Reliability Engineering: Today and Beyond

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by

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Outline

- A New Era in Reliability Engineering
- Reliability Engineering Timeline and Research Frontiers
- Prognostics and Health Management
- Physics of Failure
- Data-driven Approaches in PHM
- Hybrid Methods
- Conclusions

New Era in Reliability Sciences and Engineering

- Started as an afterthought analysis
  - In enduing years dismissed as a legitimate field of science and engineering
  - Worked with small data
- Three advances transformed reliability into a legitimate science:
  - 1. Availability of inexpensive sensors and information systems
  - 2. Ability to better described physics of damage, degradation, and failure time using empirical and theoretical sciences
  - 3. Access to big data and PHM techniques for diagnosing faults and incipient failures
- Today we can predict abnormalities, offer just-in-time remedies to avert failures, and making systems robust and resilient to failures

Seventy Years of Reliability Engineering

- Reliability Engineering Initiatives in 1950's
  - Weakest link
  - Exponential life model
  - Reliability Block Diagrams (RBDs)
- Beyond Exp. Dist. & Birth of System Reliability in 1960's
  - Birth of Physics of Failure (POF)
  - Uses of more proper distributions (Weibull, etc.)
  - Reliability growth
  - Life testing
  - Failure Mode and Effect Analysis (FMEA)
- Logic Models: Fault Tree Analysis in 1970's
  - Probabilistic Risk Assessment (PRA)
  - Common Cause Failures (CCFs)
  - Uncertainty analysis

Timeline (Cont.)

- Accelerated Life and Degradation Testing in 1980's
  - Environmental screening
- Revival of Empirically based Physics in 1990's
  - Probabilistic Physics-of-Failure (PPoF)
  - Time varying accelerated tests (e.g., Step-Stress Test)
  - Highly Accelerated Life Testing (HALT)
- Hybrid Reliability and Prognosis Models in 2000's
  - Powerful simulation tools (MCMC, Recursive Bayes and Particle Filtering)
  - Integrated logic models and probabilistic models (e.g. BBN)
  - Machine Learning (ML) tools for PHM

Timeline (Cont.)

- Emergence of Fundamental Sciences of Reliability, 2010's
  - Entropy as damage and as science of reliability
  - Semi-supervised and unsupervised deep learning reliability predictive
  - Reliability in the age of autonomous and cyber-physical systems
  - PoF-informed deep learning (DL) models
  - Discovering physics from system performance data
- Beyond 2020
  - Reliability as fundamental discipline of engineering
  - Reliability sciences
  - Hybrid PoF, ML, DL PHM in Design and Operations

Frontiers of Research in Reliability Engineering

- Probabilistic Physics-of-Failure (PPoF)
  - More than 50-years of history in PoF (More Recently PPoF)
  - Unit-Specific reliability assessment
  - Simulation-based reliability
- Fundamental Sciences of Reliability Engineering
  - 2^{nd} Law of thermodynamics and entropy
  - Statistical mechanics
  - Information entropy
- Prognosis and health management (PHM)
  - Hybrid System Reliability
    - Combined Techniques: DNN, CNN, BN, POF,. . .
  - Deep Learning, Sensor-Based Reliability Analysis
    - Diagnostic and prognostic reliability: Data Fusion, Predictive Analytics, Deep Learning, Uncovering physics from data

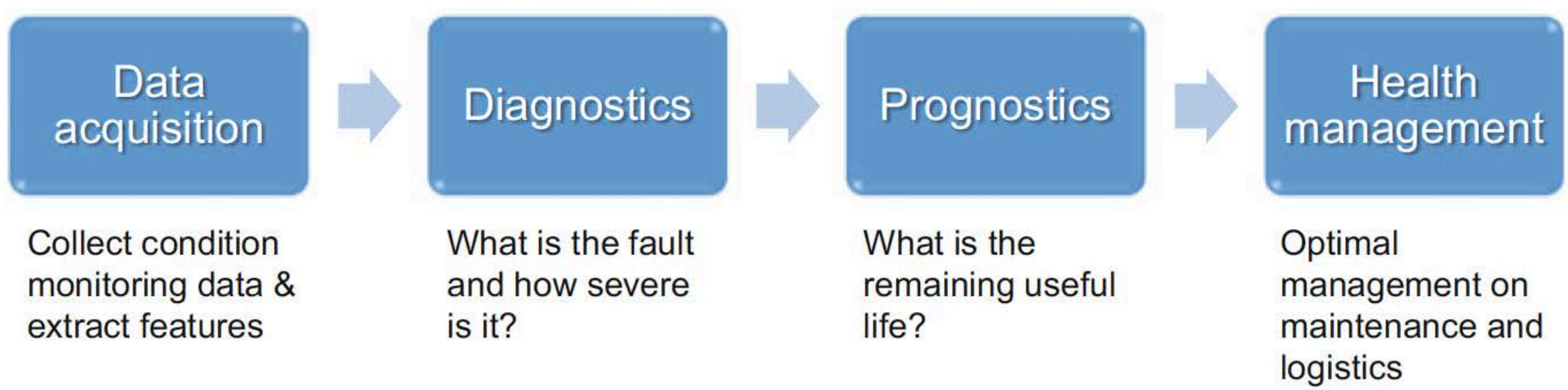
PROGNOSIS AND HEALTH MANAGEMENT

Prognosis and Health Management (PHM)

- PHM has overcome limitations of traditional reliability analysis
- PHM is a holistic approach towards an effective and efficient system health management
- A PHM framework in reliability engineering seeks to:
  - Link failure mechanisms of a system with its lifecycle management
  - Accurately predict the future behavior of a system
  - Minimize the system's downtime and maximize its usage and profits by supporting the maintenance decision making
    - Prognosis allows proactive maintenance strategies, avoids reactive ones
- PHM generally produces two tangible outcomes:
  - Detecting incipient failures
  - Predicting remaining useful life (RUL)

PHM (Cont.)

