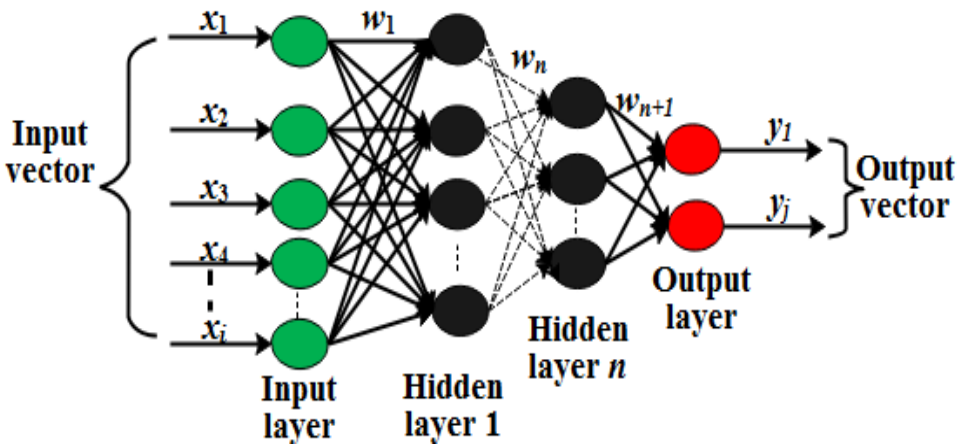
State-of-the-Art Data Analytics for BOTDA



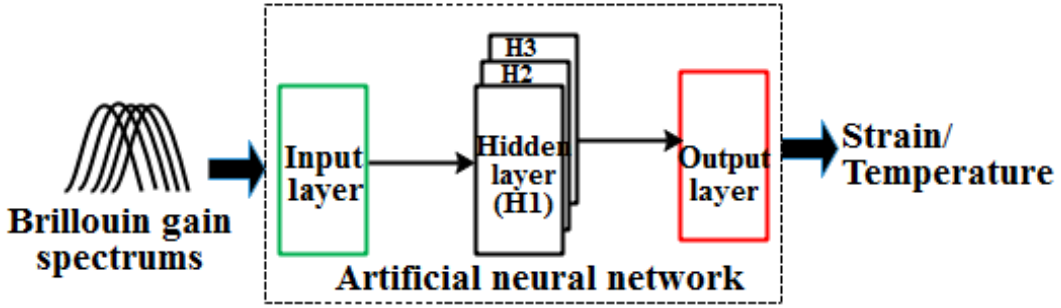


	Curve Fitting	Supervised Machine Learning
Methodology	Fit a model to gain spectra measurements and estimate Brillouin frequency shift (BFS) from model parameters	Train a model to directly estimate BFS from measurements. Support vector machines and deep neural networks proposed in literature
Pros	• Physics motivated • Interpretable	• Small data processing time • Can extract peak Brillouin frequency from low SNR data
Cons	• **Large data processing time** • **Poor performance in low SNR data**	• Lack of interpretability • Overfitting can lead to erroneous confidence in predictions

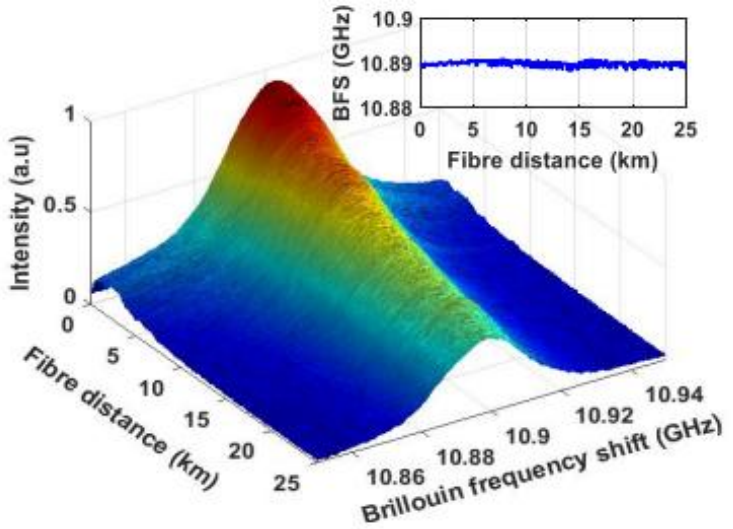
Data Processing Using Artificial Neural Network (ANN)



Schematic Structure of ANN with "n" Hidden Layers



Operating Principle of ANN-Based Curve-Fitting Method



Measured Brillouin gain spectrum over 25 km fiber distance

Comparison Between Conventional Lorentz Curve Fitting, and ANN

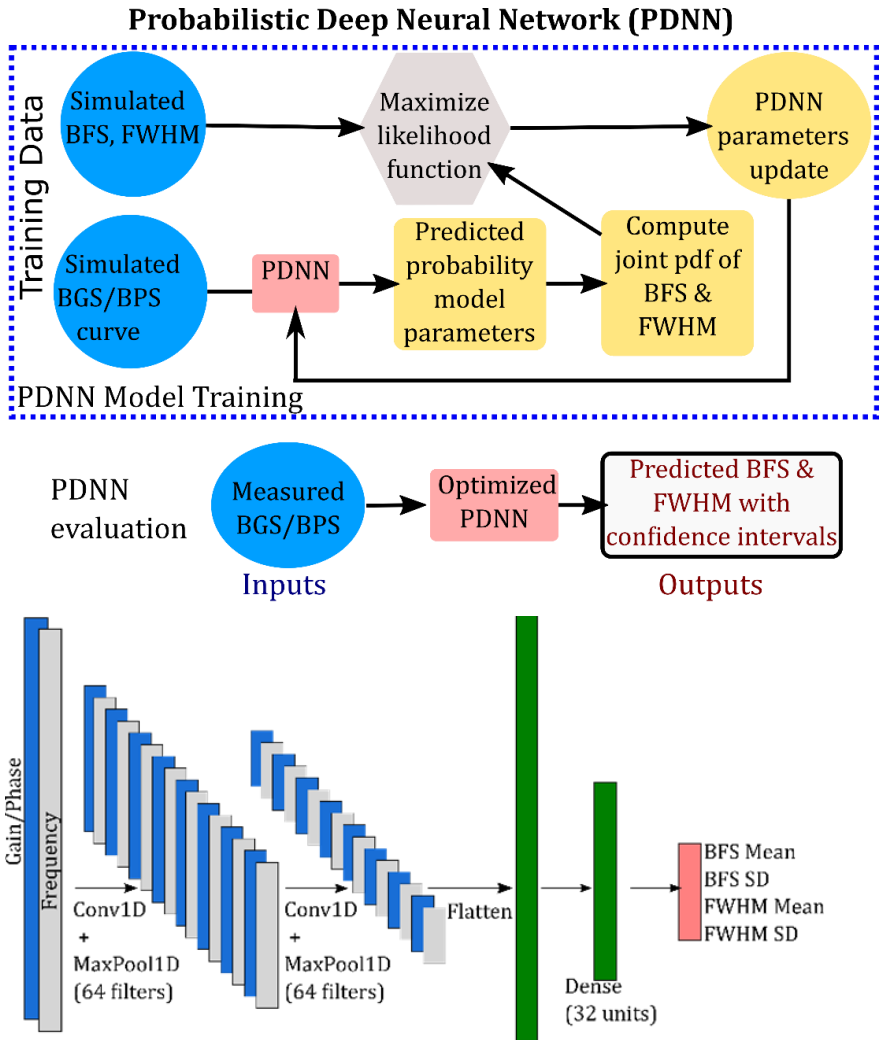
Metric	Standard Curve-Fitting Signal Processing	ANN
Computation Time (seconds)	**132.5 s**	**14.4 s**
Average BGS MSE ($\times 10^{-4}$)	1.689	0.962
Standard deviation of BFS (MHz)	2.6	1.2

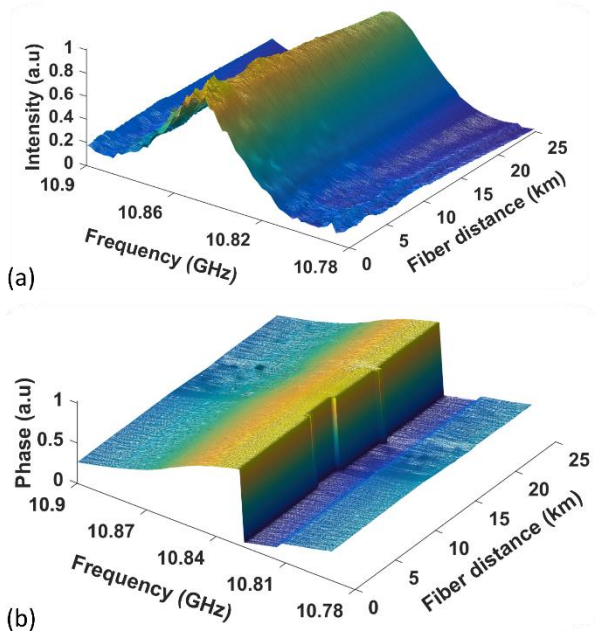
ANN performed better than conventional curve fitting models; improved the computational speed (10 times) and BFS estimation accuracy.

