Presentation at the Panel on Deep Learning in R&M: Challenges, Opportunities and Future Perspective

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Outline

- Research Frontiers in RAMS at UMD
- Prognostics and Health Management (PHM)
- Probabilistic Physics of Failure (PPoF)
- Machine Learning (ML) & Deep Learning (DL) in R&M
- Hybrid PPoF-ML Methods
- Conclusions

RAMS-Related Research in My Group

- Probabilistic Physics-of-Failure (PPoF)
  - PoF has nearly 60-years of history in PoF (More Recently PPoF)
  - Unit-Specific reliability assessment
  - Empirically developed
  - Simulation-based reliability
- Physics Laws as the Fundamental Sciences of Reliability
  - 2^{nd} Law of thermodynamics and entropy
  - Statistical mechanics and Statistical thermodynamics
  - Information entropy and Relative entropy
- Prognosis and Health Management (PHM)
  - PPoF and Entropic models of degradation and failure
  - Deep Learning, Sensor-Based Reliability Analysis
    - Diagnostic and prognostic reliability: Data Fusion, Predictive Analytics, Deep Learning, Uncovering physics from data
    - Combined Techniques: DNN, CNN, BN, PPOF,. .

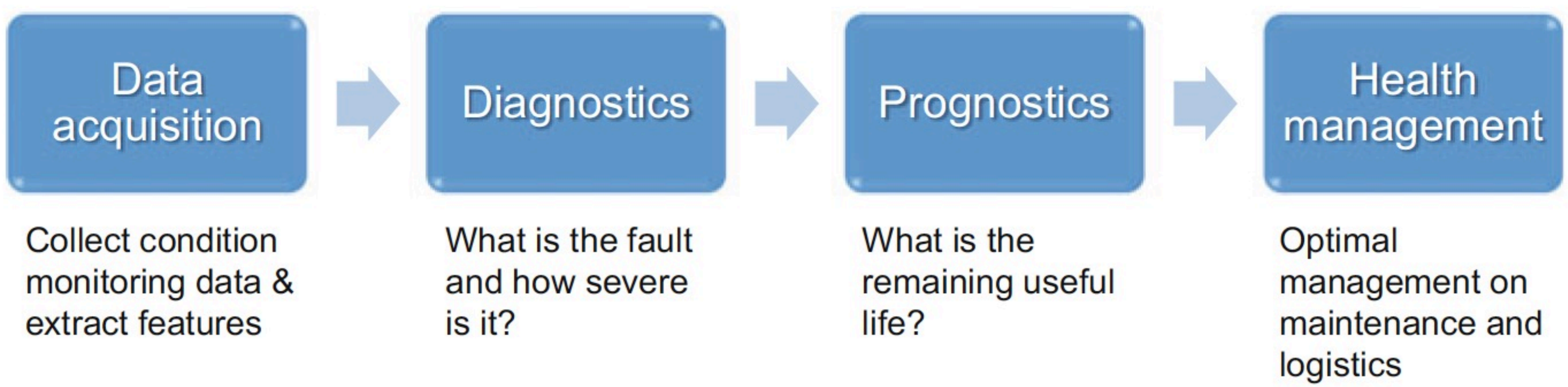
PROGNOSIS AND HEALTH MANAGEMENT

Prognosis and Health Management (PHM)

- PHM has overcome limitations of traditional reliability analysis
- PHM is a holistic approach for effective and efficient system health management
- A PHM framework in RAMS seeks to:
  - Link failure mechanisms with lifecycle management
  - Accurately predict the future behavior of a specific system
  - Minimize the system's downtime and profits with predictive maintenance decision making
- PHM generally produces two tangible outcomes:
  - Diagnostics and Detection of incipient faults
  - Predicting remaining useful life (RUL)

PHM (Cont.)

- PHM provides early detection and isolation of incipient faults
  - Means to monitor and predict the progression of the fault
  - Predict and assess options for autonomous maintenance schedule and asset health management



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PHM (Cont.)