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



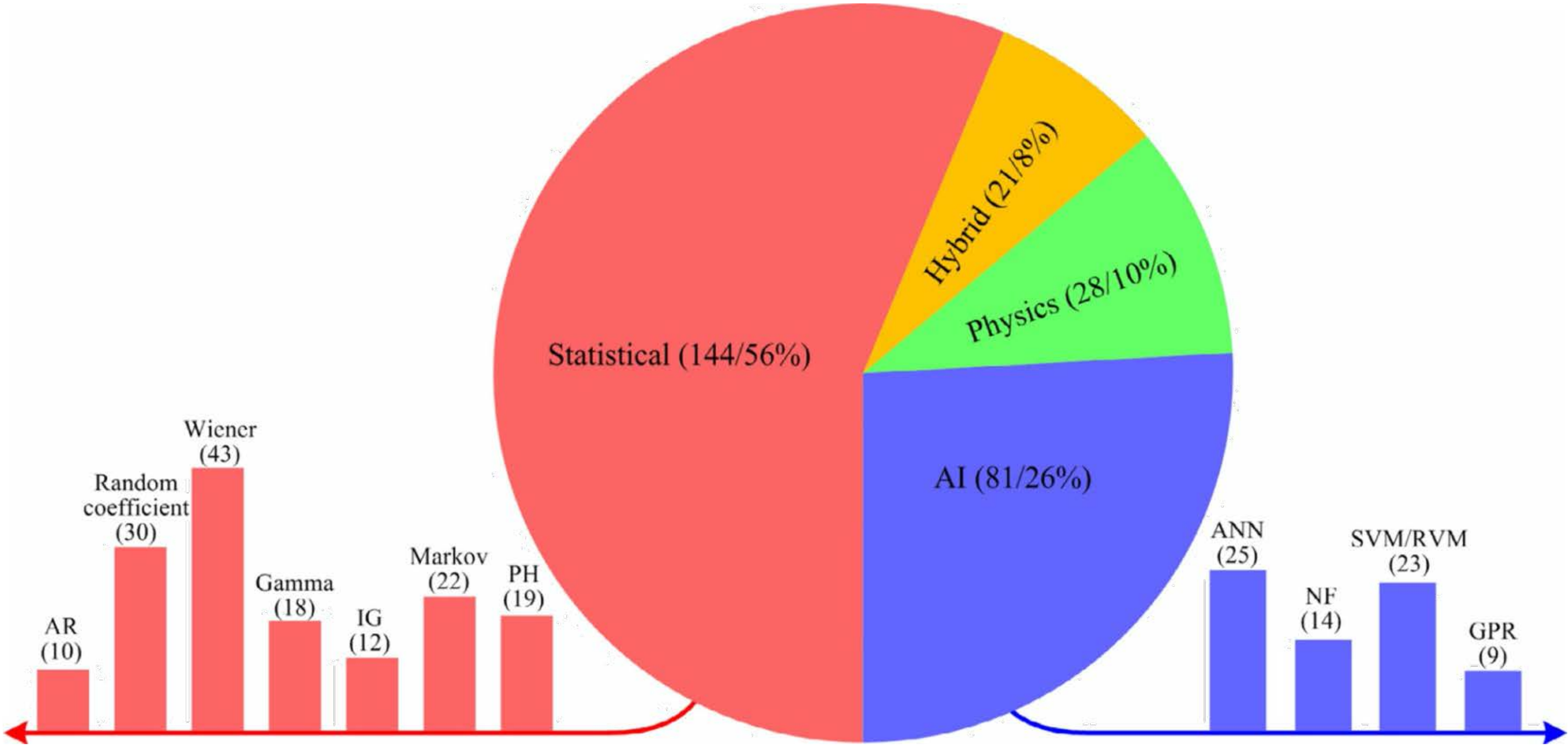
[From:DOI 10.1007/978-3-319-44742-1

PHM (Cont.)

- Most research efforts in PHM go to developing techniques for the diagnostics and prognostics of systems
- Depending on the system and the available information, these PHM steps can be addressed through:
  - Physics based models (PBM)
    - e.g., Paris' Law, 2nd Law of Thermodynamics
  - Data-driven approaches (DDA)
    - Machine learning models
    - Deep learning models
  - Hybrid approaches
    - Combine PBM and DDA

PHM (Cont.)