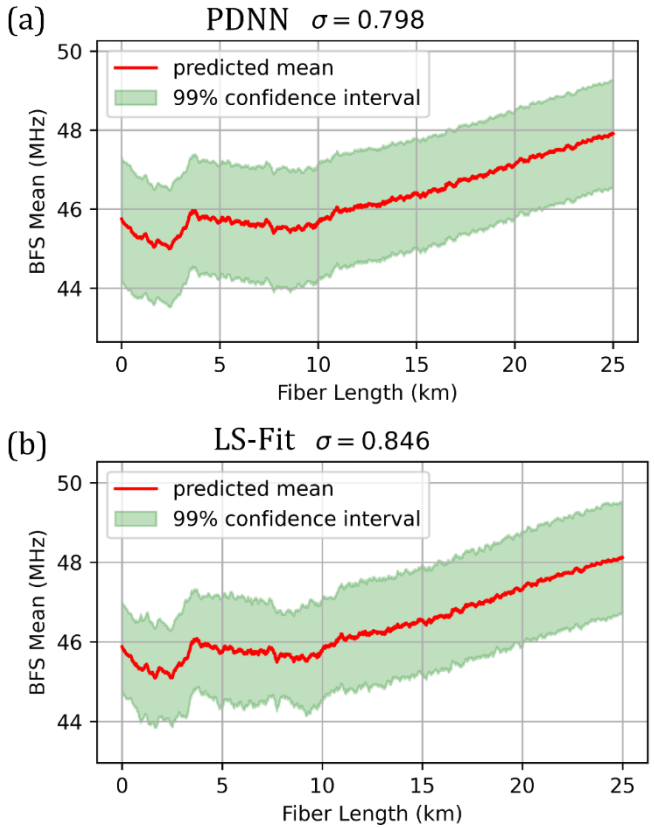
A. Venketeswaran, N. Lalam, P. Lu, P. Ohodnicki and K. P. Chen, " Enhanced Signal Processing of Distributed Brillouin Fiber Sensors using a Decoupled Radial Basis Function Network," in *27th International Conference on Optical Fiber Sensors (OFS)*, 2020 Special Edition, paper T3.51.

Advanced Data Analytics for Distributed OFS

Probabilistic Deep Neural Networks (PDNN) Proposed for VBOTDA Analytics

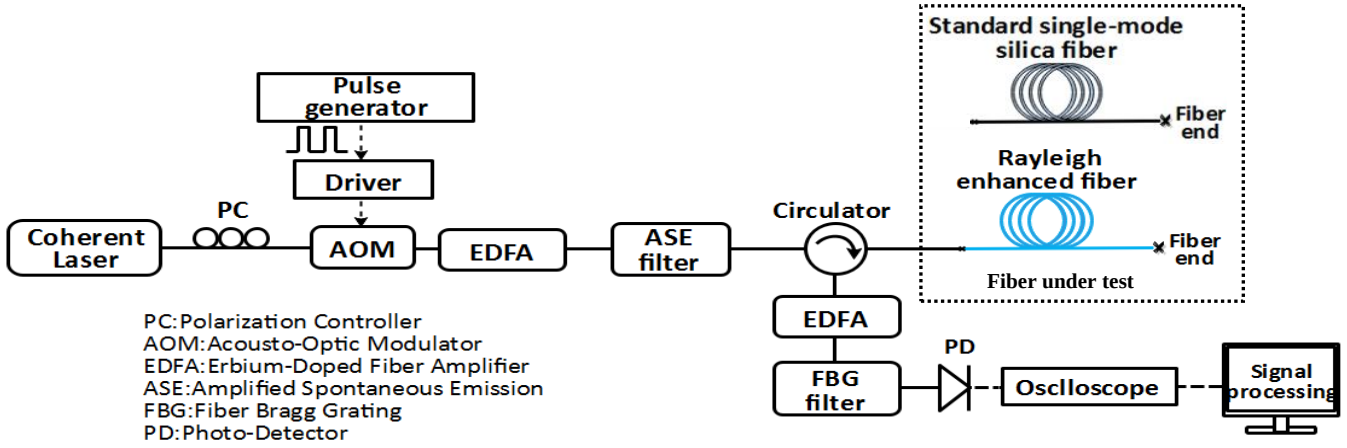


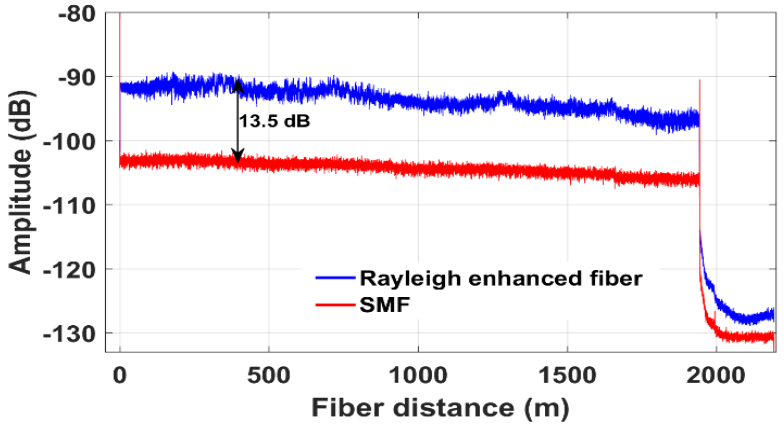


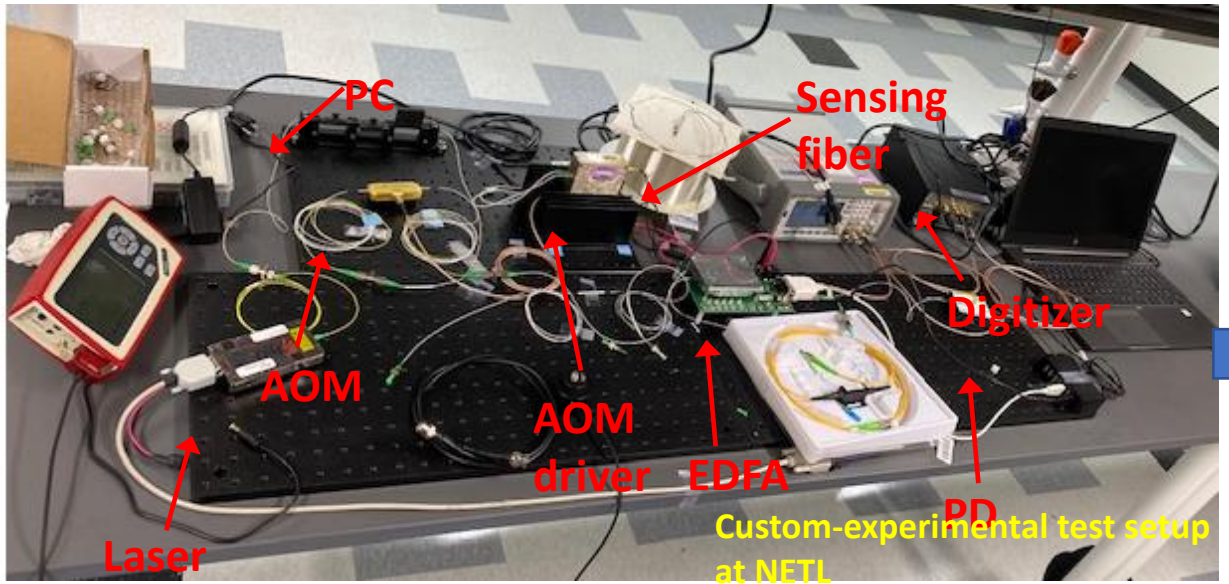


- PDNN processes the BGS and BPS data in real-time (1 sec).
- Propagates noise in data as prediction uncertainty.
- Findings submitted to Optics Letters. Currently under review.