- PHM generally include:
  - Physics based models (PBM)
    - e.g., Empirical models such as Paris' Law, 2nd law of thermodynamics
  - Data-driven analytics (DDA)
    - Machine learning models
    - Deep learning models
  - Hybrid approaches
    - Combine PBM and DDA

Prognostics & Health Management:

DATA ACQUISITION AND ANALYSIS

Data Acquisition for PHM

- PHM frameworks rely on information extracted from the data collected through on-line and off-line monitoring systems:
  - Data types include
    - Physical variables, e.g., pressure and temperature
    - Signal variables, e.g., acoustic emission (AE) and vibrations.
    - Categorical variables, e.g., operation states
- Low-cost sensors allow massive data collection:
  - Massive data can be collected by monitoring the entire systems during their lifecycle
  - Some of the data correlate well with the degradation processes

Data Acquisition for PHM (Cont.)

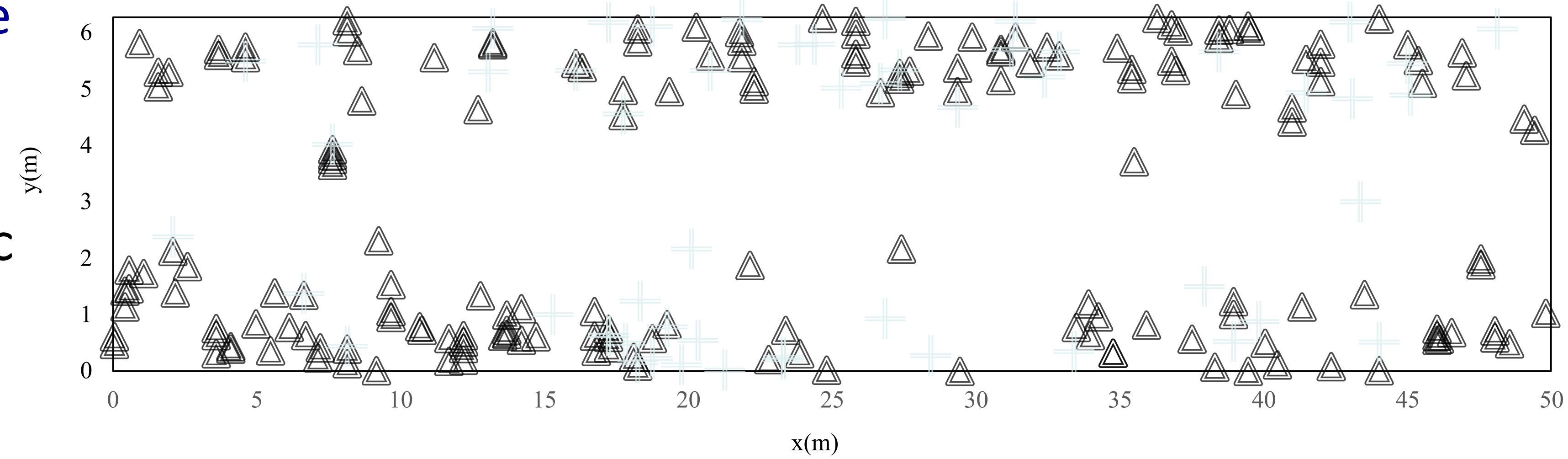
- Design for reliability processes can consider the sensor selection and placement
  - Sensor selection for a reliable monitoring network
  - Selection of proper mixture of sensing and measurement tools
  - Optimize sensor layout that maximize probability of damage/fault detection while minimizing costs
- Collected data need cleaning and processing
  - Outlier detection
  - Redundant variables
  - Feature engineering

Data Acquisition for PHM (Cont.)