- Publications in PHM-reliability are related to four categories



From [https://doi.org/10.1016/j.ymssp.2017.11.016]

Prognostics & Health Management:

DATA ACQUISITION AND ANALYSIS

Data Acquisition for PHM

- PHM frameworks rely on information embedded in the data collected through a monitoring system:
  - Data types will determine the capabilities of the framework
    - 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 daily monitoring entire systems during their lifecycle
  - Some of the data correlate well with the degradation processes

Data Acquisition for PHM (Cont.)

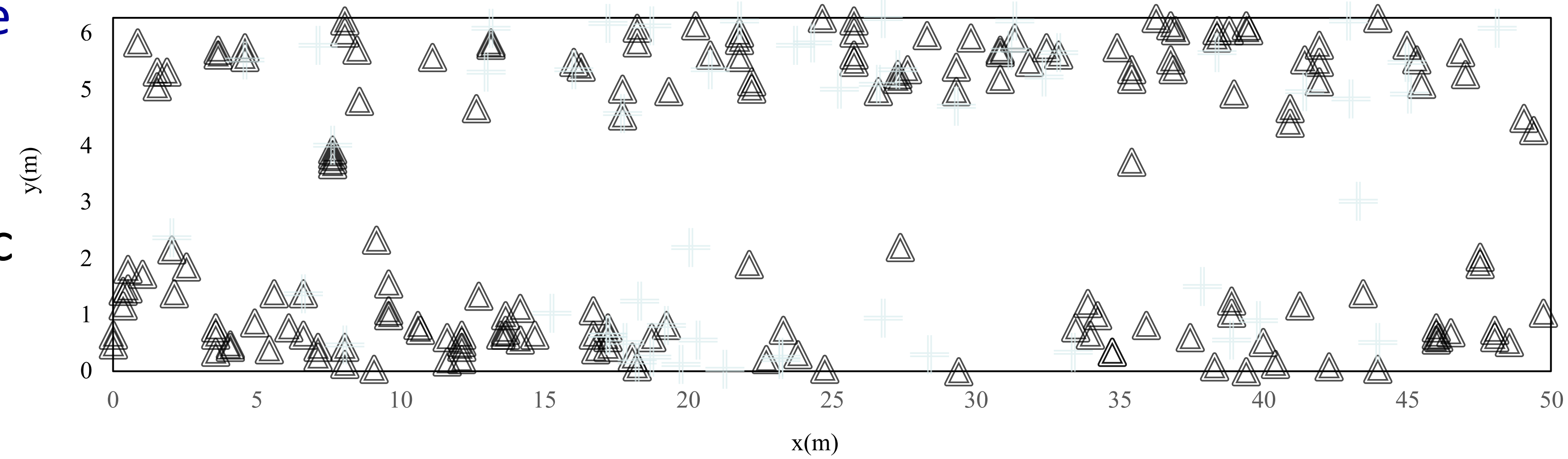
- Design for reliability processes can consider the sensor selection and placement
  - Sensor selection for a reliable monitoring network
  - Selection of proper mixture of sensing and measurement tools
  - Optimize sensor layout that maximize probability of damage/fault detection while minimizing costs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

Data Acquisition for PHM (Cont.)

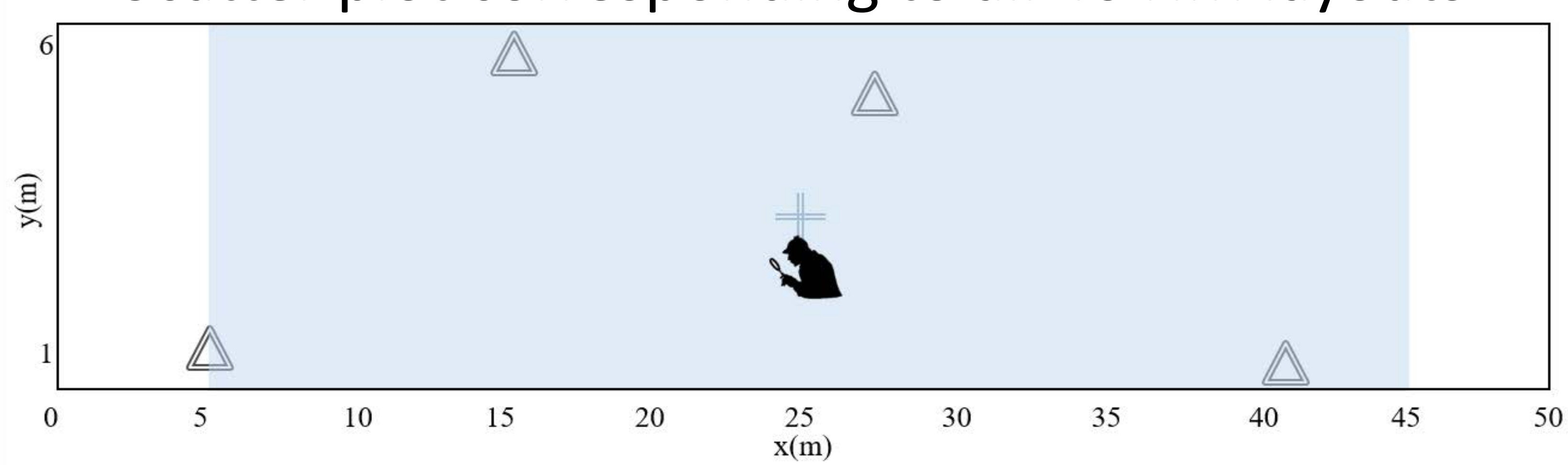
- Collected data from systems present challenges
  - High noise contamination level
    - These uncertainties can propagate towards the diagnostics and prognostics analysis.
  - Incomplete data due to high presence of NaN values and missing information
    - Damaged or faulty sensors
    - Unsynchronized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

