OCTOBER 2020

Conference Proceedings Report

Organizers

Katrina Groth, Mohammad Pourgol-Mohammad, Mohammad Modarres

UMD Center for Risk and Reliability

ASME Safety Engineering and Reliability/Risk Division

CENTER FOR RISK AND RELIABILITY

ASME SETTING THE STANDARD

1. Table of Contents

2. SUMMARY 1
3. AGENDA 2
4. WORKSHOP WELCOME, INTRODUCTION, AND OBJECTIVES: KATRINA GROTH, UMD CENTER FOR RISK AND RELIABILITY 3
SPEAKER BIOS 7
5. OPENING SPEECH, RICHARD LAUDENAT, ASME PRESIDENT 2019-2020........ 9
6. THE PRA PERSPECTIVE, CURTIS SMITH, INL........ 12
7. THE PHM PERSPECTIVE, ENRIQUE LOPEZ DROGUETT, UNIVERSITY OF CHILE 18
8. BREAKOUT GROUP OUTPUTS........ 36
9. REGISTERED PARTICIPANTS........ 38
10. ZOOM CHAT LOG (ONLY INCLUDES CHAT SENT TO EVERYONE) 39

2. Summary

The core of U.S. economy, security and quality of life depends on *complex engineering systems* that range from power plants, energy systems, and pipelines to aircraft, defense, and transportation systems. These complex engineering systems consistent of interconnected and diverse hardware, software, and human elements in dynamic conditions, physical processes, and environments.

Probabilistic risk assessment (PRA or QRA), and Prognostics and Health Management (PHM) both play a key role in ensuring safety, security, and reliability of these systems. However, Moradi & Groth 2020[1] found only a handful of articles at the intersection of PRA and PHM for complex systems. Over the past decades, significant advances in sensing and computing have led to an explosion of new data and PHM algorithms designed to monitor component reliability However, the methods and tools applicable at a component level are unsuitable for modeling complex engineering systems, which typically fall into the domain of PRA data and models.

This event is the first in a two-part series. Initially the workshop was planned as a fully in-person workshop to be held in April, 2020, but as with many events in 2020, it was postponed due to the travel restrictions resulting from COVID-19 pandemic. The organizers recognized that the online format isn't amenable to the deep discussions which were intended to be at the heart of the in-person workshop, but we decided to try an experiment: to see if we could make a "pre-workshop" as interactive possible in an era of webinar fatigue. Thus the workshop was reimagined as an online, interactive pre-workshop in 2020, to be followed with the in person, discussion-heavy workshop to be held when we are able to travel again in 2021.

We held the 2.25 hour event included introduction & workshop objectives from the organizers, opening remarks from Richard Laudenat, the immediate past president of ASME, and then two 20 minute talks designed to give enough of an introduction to PRA and PHM to allow the audience from both background to have meaningful discussions during the breakouts. We then broke into 5 breakout groups to address the pre-workshop question "What is the relationship between PRA & PHM? How can they synergize?" and ended with then report-outs from the breakout groups.

The pre-workshop attracted 38 registered participants and a lot of exciting discussion. While I still believe the online format still isn't ideal for building community or tackling complex issues, this was the most engaging format I've seen in any web-based meeting during the pandemic-induced shift to virtual meetings. Many participants commented that they wish the pre-workshop had been longer – which I consider to be high praise in the year that saw the invention of the term "Zoom fatigue." I thank all of our speakers and participants for playing a key role in creating the level of engagement and discussion that was exceptional and unique in a year of many firsts.

See you for the full workshop in person in 2021,

Katrina Groth, Ph.D.
Assistant Professor, Mechanical Engineering Department Associate Director for Research and Outreach, Center for Risk and Reliability
University of Maryland

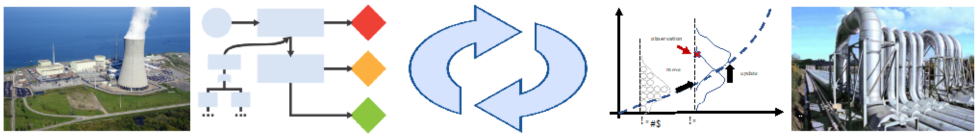
[1] R. Moradi, K. M. Groth, Modernizing risk assessment: A systematic integration of PRA and PHM techniques, Reliability Engineering and System Safety. 204 (2020). https://doi.org/10.1016/j.ress.2020.107194.