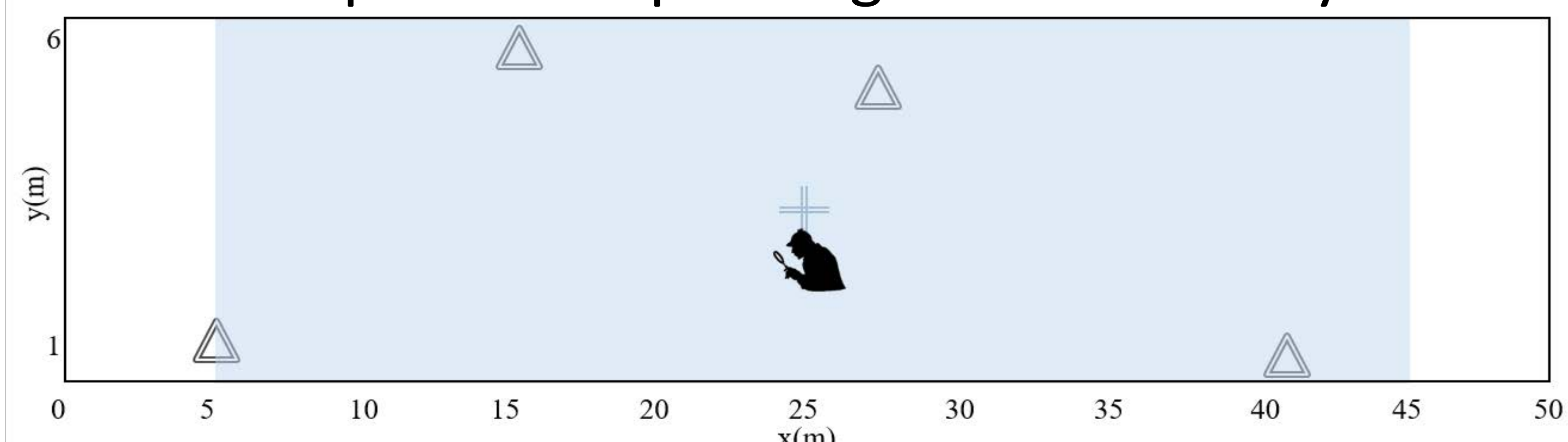
- Collected data from systems present challenges
  - High noise contamination level
    - These uncertainties can propagate towards the diagnostics and prognostics analysis.
  - Incomplete data due to high presence of NaN values and missing information
    - Damaged or faulty sensors
    - Unsynchronized sampling frequencies from different sensors
  - Not optimized Sensor layout
  - Redundant information among sensors

An Example of Optimum Sensor Placement for PHM

- 46 random realizations are aggregated to find the final sensor layout
  - Triangles: 176 Acoustic emission sensor
  - Pluses: 54 human Inspection Nodes
- On average , each aggregate layout has:
  - 4 acoustic emission sensors
  - 1 human inspection
- Final layout is obtained using K-means clustering



Scatter plot corresponding to all 46 HM layouts



Final Aggregate Layout

Prognostics & Health Management:

DATA DRIVEN APPROACHES

Data-Driven Analytics for PHM Analysis

- DDA an alternative to PoF
  - Do not require specific knowledge of the system
  - Analytic-based models extract information directly from the data
  - Trained models can be scaled and adapted to different systems
- DDA are black-box models
  - Difficult to interpret their results
  - Do not necessarily follow the laws of physics
  - Require large amounts of data to train the models
- Main DDA applied to PHM these days
  - Machine learning (ML)
  - Deep learning (DL)