Distributed Acoustic Sensing with Phase-OTDR







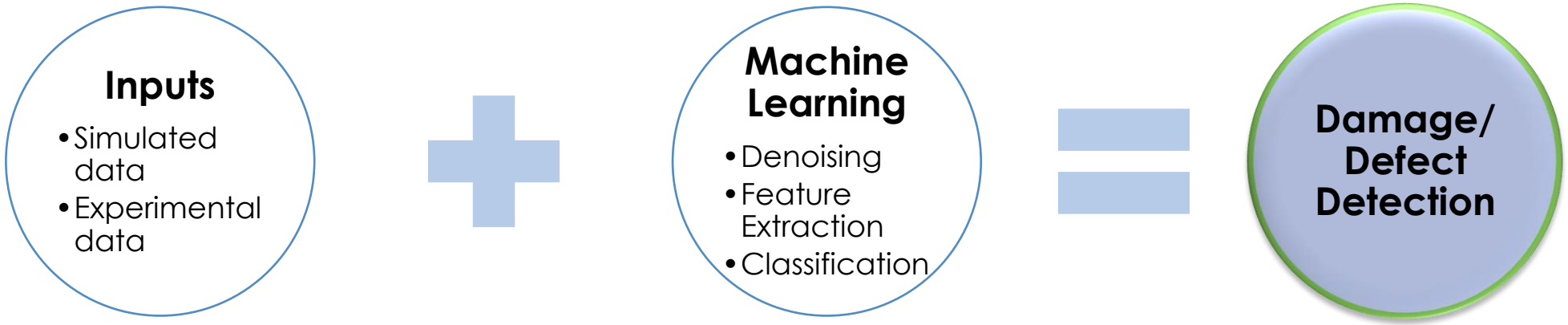
Phase-OTDR Sensing System



N. Lalam, P. S. Westbrook, J. Li, P. Lu, and M. P. Buric, "Phase-Sensitive Optical Time Domain Reflectometry With Rayleigh Enhanced Optical Fiber," *IEEE Access*, vol. 9, pp. 114428-114434, 2021.

Vibration Methods for Damage Detection

- Conventional damage/defect detection approaches based on detecting natural frequency/mode shape changes
- Low-frequency vibrations useful to detect large damages
- High-frequency (ultrasonic) vibrations used to detect small notches, cracks, etc.



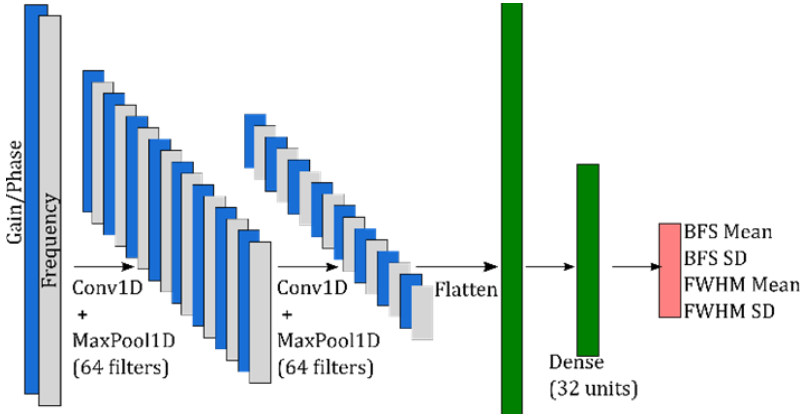
Deep Learning (DL)-Based Damage Detection

- Provide end-to-end solutions including denoising, feature extraction, and large multi-label classification tasks
- Require annotated large datasets: Multi-physics models can be used to simulate sensor responses
- **Unsupervised Domain Adaptation**: Recent works in computer vision have shown the possibility of training DL models on simulated data and adapting models to experimental data

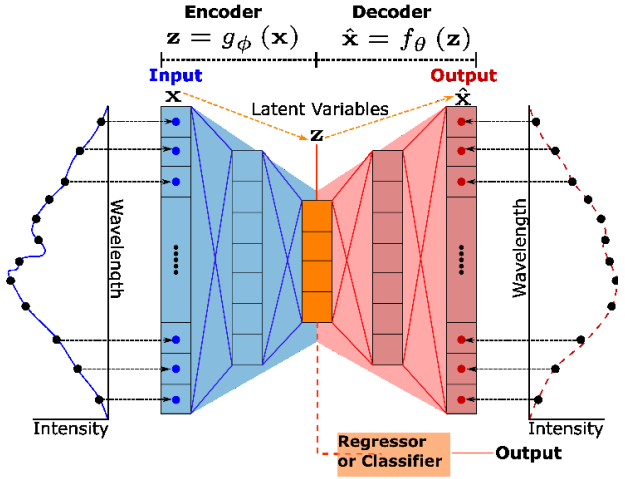
Recent Advances in ML for FOS Applications

Deep Neural Networks Identified for Intelligent FOS Data Analytics

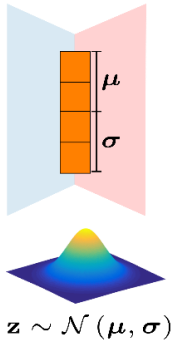
Conventional Machine Learning	Deep Learning
Good performance with small datasets	Good performance with large datasets
Manual feature engineering	Automatic feature engineering
Accuracy plateaus with dataset size	Accuracy improves with large datasets



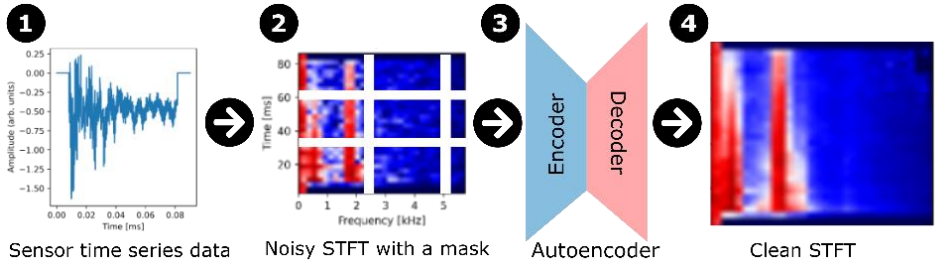
Convolutional neural network (CNN) architecture for BOTDA data analytics



(a) Autoencoder (AE): Dimensionality reduction and multi-parametric sensing



(b) Variational AE : Data compression and generation

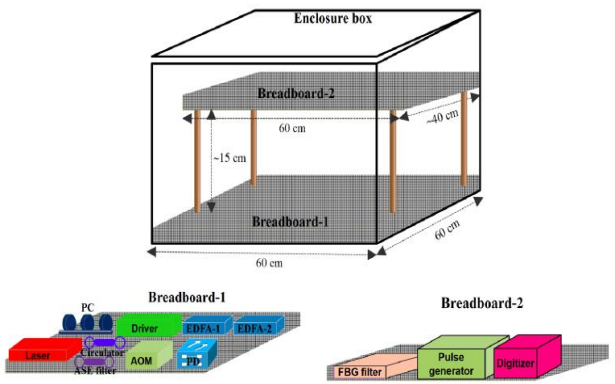


(c) Denoising AE: Improve SNR DAS data

Progress and Field Demonstration

TRL 2-3	TRL 4	TRL 4-5	TRL 5	TRL 6	TRL 7-8
Analytical and experimental demonstration	Fiber system validation in laboratory environment	Portable interrogator packaging	Portable prototype field-tested for natural gas pipeline	Optimization of sensor system and validation	Full-scale sensor system demonstrated