PHYSICS-OF-FAILURE MODELS

Physics-of-Failure Models in PHM

- PoF is a regression-based mathematical model of failure, developed based on the empirical science of failure mechanisms such as fatigue, fracture, wear, and corrosion
- PoF is of the form:
- Damage (or life)=$\boldsymbol{f}(\boldsymbol{stress\ variables}, \boldsymbol{geometry}, \boldsymbol{envirnmental\ variables}, \boldsymbol{model\ parameters})$
- When model error, parameter uncertainties in the mathematical PoF model are also estimated, the model is called Probabilistic PoF (PPoF)

PoF-Based Modeling in Reliability and PHM

Is used when:

- Facing long and costly life tests
- Identical units for testing is costly or unavailable
  - Large systems like off-shore platforms, space vehicles
  - One-of-a-kind or highly expensive systems
  - The products that must work properly at the first time
- Prototype during the design not available
- Highly reliable products and systems analyzed
- Predicting the occurrence of rare or extreme events

Prognostics & Health Management:

DATA DRIVEN APPROACHES

Data-Driven Approaches 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)

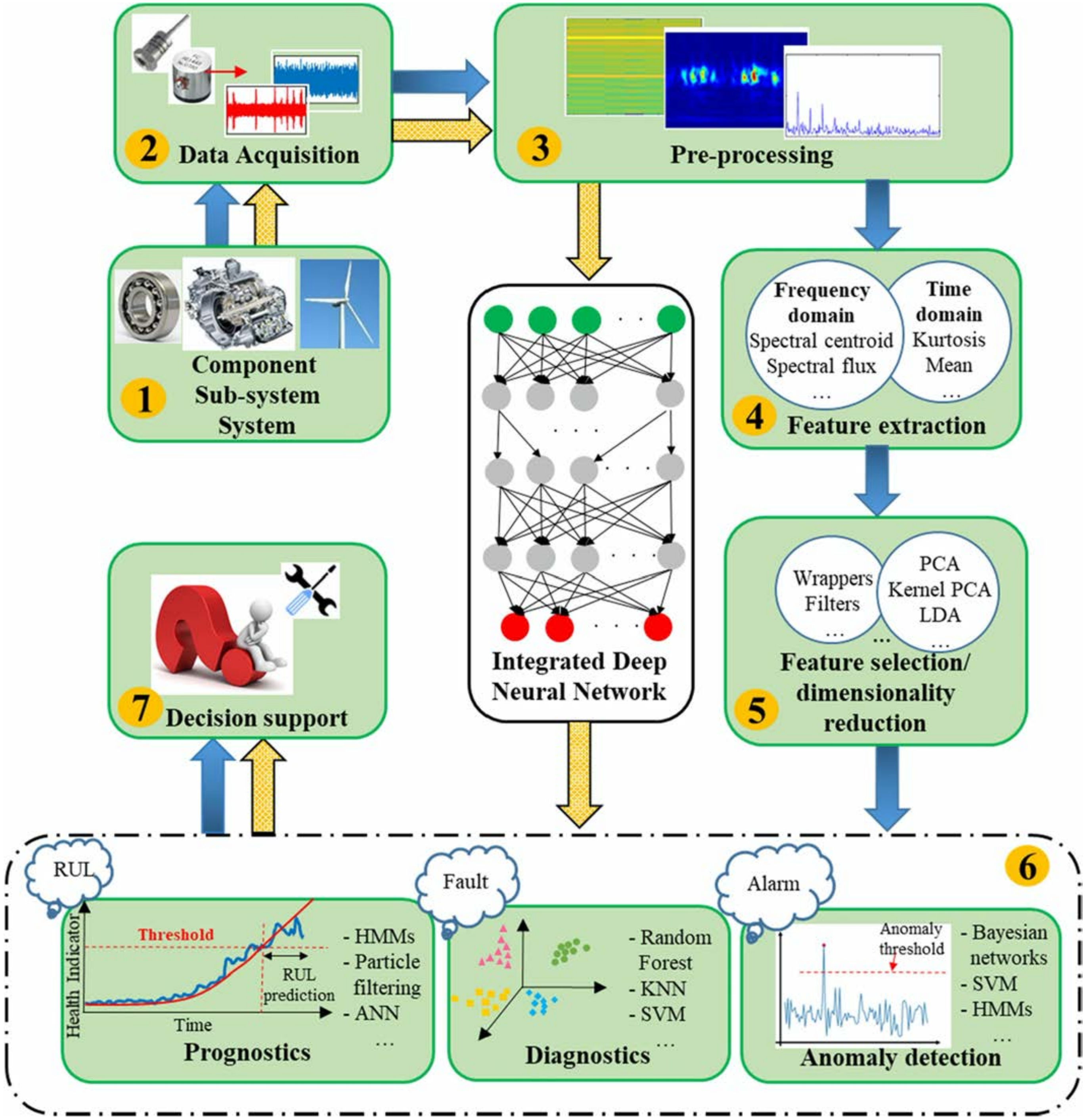
Machine Learning in PHM

- Machine learning models are statistics-based analytics
  - They map a set of inputs *X* into a set of desired outputs *Y*
  - Common algorithms are support vector machines (SVM) and random forest (RF)
  - ML models can be used for fault diagnosis and/or prognostics
- 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