3. Agenda

1:00-1:10	*Welcome, introduction & objectives*
	Katrina Groth, UMD
1:10-1:20	*Opening speech*
	Richard Laudenat, 2019-2020 ASME President
1:20-1:45	*The PRA Perspective*
	Curtis Smith, Idaho National Laboratory
1:45-2:10	*The PHM Perspective*
	Enrique Lopez-Droguett, University of Chile
2:10-2:25	Q*uestions for speakers & general discussion*
2:25-2:30	*Breakout assignments & question prompt*:
	"What is the relationship between PRA & PHM? How can they synergize?"
2:30-2:50	*Breakout groups* (Groups of ~4, randomly assigned)
2:50-3:15	*Report out & next steps*

4. Workshop Welcome, Introduction, and Objectives: Katrina Groth, UMD Center for Risk and Reliability

SYRRA



ASME-SERAD and UMD-CRR

Interactive seminar & pre-workshop on the intersection of PRA and PHM

Katrina M. Groth, Mohammad Pourgol-Mohammad, Mohammad Modarres

University of Maryland, Center for Risk and Reliability

ASME, Safety Engineering and Risk Analysis Division

Zoom Meeting ID **988 6805 2385**. Password: **PACES**

Link to Download Materials: https://umd.box.com/v/PreWorkshop2020

A. JAMES CLARK SCHOOL OF ENGINEERING

2 October 2020

SYRRA

Workshop Organizers

Prof. Katrina Groth | **Prof. Mohammad Modarres** | **Prof. Mohammad Pourgol-Mohammad**

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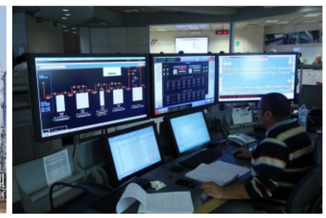
2

Motivation

- The core of U.S. economy, security and quality of life depends on *complex engineering systems (CES)* that range from power plants, energy systems, and pipelines to aircraft, defense, and transportation.
- Probabilistic risk assessment (QRA or PRA), and Prognostics and Health Management (PHM) both play a key role in ensuring safety, security, and reliability of CESes.
- **Moradi & Groth (2020) found only a handful of articles at the intersection of PRA and PHM for complex systems.**





R. Moradi, K. M. Groth, Modernizing risk assessment: A systematic integration of PRA and PHM techniques, Reliability Engineering and System Safety. 204 (2020). https://doi.org/10.1016/j.ress.2020.107194.

Challenges & opportunities motive deeper thinking for CES risk, reliability

- **Complexity**: Systems involve many dynamic, interconnected, and adaptive components (Human + machine + environment + physical phenomena + software / algorithms /AI elements…)
- **Evolving hazards / threats**: disasters, climate change, environmental hazards, aging systems, aging workforce, security threats & vulnerability
- **Data**: We have more data, in more formats, at more scales, than ever before
- **Computing**: advances in computer science, machine learning, big data, data science/analytics
- **Uncertainty**: "Prediction is hard, especially about the future"
- **Decision scale / context**: Informed by models, engineering expertise, preferences, resources, and data, (Not "just" data)

PRA, PHM, and complex engineering systems are widely researched, but silo-ed

Key elements in both fields are being researched extensively, but separately:

- Algorithms
- Data analysis methods
- New hazards, causal factor models
- Decision-support tools

There is a strong need for, and considerably less work on:

- **A unifying conceptual & mathematical framework** for connecting PHM data, algorithms, to PRA models and decisions in the context of complex engineering systems

Objective & Research Question

- Bring together a community of participants to explore the intersection between PRA & PHM
  - Today: Initial concepts, conversations, and cross-disciplinary community building
  - To set the stage for 2.5 in-person workshop (TBD in 2021):
    - Elements of PRA and PHM
    - Their interconnection
    - Defining applications & value proposition
- *To advance research toward a framework for connecting PHM data, algorithms, to risk (PRA) models and decisions in the context of complex engineering systems*