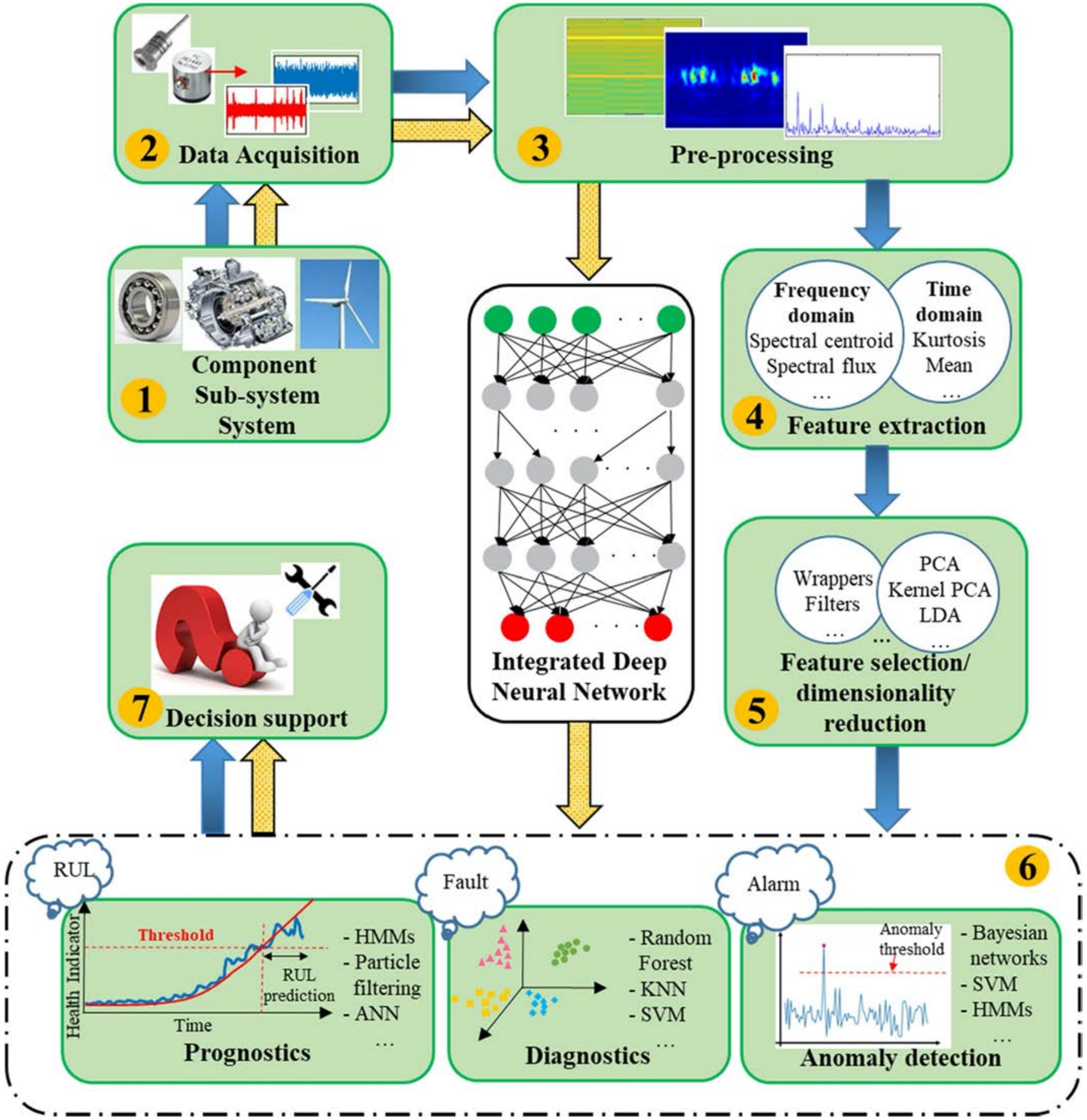
Machine Learning in PHM

- ML models are statistics-based analytics
  - Maps a set of inputs X into a set of desired outputs Y
  - Common analytics are support vector machines (SVM) and random forest (RF)
- ML models are extremely sensitive to their input values
  - Raw data requires to be first processed to obtain useful features
  - Experts and prior knowledge of signal processing is usually required to manually select and extract meaningful features