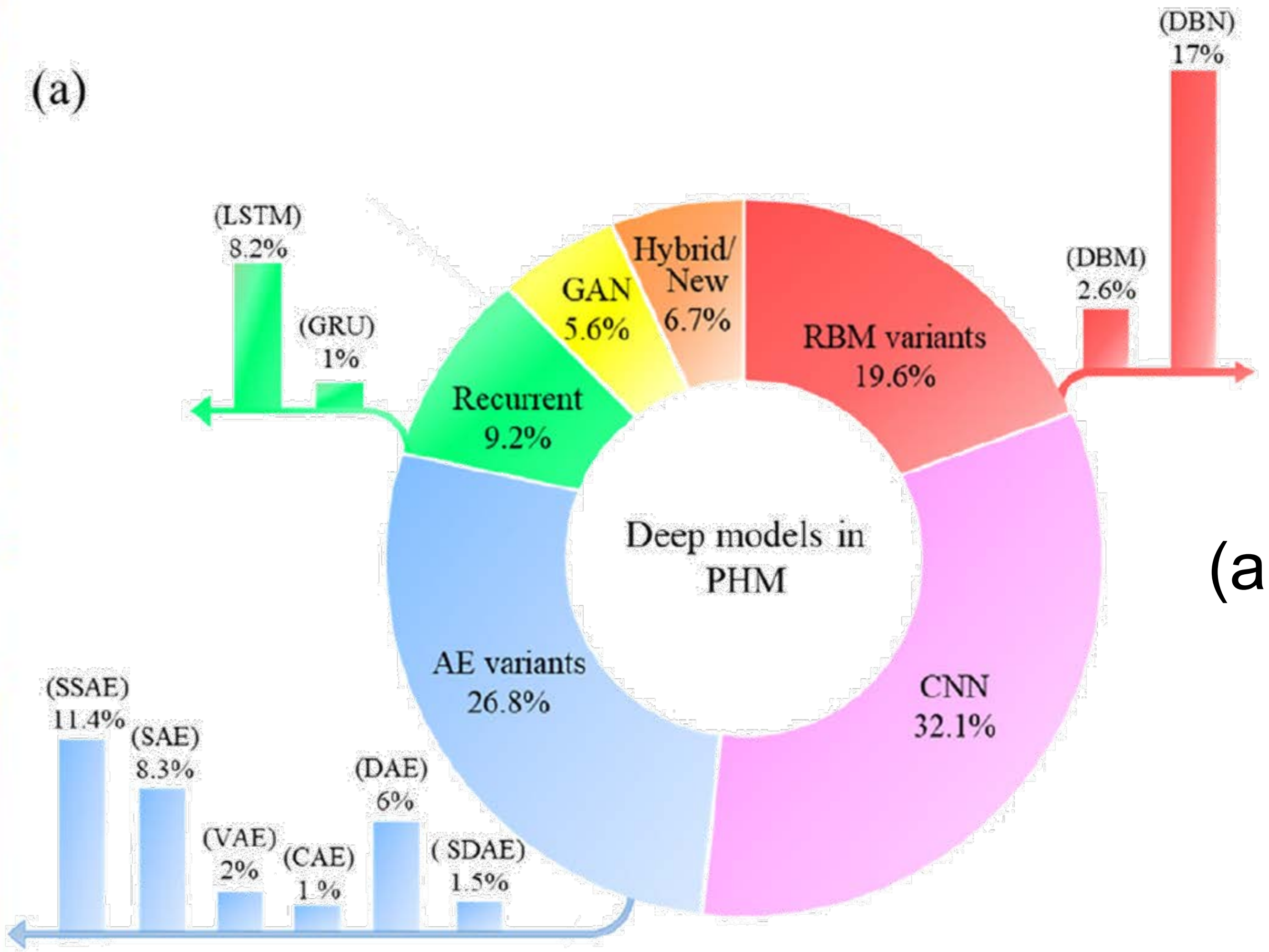
- Deep Learning (DL):
  - Deep neural networks are the main structure of DL models
  - DL automatically process raw data to extract highly abstract and complex features.
    - Eliminates reliance on domain knowledge
    - Does not require feature engineering or manual feature selection
    - Offers an 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