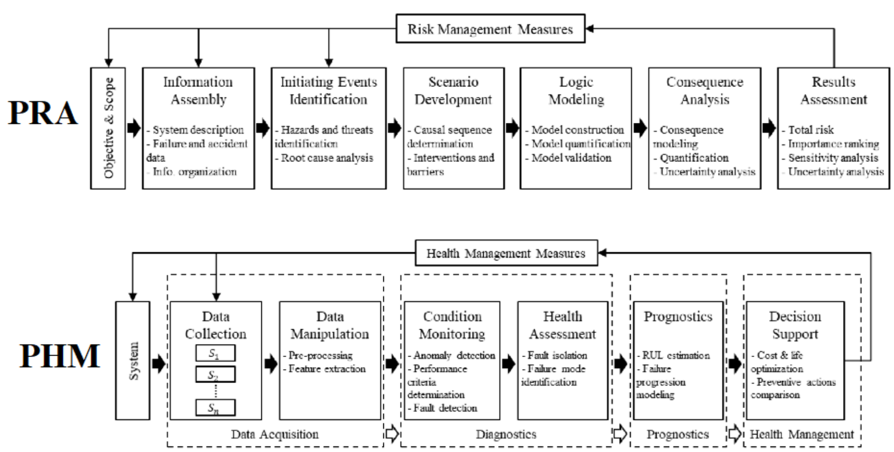
A simplified comparison of PRA & PHM

SYRRA

	PRA / QRA (Probabilistic risk assessment)	PHM (Prognostics and health management)
Uses	Systems engineering and reliability engineering methods	Computer science methods: Online monitoring (sensor) data, data preprocessing, and feature extraction
To	Identify system failure scenarios, estimate the probability of events, and define consequences.	Perform health state assessment, fault diagnostics and prognostics, and Remaining Useful Life (RUL) prediction
Pros	Well-established in high-consequence industries – blends data, models, and expert knowledge & connects with decision makers	Enables online data processing & decision support
Cons	Mainly done offline and in the updated annually (or less)	Applies to components & simple systems only; significant scalability challenges.

Key aspects of PRA & PHM
(Moradi & Groth 2020)

SYRRA



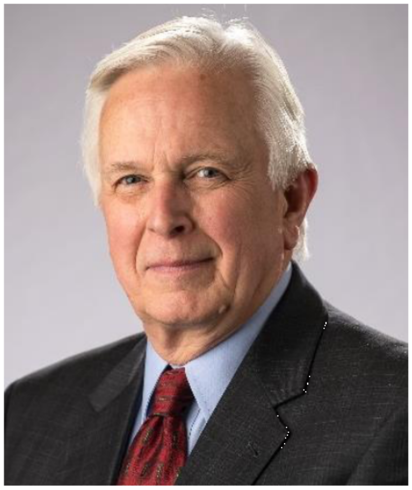
What would it look like if we put these together?
Could we enhance system safety, reliability?

R. Moradi, K. M. Groth, Modernizing risk assessment: A systematic integration of PRA and PHM techniques, Reliability Engineering and System Safety. 204 (2020). https://doi.org/10.1016/j.ress.2020.107194.

3.1 Speakers

SYRRA

Richard T. Laudenat, P.E.



Richard T. Laudenat, P.E., served as the 138th president of The American Society of Mechanical Engineers (ASME) for the 2019-2020 term. Mr. Laudenat has been an active member in ASME since 1991. Laudenat, an ASME Fellow, has spent his career in the field of energy generation.

Among his leadership positions at ASME, Laudenat served as a member of the Board of Governors; vice chair of the Sector Management Committee; senior vice president, Knowledge and Communities; and chair of the Council on Engineering Finance Committee. In 2010, he was named a recipient of the ASME Dedicated Service Award.

Prior to his work at ASME, he served as plant manager at GDF Suez (now ENGIE), a leading global energy operator, where he was responsible for the operation of 30 electric generators at 10 plants throughout Connecticut. Laudenat received both his master's degree in mechanical engineering and his MBA in management from the Hartford Graduate Center.

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10

SYRRA

Curtis Smith, Ph.D.

Dr. Curtis Smith is the Director of the Idaho National Laboratory's Nuclear Safety & Regulatory Research Division. He is the Risk Informed Systems Analysis Pathway lead under the DOE Light Water Reactor Sustainability Program and served as the project manager for the NRC's SAPHIRE risk analysis software. His most recent appointment is the lead for the Risk Integration and Uncertainty Working Group of the NASA Interagency Nuclear Safety Review Panel for the Mars 2020 mission.

Dr. Smith has been in the risk and reliability assessment field for more than 30 years. He has worked at INL as a risk analysis specialist for a diverse set of organizations including the DOE, the NRC, NASA, the International Atomic Energy Agency, and the Federal Aviation Administration. Dr. Smith has published over 260 papers, books, and reports on risk and reliability theory and applications. He holds a Ph.D. in nuclear engineering from Massachusetts Institute of Technology.

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11

Enrique López Droguett, Ph.D.

Dr. Enrique López Droguett is an Associate Professor in the Mechanical Engineering Department at the University of Chile, Adjunct Associate Professor at the University of Maryland, USA, and Associate Editor for the Journal of Risk and Reliability.

Dr. López Droguett conducts research on computational methods for risk and reliability, and prognostics and system health management based on deep learning for big machinery data, and predictive maintenance optimization. He has led many major studies on these topics in the oil and gas sector, defense, mining and energy distribution networks. Dr. López Droguett has over 250 papers in archival journals and proceedings of conferences and 2 books in various areas of reliability and maintenance.

5. Opening Speech, Richard Laudenat, ASME President 2019-2020

Greetings to all of you. Thank you for joining in today.

For any of you who may not know me, my name is Richard Laudenat. It was my good fortune to serve as ASME's 138th President last year, during the Society's 2019-2020 term. My professional experience is mostly in the nuclear power industry, both in design and operations; I also did a tour of duty in the merchant energy business.