Deep Learning in PHM

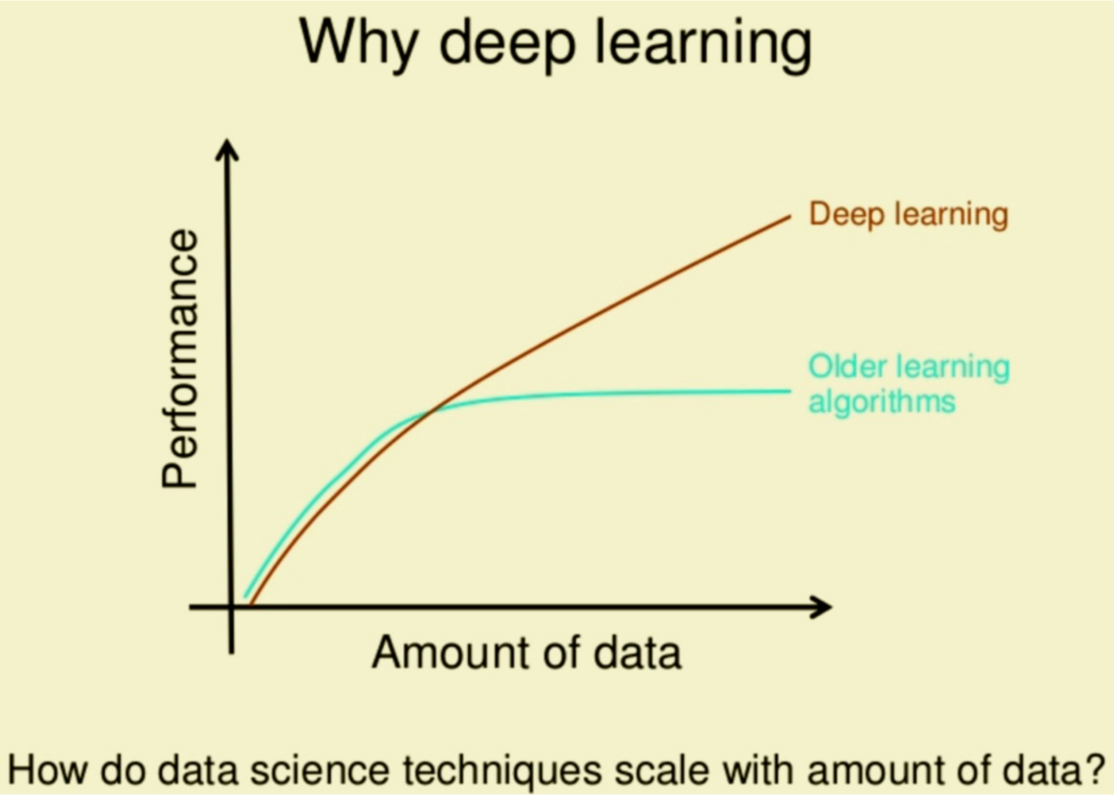
- Deep Learning (DL):
  - Deep neural networks are the main structure of DL models
  - DL automatically process raw data to extract highly abstract and complex features.
    - Eliminates reliance on domain knowledge
    - Does not require feature engineering or manual feature selection
    - Offers an end-to-end learning process from raw data
  - DL models learn hierarchical representations of large-scale data automatically
    - Advantageous in high volume and multi-dimensional industrial data
- Big data collected from sensor networks and improvements in computational analysis have made DL popular in reliability

Data-driven PHM vs. Deep Learning PHM



[From DOI 10.1016/j.measurement.2020.107929

- ML models have no explicit information on the system under study
  - Models are bound to the quality of the available data
  - Interpreting its results can be challenging
- DL models are more flexible than ML models
- DL has received most research attention recently