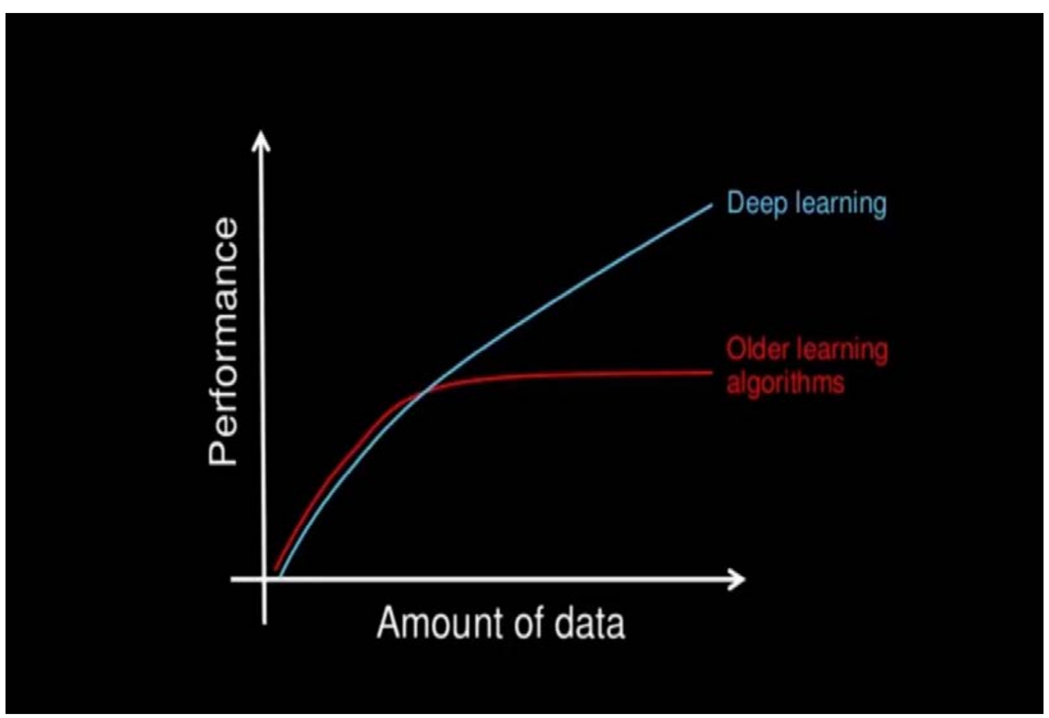


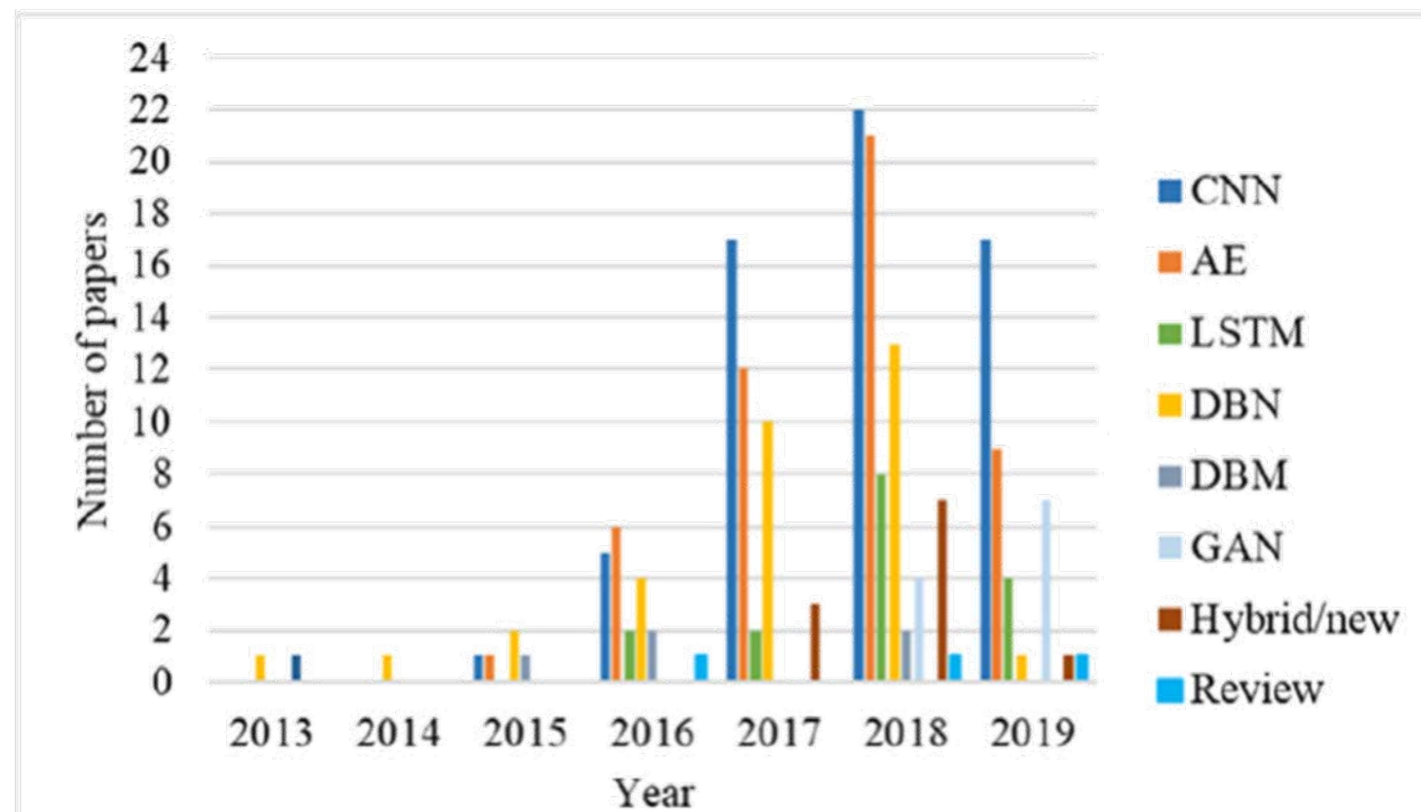
[From DOI 10.1016/j.measurement.2020.107929