In my nuclear career, I watched probabilistic risk assessment grow from a mere concept to the a widely-implemented safety management tools we've come to know
In my merchant energy career, I had the opportunity to work with state-of-the-art remote monitoring and diagnostic tools on one of our most advanced gas turbines. Those leading-edge diagnostics saved our company literally millions of dollars in what would have been forced outage costs … by detecting incipient engine issues before they happened and allowing for scheduled preventive maintenance to avert problems before they ever arose.

I'd like to offer my thanks to ASME's Safety Engineering and Risk Assessment Division and the University of Maryland's Center for Risk and Reliability for organizing today's seminar, and for their kind invitation to offer a few opening comments as an introduction to the day ... I am humbled. It's an honor to be among you today. Just a cursory review of today's attendee list shows what an excellent gathering they have put together, with distinguished representatives from the worlds of academia, several national laboratories, and industry as well.
I am confident that this gathering will contribute meaningfully to the conversation around complex system safety and how today's simulation techniques will allow us a holistic view of the entire sociotechnical system.

You may be aware that ASME considers the entire topic of "digital transformation" to be one of its highest priorities. Digital transformation necessarily takes on different forms and applications in each individual technology discipline we engineers work with. But taken as a whole, it truly represents a revolution It calls on us to seek out fundamentally new ways to think about and work with technologies we've been using and depending on and improving otherwise for many years.

ASME's Industrial Advisory Board (our "IAB") is an eclectic group of industry executives who come together to offer expertise and perspective to ASME's leadership on emerging trends in today's cutting-edge technology applications … whether in super-computing, medical device development, big data applications for the Oil & Gas industry, advanced renewable power systems, or any other of a wide range of cutting-edge technologies.

The topic of digital transformation is so vital to the future of engineering that the IAB is devoting a series of meetings just to this single topic, and to formulating recommendations regarding which technology areas call most urgently for ASME's focused attention.Today's workshop will provide a similarly important forum for discussion, from the perspective of probabilistic risk assessment as well as of prognostics and of health monitoring … vital considerations for the design and operation of any complex sociotechnical system.

I should also mention that ASME is also in the midst of organizing an event in November to foster discussion of how best to leverage Digital Twin Technology for industrial applications. As you know, computing technology and process simulation tools have now advanced to the point where it is possible to create a "digital twin" of almost any industrial or engineered process. Such "digital twin" modeling requires a fundamental understatement of the operations of the "real" system -- while maintaining requisite fidelity to that system.

But it is now entirely possible to perform complex perturbations to a digital twin model which can precisely and reliably predict the response of the real system without impact to that system… whether it be a manufacturing process, an aircraft, a power system grid or some other highly complex machine. As pointed out by Ananthan Chandrakasan, Dean of the School of Engineering at MIT in his advance praise of Tom Siebel's Digital Transformation … "Today we live in the confluence of four technologies: cloud computing, big data, the internet of things and artificial intelligence."

This confluence means that we are faced today both with daunting risks and unprecedented opportunities. How will we as engineers best approach them? I hope you'll agree with me that these challenges provide a fine basis for today's discussions.

As we work from the abstract to a more concrete set of values as part of this conversation, it bears repeating that both ASME and the National Society of Professional Engineers state in their Code of Ethics:

- ... "*Engineers shall hold paramount the safety, health and welfare of the public in the performance of their professional duties*."

Today we face complex system interaction failures that challenge us to those very roots. Each involved sociotechnical system contains hardware, software, individual human beings, complex organizations, and environmental systems. Each element of those systems is hurt when any one of them fails.

Let's consider just three such unforgettable system failures as a way to start this conversation:

- In 1986 the Space Shuttle Challenger exploded shortly after liftoff, killing everyone onboard and arguably setting back the U.S. Space Program for a generation;

- In the spring of 2010, a massive oil spill at the Deepwater Horizon drilling platform in the Gulf of Mexico stretched on for 91 days.

- Wildlife, ecosystems, and countless livelihoods were devastated and needed many years even to begin to recover.

- More recently, the Boeing 737MAX remains grounded after two fatal crashes took the lives of 349 human beings. Beyond the immediate tragedy, the jet's grounding has also contributed significantly to a worldwide transportation crisis, which has hurt the global economy and many millions around the world.

Similar high impact low probability events like these will continue … it's inevitable in our high technology society. What's essential is that we approach complex system safety in a holistic manner. Catastrophes like these, which take a toll both in terms of lives lost as well as in social, economic and environmental costs, should remind us of both the power and importance of these systems to our way of life, as well their potential for failure if challenged beyond design basis or when the design basis is not correct.

Fundamentally, how do we address the challenges with high impact low probability events within conventional prioritization and ROI methodologies … particularly if the cost is high. A key facet could be introducing system resiliency and sustainability into digital systems and into decisions the digital twins can actively support. It's precisely because of the tremendous success and vigor of most of our complex systems that we tend to take their reliability for granted. But we obviously cannot.