Portable Custom Optical Fiber Interrogator





In-House Design and Construction

High-Pressure Loop Natural Gas Pipeline

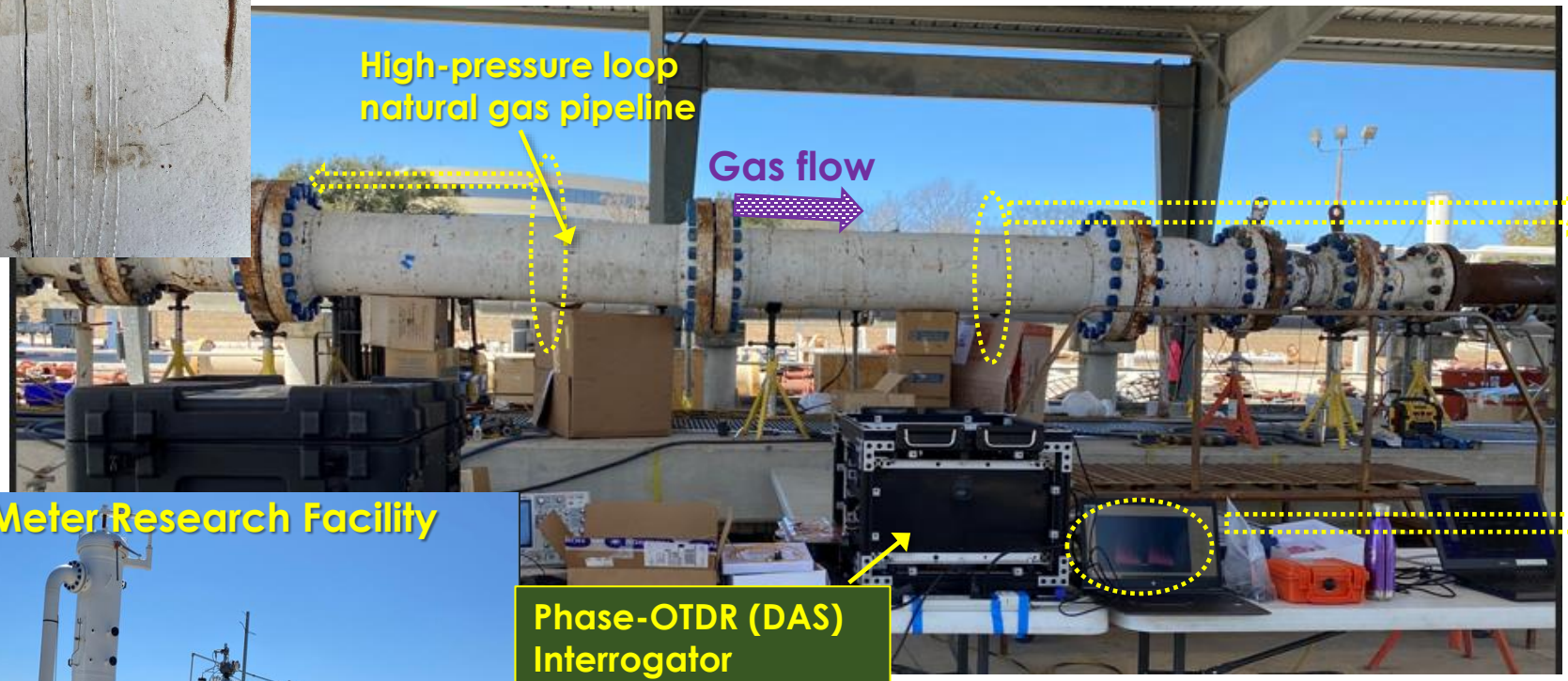


SwRI
SOUTHWEST RESEARCH INSTITUTE
San Antonio, Texas

Phase-OTDR (Distributed Acoustic sensor) Field-Demonstrated for Natural Gas Pipeline Monitoring

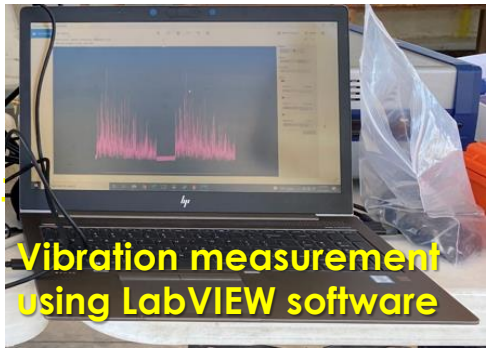
Natural Gas Pipeline Monitoring Based on Phase-OTDR