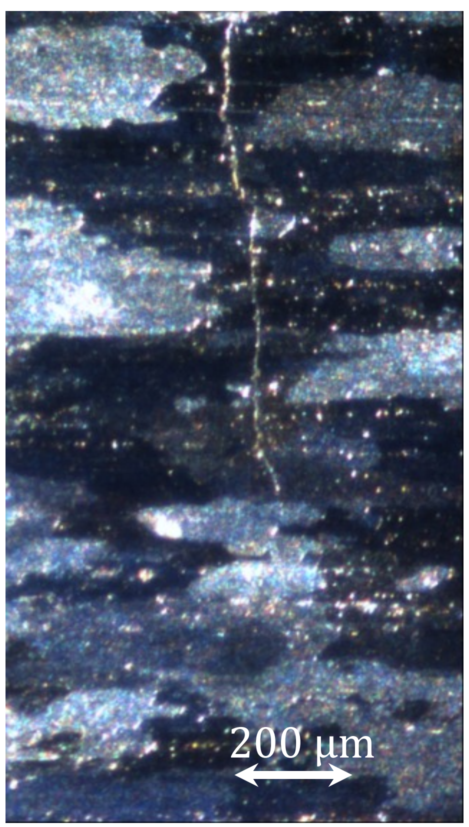


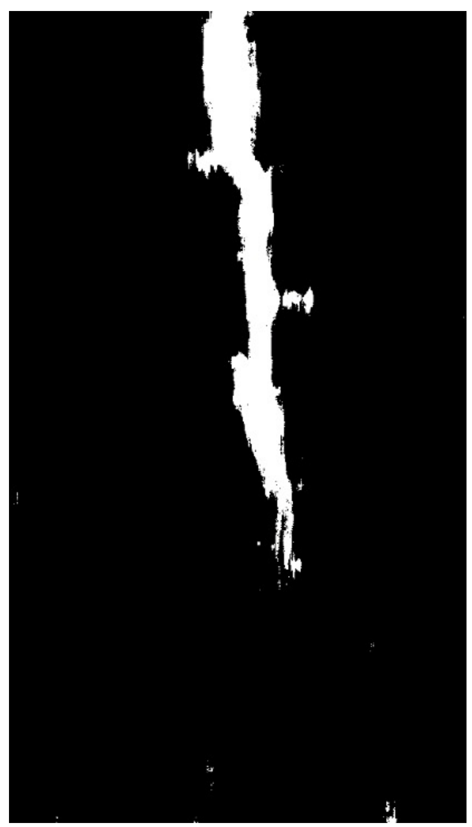
Recent researches have implemented DL models to generate and solve partial differential equations (PDE) from system data

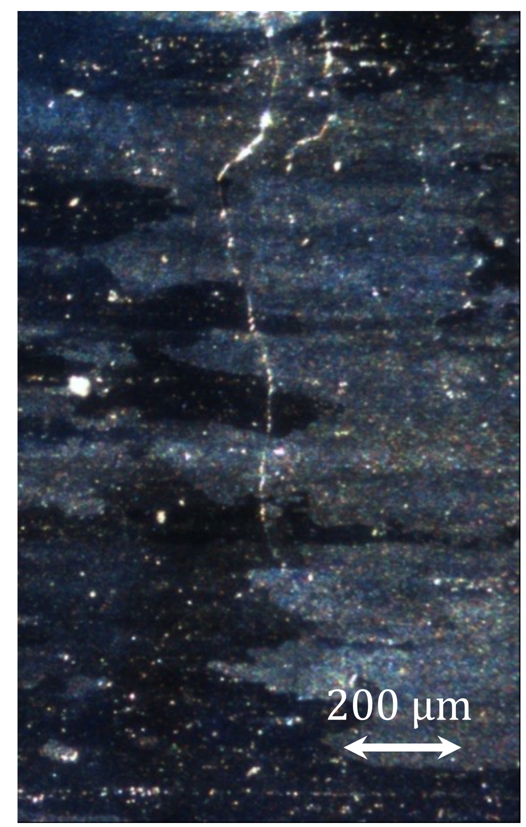
[From DOI 10.1016/j.measurement.2020.107929

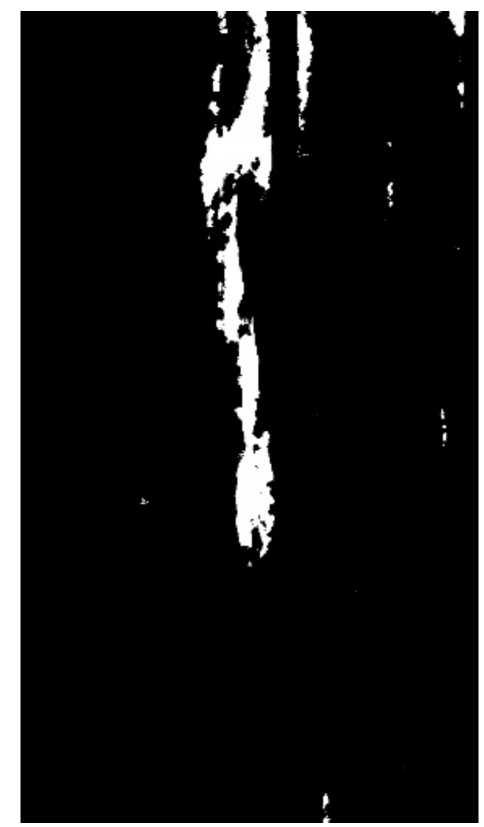
Example of Deep Learning in Diagnostics

- Automated crack length estimation using CNNs
  - Images correspond to experiments conducted at Center for Risk and Reliability