- 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
  - Compact steps of the PHM framework
- DL received most research attention recently



(a) Deep learning architectures in PHM 2013 - 2019,



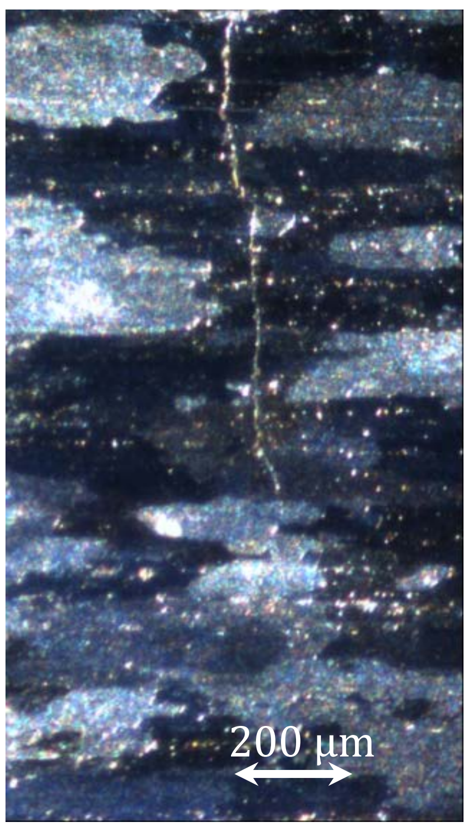


(B) Publications

[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



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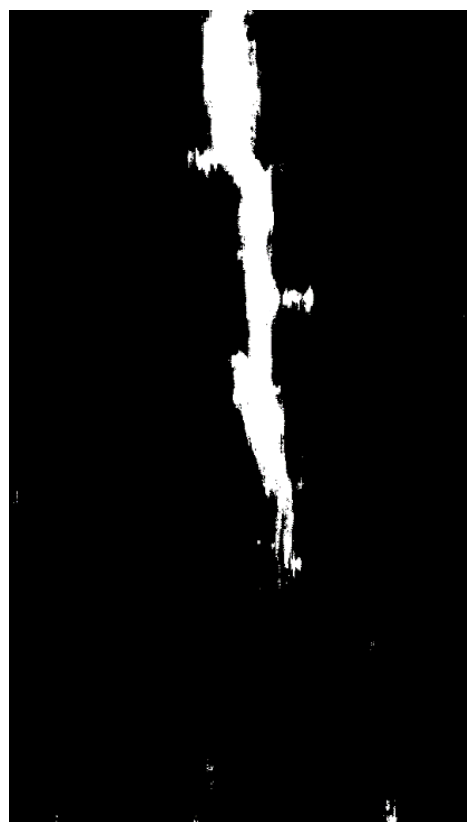
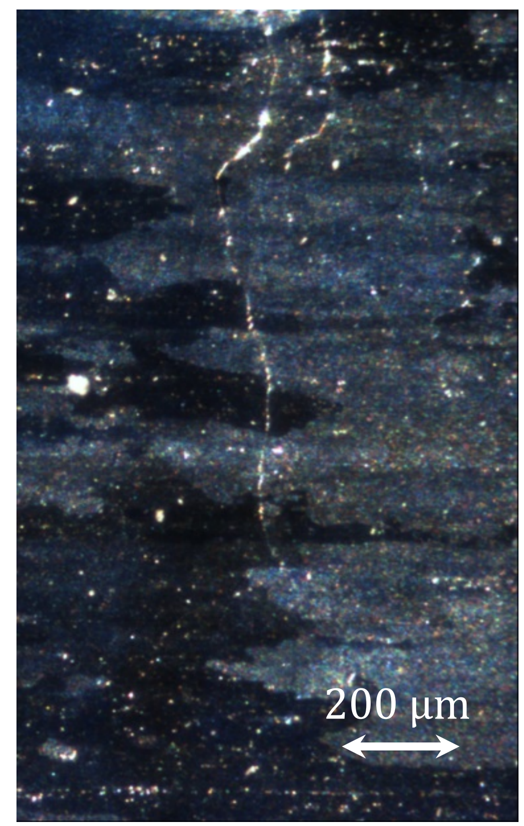