Installed fiber acoustic sensor on pipeline



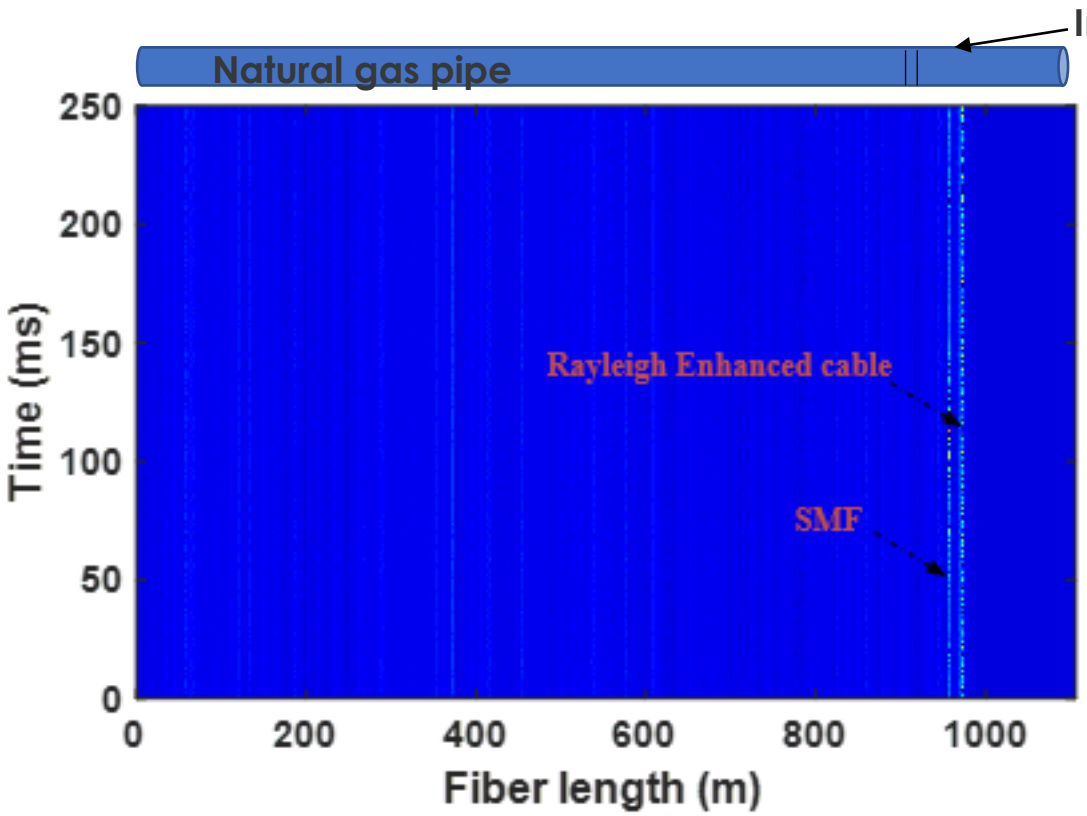


SOUTHWEST RESEARCH INSTITUTE
San Antonio, Texas

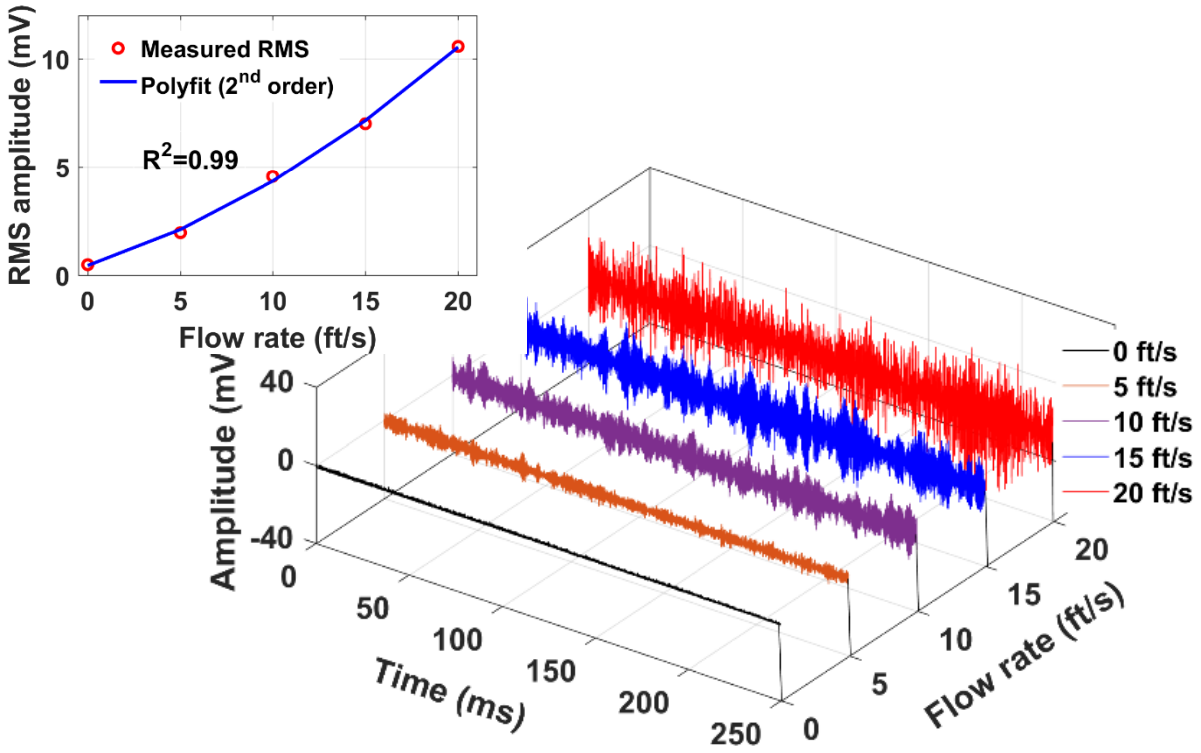
Pressure: **800/900/1000 psi,**

Flow rate: **5/10/15ft/s**

Natural Gas Pipeline Monitoring-Field Test

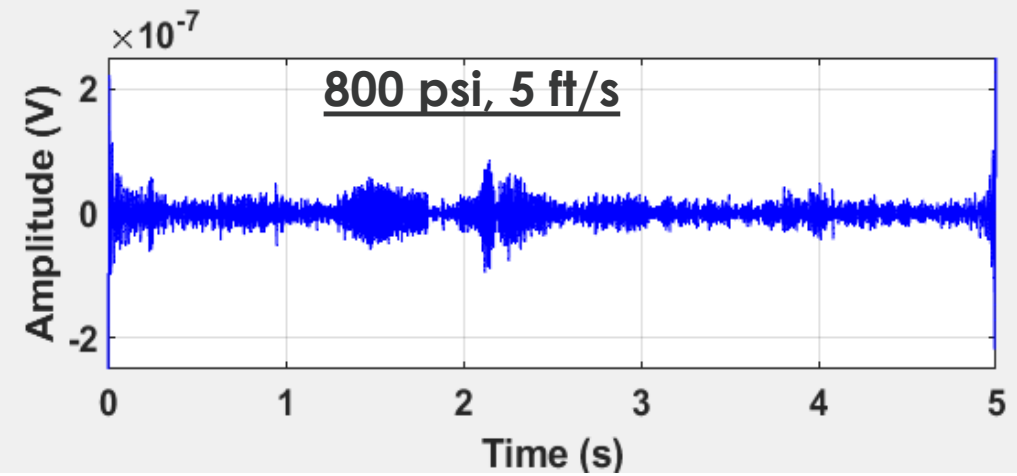


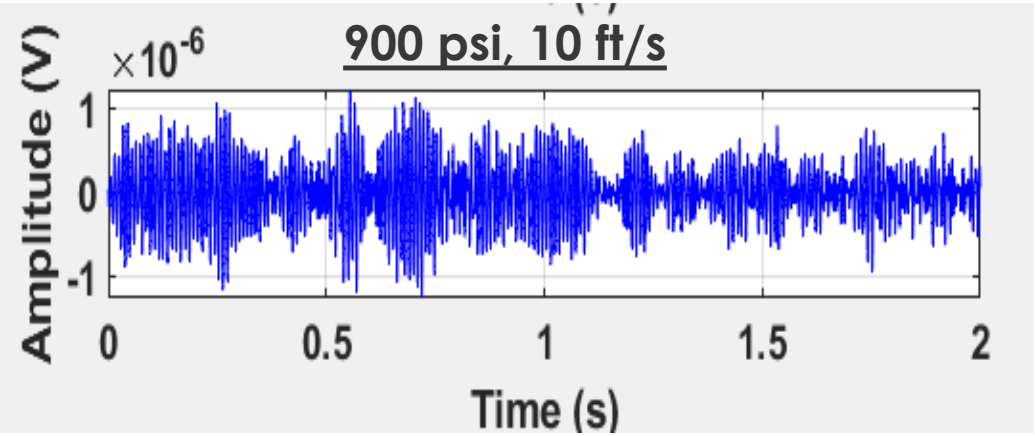
The gas flow-induced vibrations at fiber installation locations on the pipeline can be observed clearly for both standard SMF and Rayleigh-enhanced fiber cable

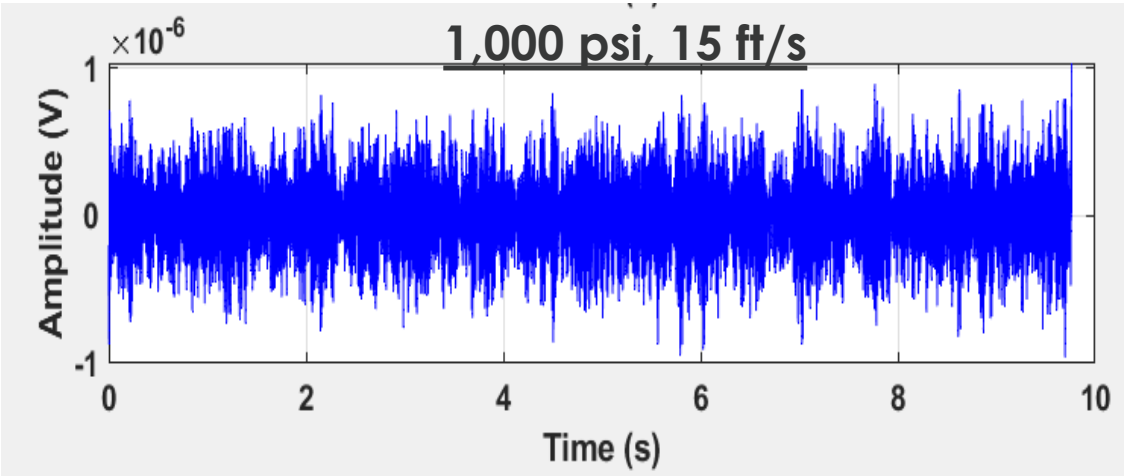


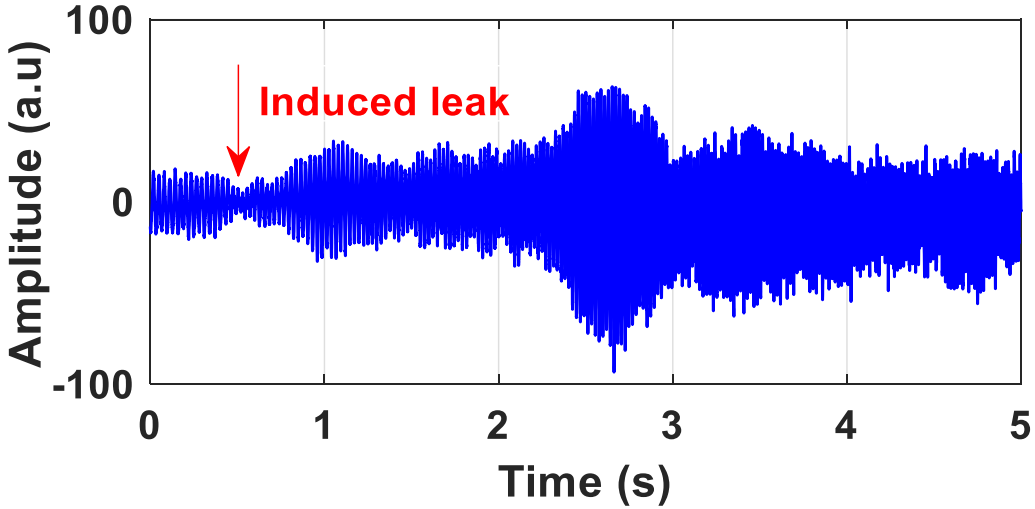
Time-domain traces of Rayleigh enhanced fiber cable at 1,000 psi pressure and different gas flow rates of 5, 10, 15, and 20 ft/s