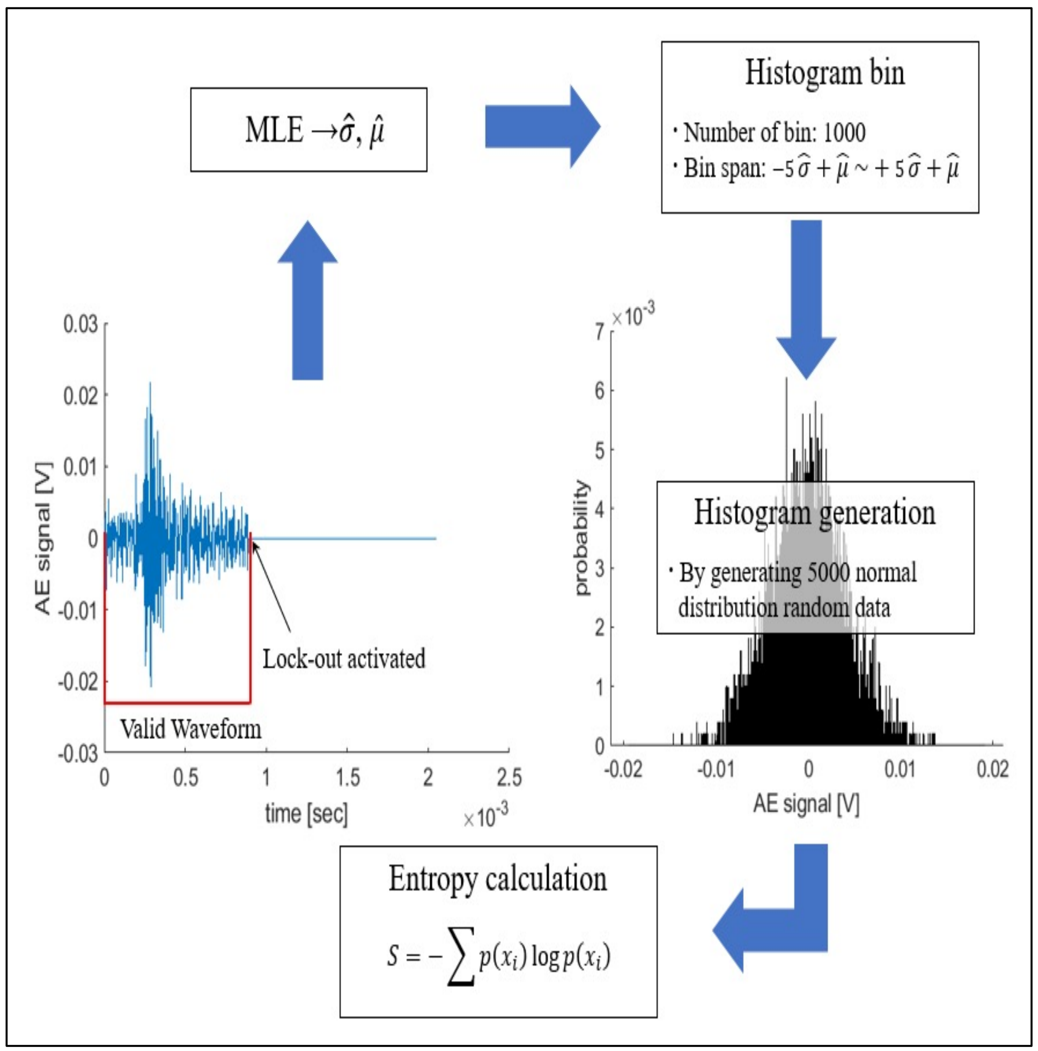


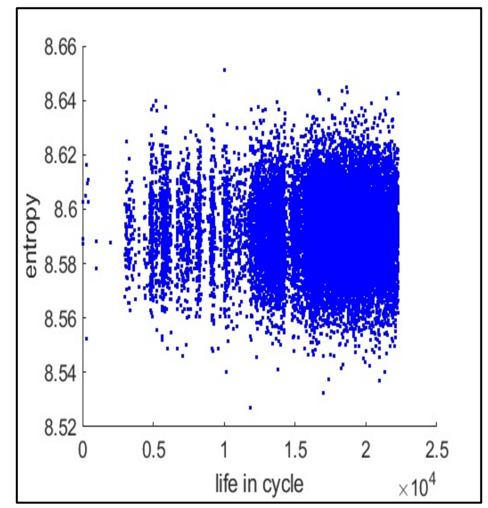


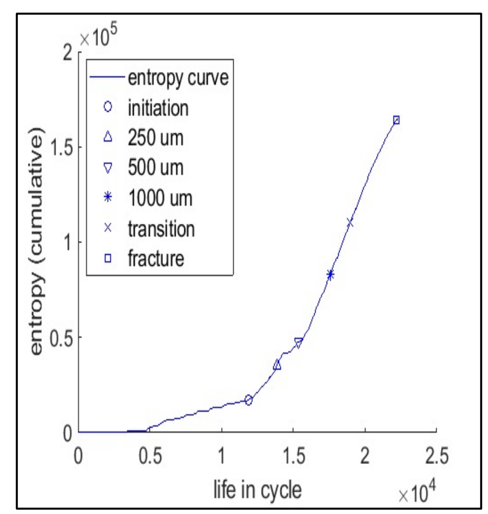


Original   CNN prediction   Original   CNN prediction

Information Theory Based Entropy

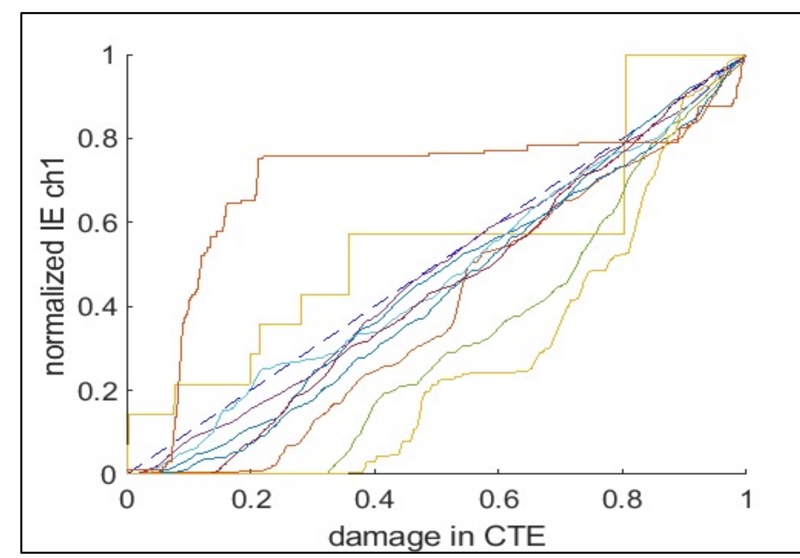






Normalized damage

$$D = \frac{M_i - M_o}{M_f - M_o}$$



AE information entropy

Current Challenges

- Industrial data characteristics
  - Noisy and incomplete data hinder the possibilities of DL applications to complex systems
- Model selection
  - In growing number of DL algorithms to choose from. Which one is better?
- Black-box tool
  - DDA approaches are hard to interpret and not many PPoF models are available to implement hybrid models
- Real-time realization and benchmarking
  - Most models are usually tested in benchmark dataset and are hard to adapt to real complex systems

For more research in DL visit my website for publicly available information
http://modarres.umd.edu

Thank you for your attention!