CNN prediction



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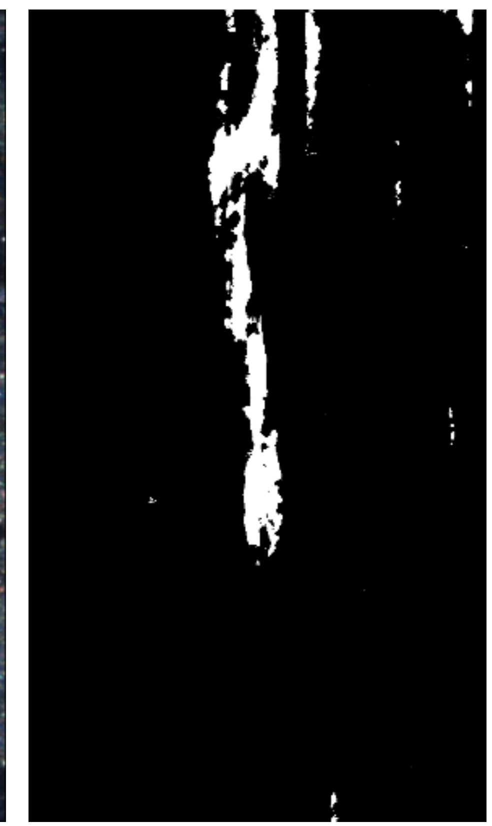


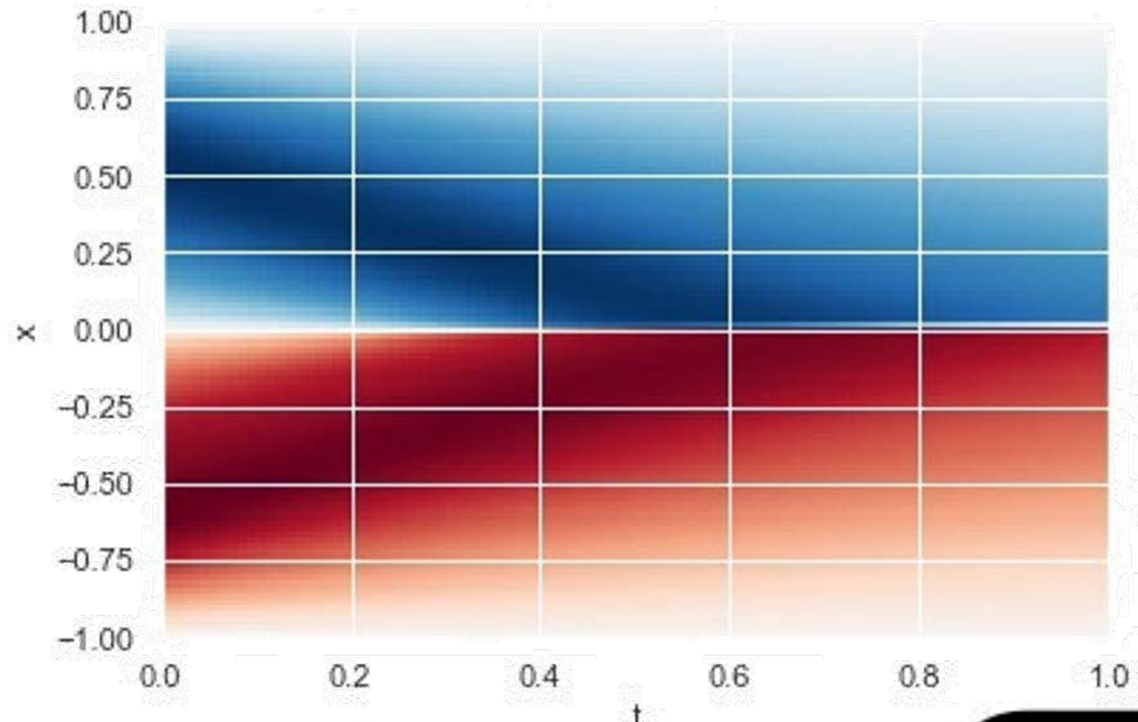
CNN prediction

Hybrid Methods in PHM

- Combine strengths of PoF and DDA methods
  - PoF allow for interpretation in Hybrid PHM models
  - DDA can handle large amounts of data and easily adapt and scale
- Aim to address drawbacks
  - A hybrid methods need less data to train and yield more accurate predictions
- Most common example is particle filtering
  - Easy to apply in damage progressive models such as crack propagation and corrosion

Physics-Informed Deep Learning Models

- Recent research have implemented DL models to solve partial differential equations (PDE)
  - This allows to embed physical model to DL models
- For example consider the Burgers Equation
  - $u_t + uu_x - \frac{0.01}{\pi} u_{xx} = 0, u(0,x) = -\sin(\pi \mathrm{x}), u(t,-1) = u(t,1) = 0$
- Solve this equation for a given domain (t, x) by considering $f := u_t + \mathrm{NN}(u)$



Current Challenges in PHM

- 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 PoF 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

Conclusions

- Reliability engineering started in the late 1940's
- The academic settings dismissed it as a legitimate engineering topic of study, let alone as a discipline
- Recent advances in physics of failure, ML, DL and PHM have revised this notion and revolutionized reliability engineering
- Reliability sciences developed through the laws of thermodynamics and information theory are and will be critical
- Academic institutions now recognized reliability engineering as a thriving field of study and legitimate discipline worldwide

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Thank you for your attention!