Lessons learned from such events have rightly changed how we look at risk, how we design for the future, how we adapt current production and processes, and, fundamentally, how we educate engineering students and practicing engineers to look deeply at the true, highly complex picture of real-world engineering challenges.

Complex systems often have so many interdependent parts that the potential for mishap can be nearly impossible to anticipate fully. Small failures cascade into nonlinear responses. Technological progress never stops moving forward at ever- increasing rates of speed; complex systems become increasingly complex; and -- we operate in a competitive marketplace.

So how shall we be guided as engineers? How will we best bring social and environmental considerations into the design and operation of such tremendously complex systems? Can we, at this moment in planetary history, responsibly design any product or system without factoring in sustainability? How should we best envision and prepare for the public health implications of our work? And most of all, how will we finally and fully establish that commercial pressures cannot be allowed to shape decision-making when it comes to public safety?

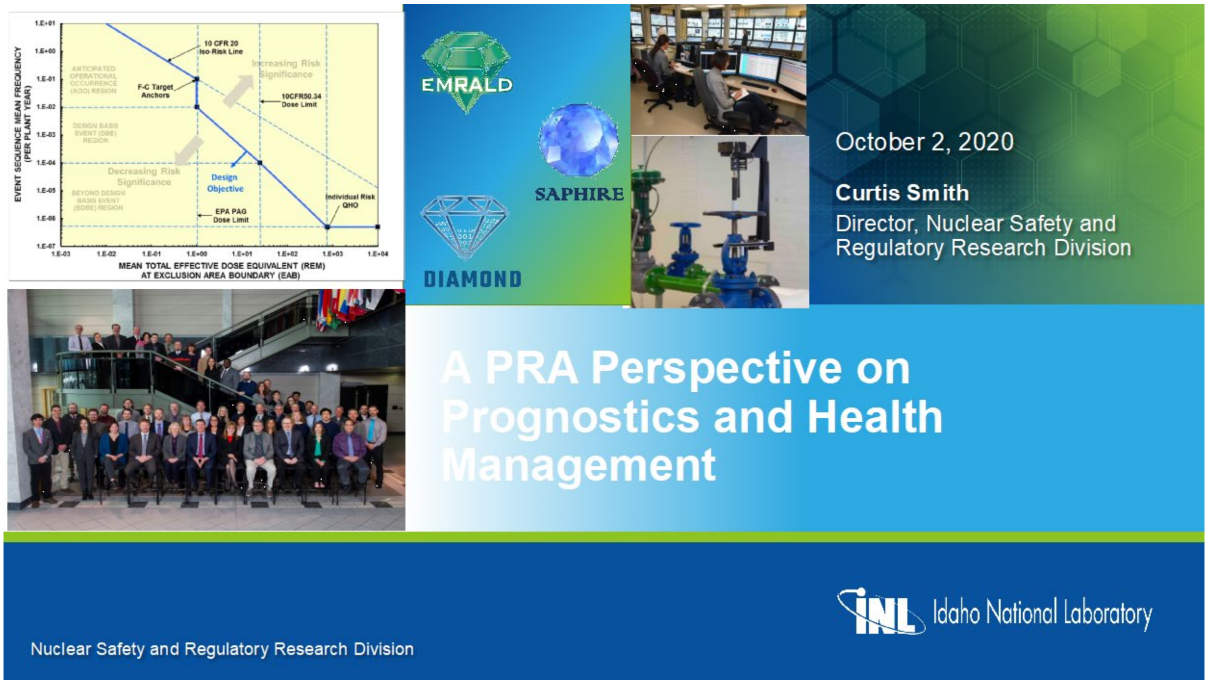
I hope you'll agree that our principles can provide a foundation upon which all of us, as engineers, can practice this profession in a way we can be proud of: proud of ourselves, of one another, and of a profession rightly dedicated to making the world a better place and to improving human welfare.

So with those few thoughts in mind, I hope you will accept my best wishes for an exciting and rewarding virtual conference. I look forward to the day when we can meet face to face again.