Natural Gas Pipeline Monitoring



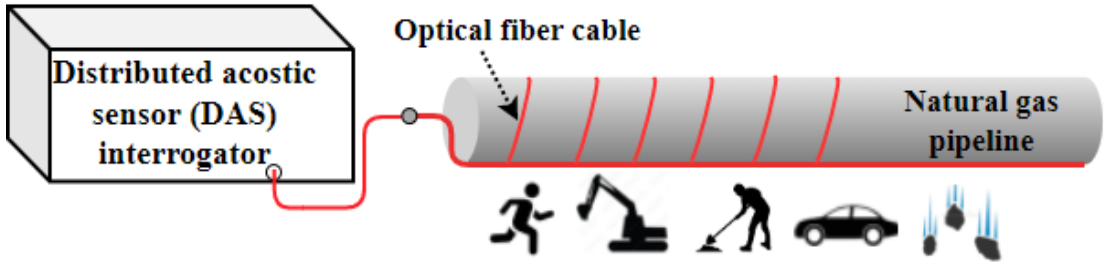




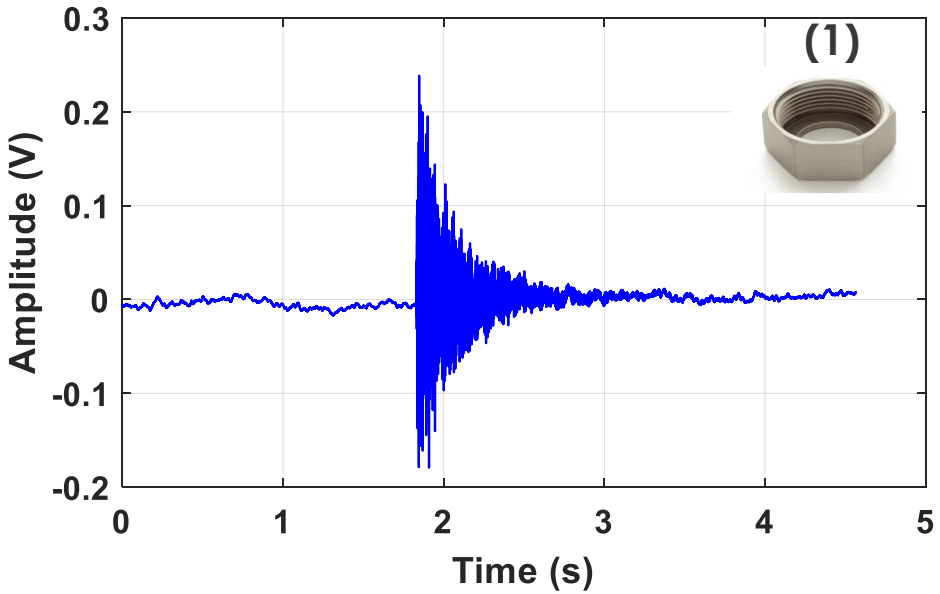


- The custom build phase-OTDR interrogator successfully measured the flow-induced vibrations
- The simulated gas leak generated distinct vibration pattern

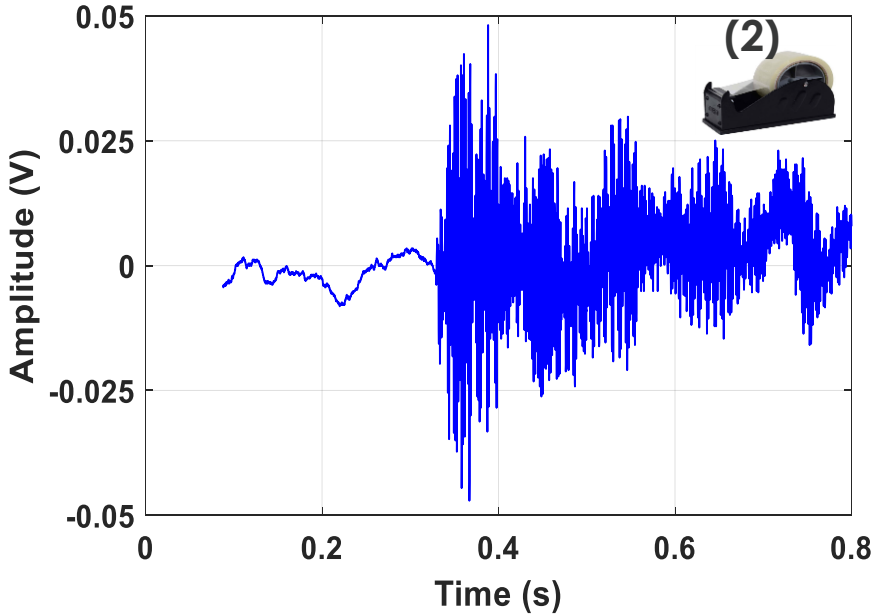
Third-Party Intrusion Detection







Dropping Stainless Steel Hex Nut on Pipe

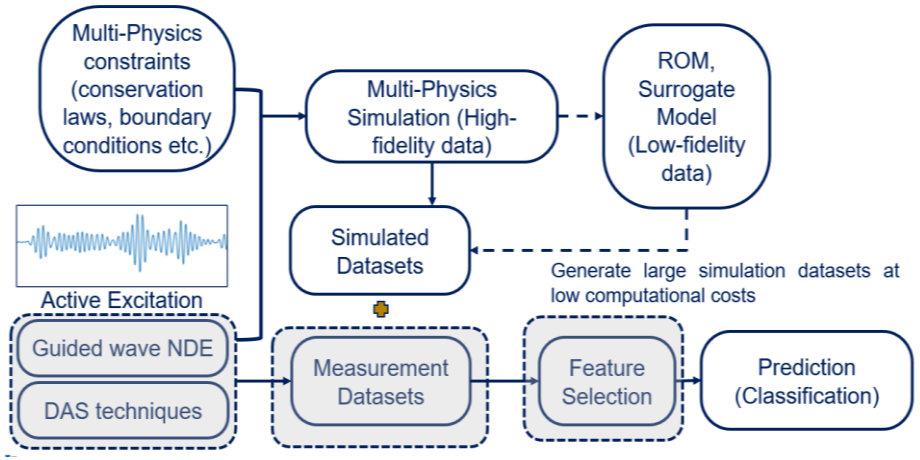


Dropping Cello Tape Dispenser on Pipe

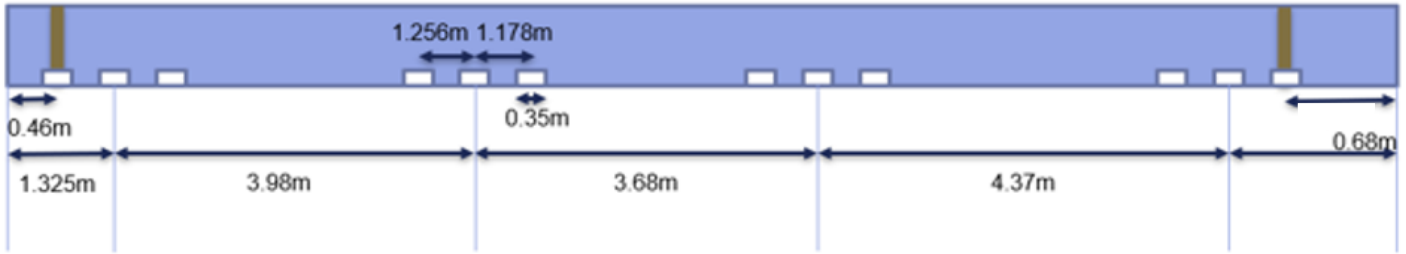
- Digging
- Land slides
- Foot steps
- Vehicle movement
- Suspicious activities
- Pipeline tampering/theft

Physics-Based Modeling + AI for Pipeline Monitoring

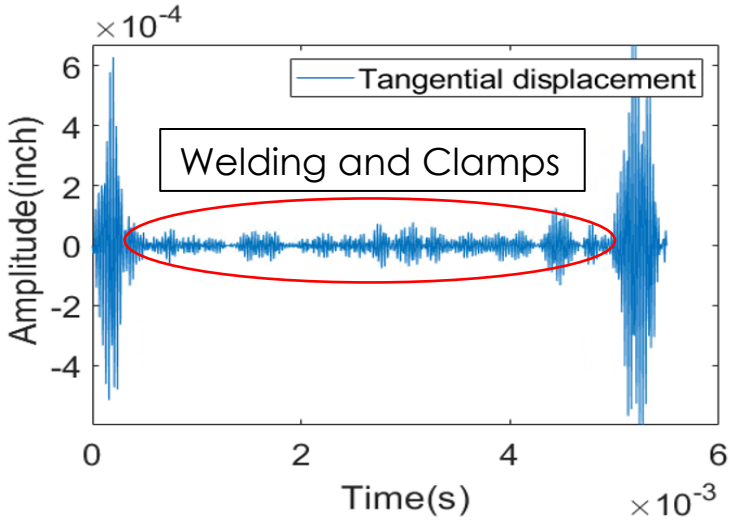
Framework Overview:



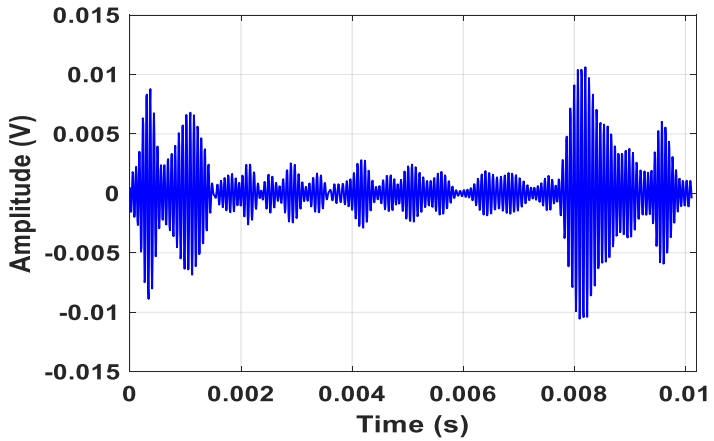
Pipe Model:

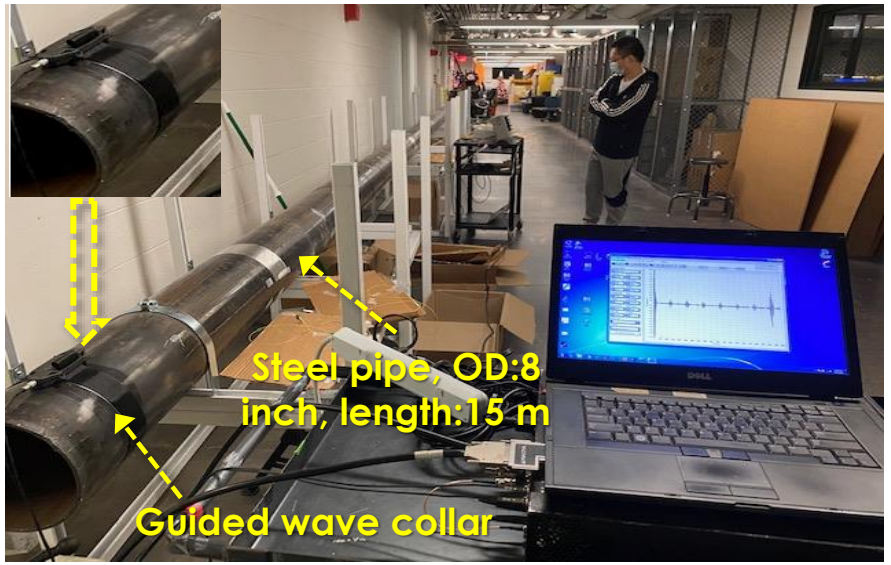


Simulated Time-Domain Signal



Experimental Time-Domain Signal

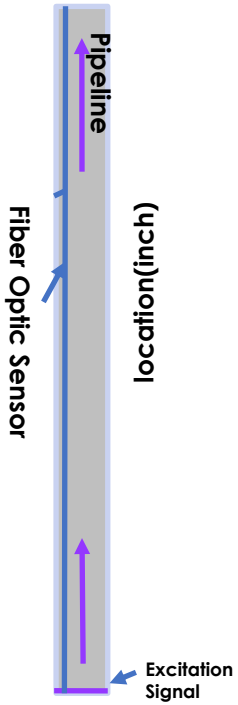


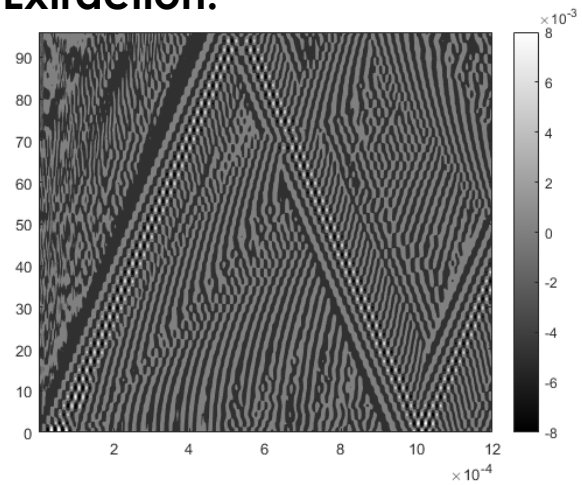


Fiber vibration sensor and guided wave acoustic (32 kHz) excitation source

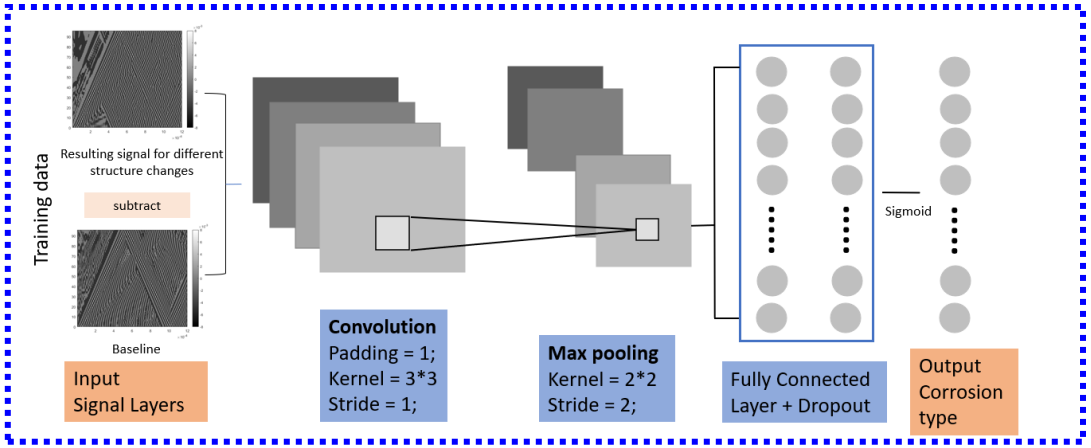
Pipeline Classification Based on CNN

Resulting Signal Extraction:

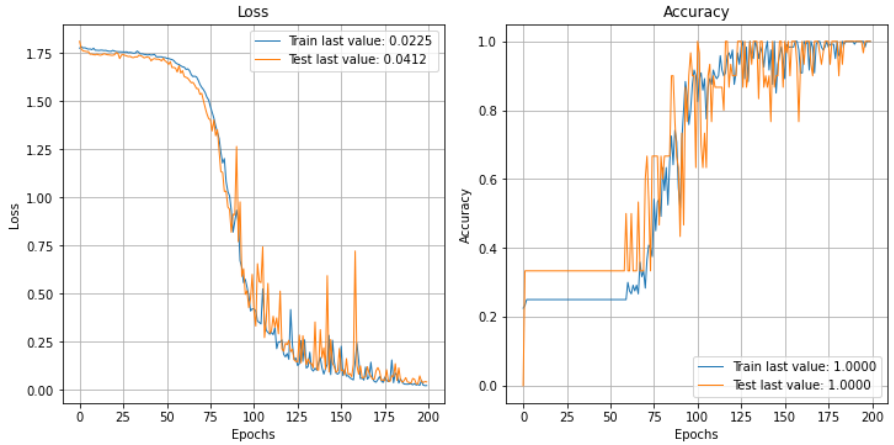




CNN Framework:



Training History:



Confusion Matrix:

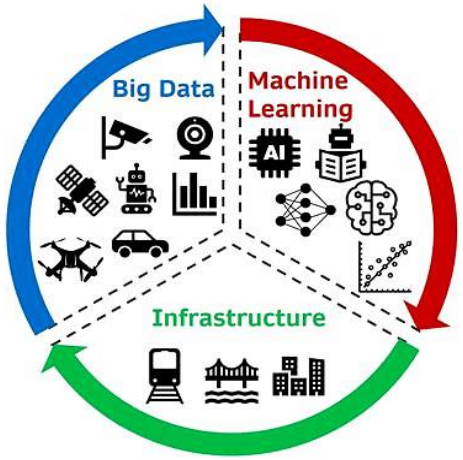
Real \ Prediction	Clamp	Local	General	Pitting	Welding
Clamp	98.02	1.05	0.45	0.23	0.25
Local	0.17	98.67	0.76	0.21	0.19
General	0	0	98.6	0.8	0.6
Pitting	0.2	3.52	0.61	95.1	0.53
Welding	0.22	0.36	0.08	0.3	99.04