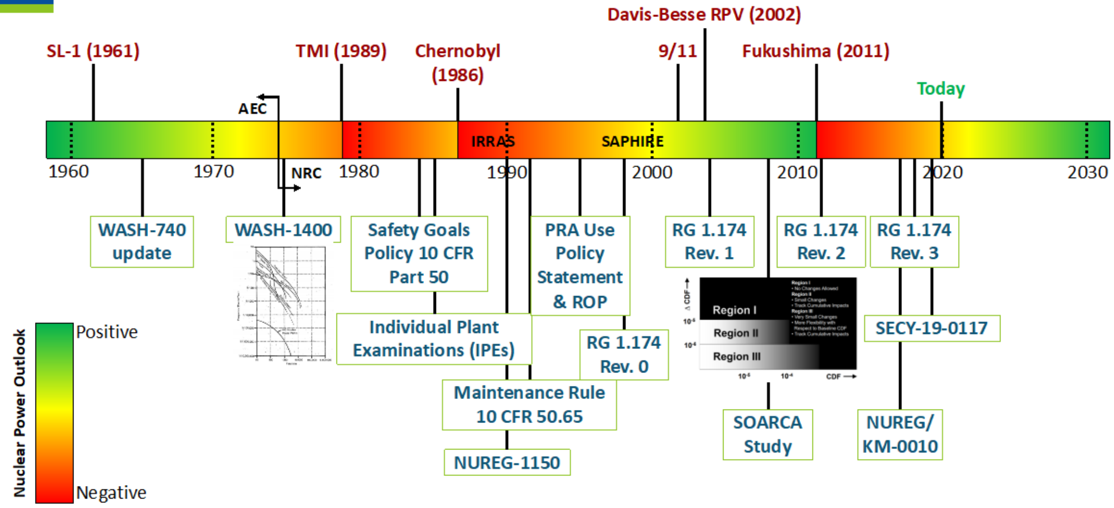
Thank you.

Richard T. Laudenat, P.E.
Immediate Past President, ASME

6. The PRA Perspective, Curtis Smith, INL



Risk-informed Timeline in Nuclear



IDAHO NATIONAL LABORATORY 3

Prognostics and Health Management (PHM)

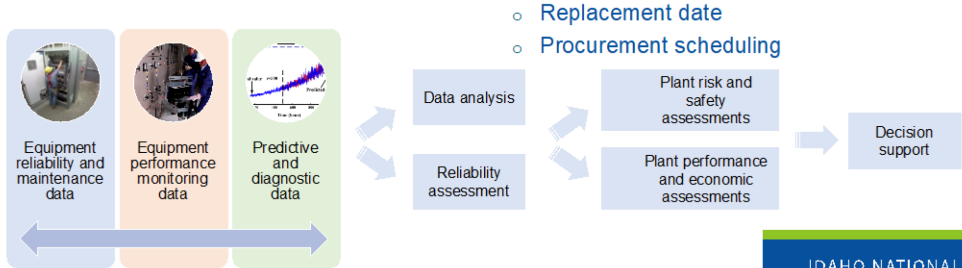
- **"Early warning" system through continuous monitoring of key health signals**
  - Used for **aircraft safety** and in **construction** (e.g. bridge monitoring)
  - In **nuclear**, PHM principles are used (may be called something else…)

- **PHM in nuclear has the potential for**
  - **NPP life extension**
    Between shutdowns the **Locations** with degradations are continuously monitored with the use of **PHM methods**
  - **Supplements passive safety with active safety "early warning"**
    New reactors rely on passive safety, PHM has supplementary safety and economic benefits

4 IDAHO NATIONAL LABORATORY

@INL: Risk-Informed Plant System Health

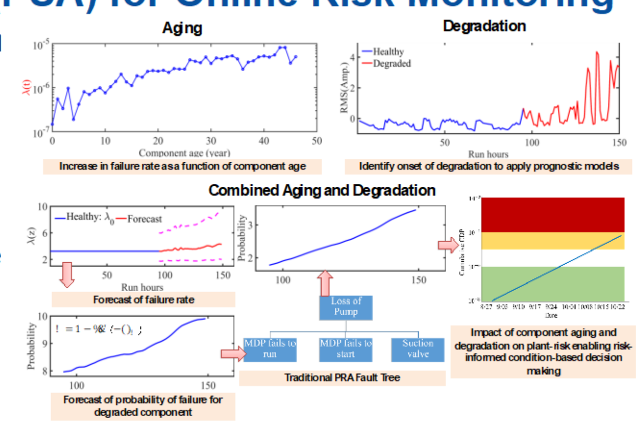
- **Continuous integration of:**
  - Plant health data (e.g., failure data, maintenance report)
  - System, structure, and component economic data
    - Maintenance cost
    - Replacement cost
    - Consequence of SSC failure
- **Provide real time risk information**
  - Safety: CDF, LERF
  - Economic: Loss of MWe
  - Regulatory: Significance Determination Process (SDP), Mitigating System Performance Index (MSPI)
- **Update plant operations**
  - Preventive maintenance schedule
  - Surveillance frequency
  - Replacement date
  - Procurement scheduling



@INL: Integration of Prognostics & Probabilistic Safety Assessment (PSA) for Online Risk Monitoring

INL has developed a novel **online risk model** with **both** aging and degradation of plant assets into traditional PSA

- Machine learning to identify change from healthy to degraded state
- Auto-regression moving average model validated to predict motor performance
  - Prognosis was used to update motor failure rate.
- Integrated the risk models into PSA framework to obtain probabilities



Enables enhanced operations and risk management at complex facilities along with risk-informed decision-making.