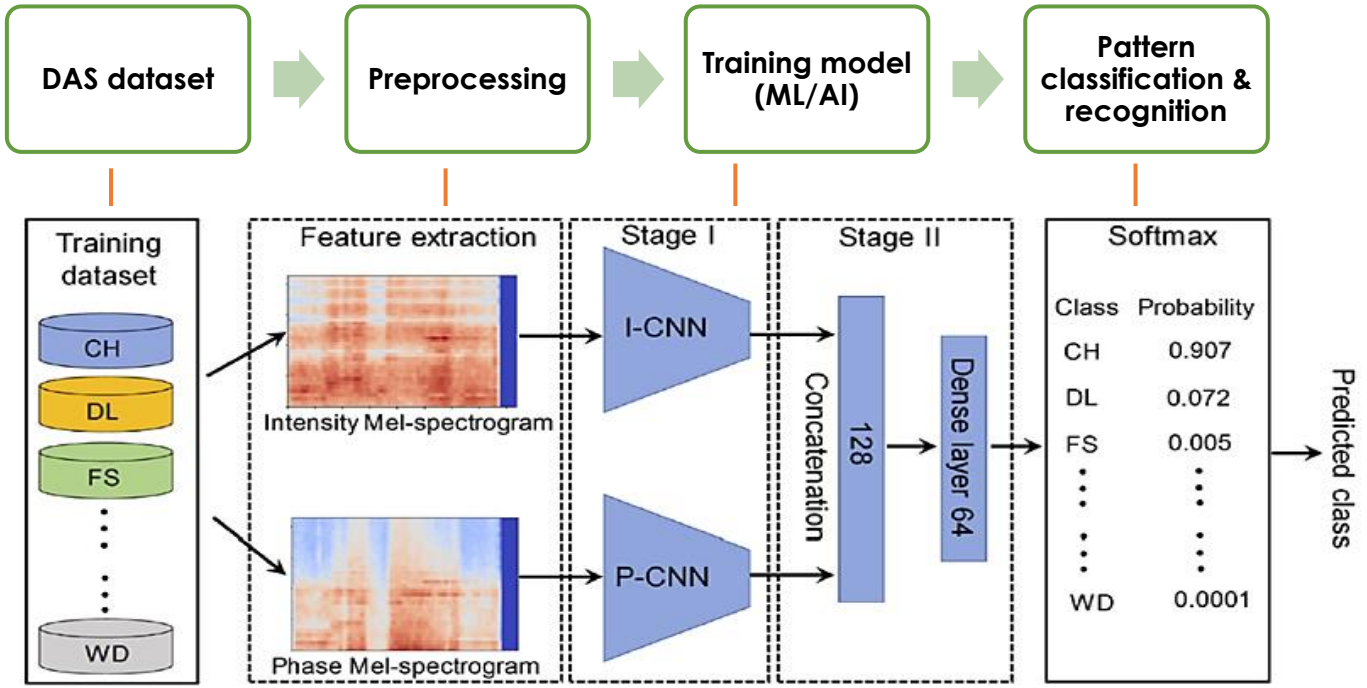
Pipeline Defect Classification Based on CNN Framework

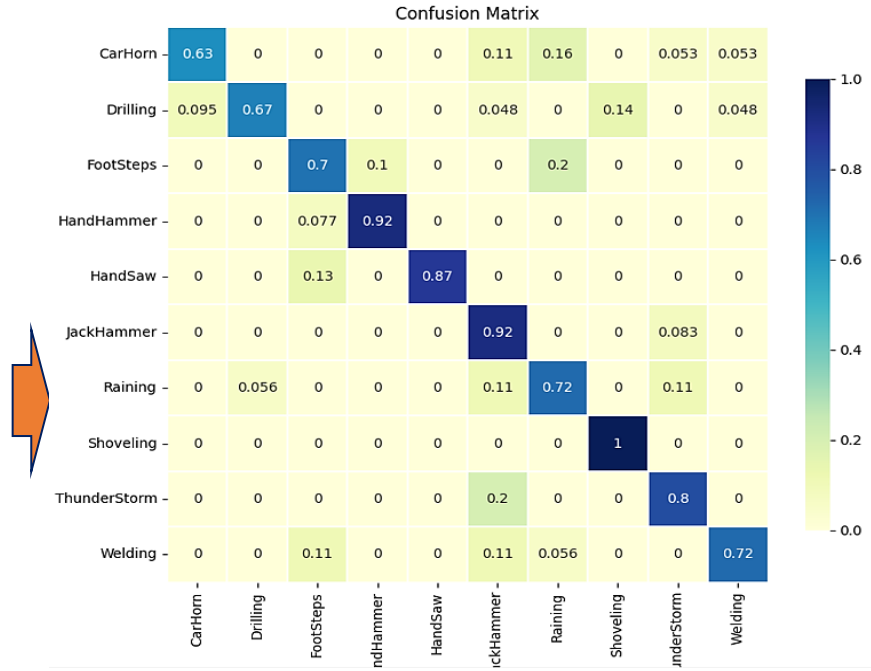
P. Zhang, A. Venketeswaran, H. Babaee, R. F. Wright, N. Lalam, and P. Ohodnicki, "Machine learning based on distributed fiber sensor for pipeline corrosions detection", SPIE, Optical Waveguide and Laser Sensors II, 2023(unpublished)

Intelligent Fiber Sensors: A Fusion of DAS & AI

- Infrastructure type: Threats analysis
- High-quality datasets: Acoustic signatures of various threats/events
- Data processing: Pre-processing and AI/ML models







Conclusions and Future Research

Conclusions

1. Enhanced distributed optical fiber sensors data processing using AI/ML data analytics
2. AI/ML-based advanced data analytics enhances the sensing performance while significantly reducing processing speed
3. Physics-based simulations are being applied for simulated training datasets
4. Enhanced capability for defect identification and classification is anticipated

Future Research

1. Apply ML-based data processing for specialty optical fibers, such as multi-Brillouin peak fibers, few-mode fiber
2. Simulated and experimental datasets of various pipeline defects
3. Develop ML- and AI-based approaches for multiparametric sensing capabilities
4. Customization for specific infrastructure problems and challenges

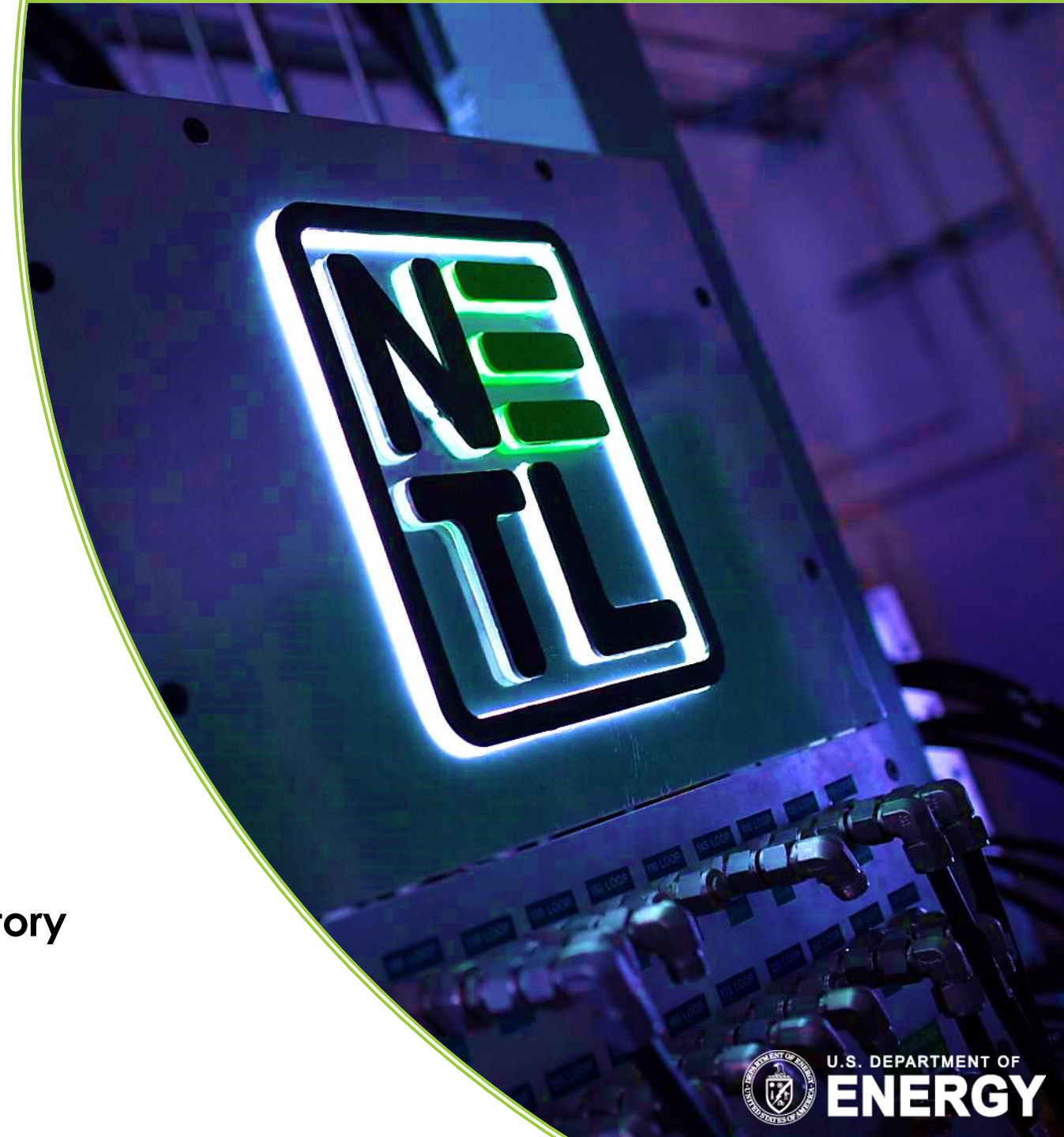
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