Computational Risk Assessment (CRA)

- **Computational Risk Assessment is a focus of current research and development**
  - An extension of PRA
- **CRA is a combination of**
  - Probabilistic (i.e., dynamic) scenario creation where scenarios unfold and are not defined a priori
  - Mechanistic analysis representing physics of the unfolding scenarios
- **CRA relies on the availability of computational tools**
  - Processors (hardware)
  - Methods (software)
- **CRA is not simply solving traditional PRA models faster or with higher precision**
  - It is a different way of thinking about the safety problem

Integrating the worlds of physics and probability leads us to predictions based upon an approach called "computational risk assessment"

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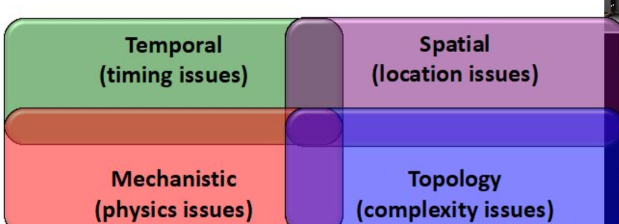
CRA driving factors

- **Computers are improving**
- **Software is improving**
  - And much of it is free
- **Analysis characteristics including**



8

Digital Twins are an Abstraction of Reality

Design, operation, safety, reliability, economics, and regulatory questions that are answered via the digital twin model.	Applications Using the Digital Twin Representation	Risk-Informed Decisions
Models for physical phenomena. Models for probabilistic outcomes. Models for reactor operation. Models for reactor physical properties. Etc.	Digital Twin Representing a Reactor and Operating Environment	Modeling
The actual reactor including how, when, and where it operates.	The World Representing the Reactor Design Characteristics and Operating Environment	Reality

9

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Summary

- PRA has a rich history
  - Still used in many applications
  - Being extended for new applications
- We are moving toward integrating PHM and PRA
  - Digital Twin concept for facility life extension, safety, and economic
  - Computational risk assessment is a key component of this concept
    - Essentially extending the idea of PRA into a new way to perform PRA

10


INL
Idaho National Laboratory
Curtis.Smith@inl.gov
Thank you!
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7. The PHM Perspective, Enrique Lopez Droguett, University of Chile

THE PHM PERSPECTIVE

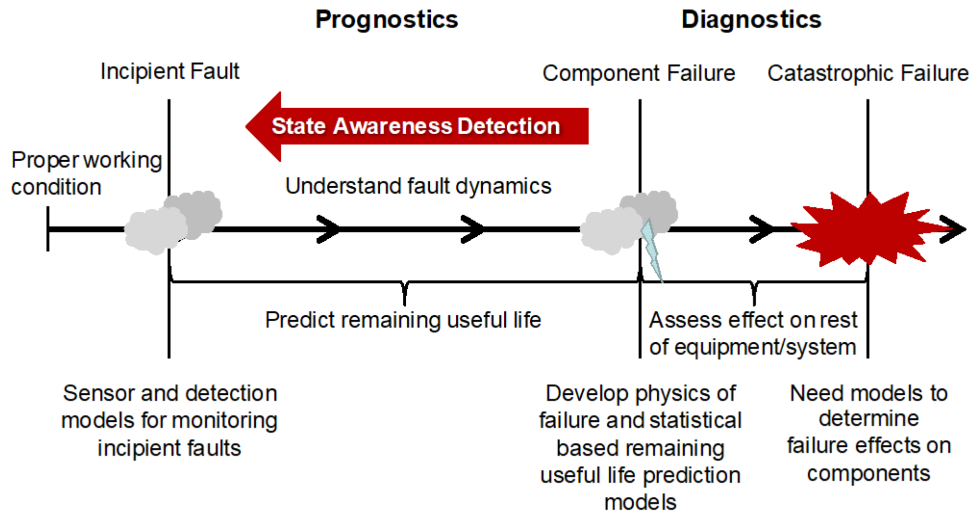
Enrique Lopez Droguett

UNIVERSIDAD DE CHILE

A REVIEW ON PROGNOSTICS AND HEALTH MANAGEMENT

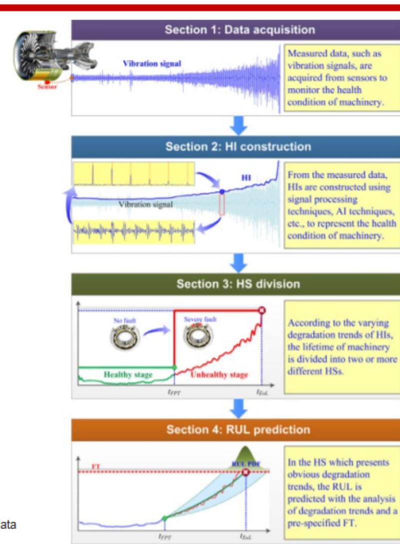
FACULTAD DE CIENCIAS FÍSICAS Y MATEMÁTICAS UNIVERSIDAD DE CHILE

FAULT PROGRESSION: DIAGNOSIS AND PROGNOSIS



PROGNOSTICS AND HEALTH MANAGEMENT (PHM)

- PHM utilizes sensor technology and data analytics to detect the degradation, diagnose faults, predict the remaining useful lifetime (RUL) and proactively manage failures



Lei, Y., Li, N., Guo, L., Li, N., Yan, T., & Lin, J. (2018). Machinery health prognostics: A systematic review from data acquisition to RUL prediction. *Mechanical Systems and Signal Processing*, *104*, 799-834.

PHM – STEPS

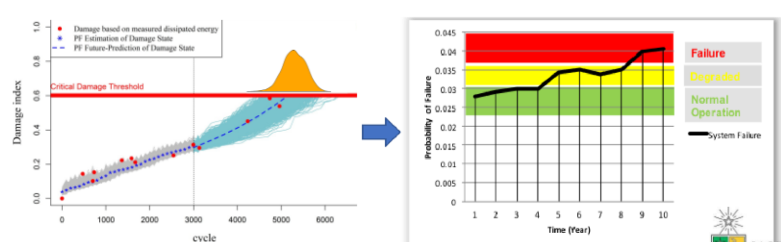
- PHM provides early detection and isolation of the incipient faults:
  - Ability to monitor and predict the progression of faults
  - Predictions and assessments are used to make or trigger autonomous maintenance schedule and asset health management

Data acquisition → **Diagnostics** → **Prognostics** → **Health management**

- **Data acquisition**: Collect condition monitoring data & extract features
- **Diagnostics**: What is the fault and how severe is it?
- **Prognostics**: What is the remaining useful life?
- **Health management**: Optimal management on maintenance and logistics

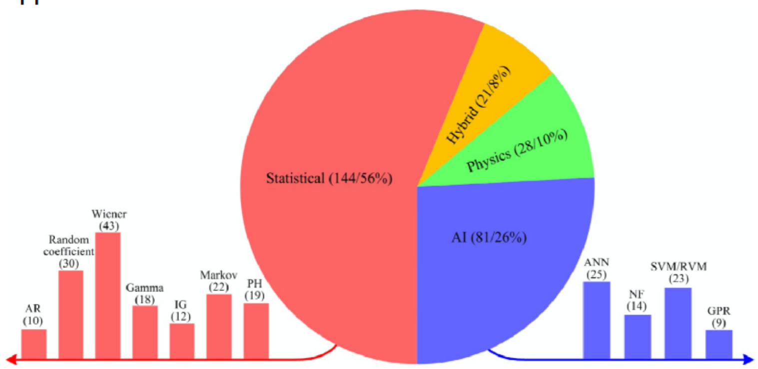
MODELING STRATEGY

Prognostics of remaining useful lifetime (RUL)



PUBLICATIONS

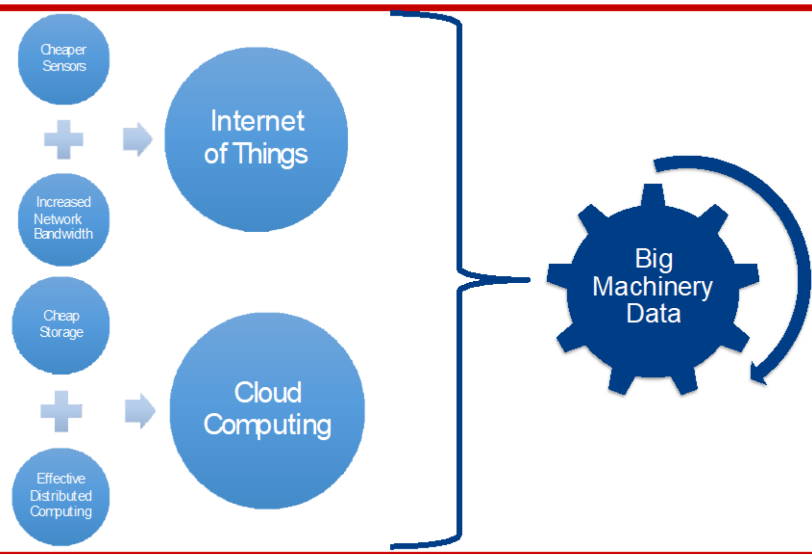
- PHM frameworks:
  - Physics based models
  - Data-driven approaches
  - Hybrid approaches



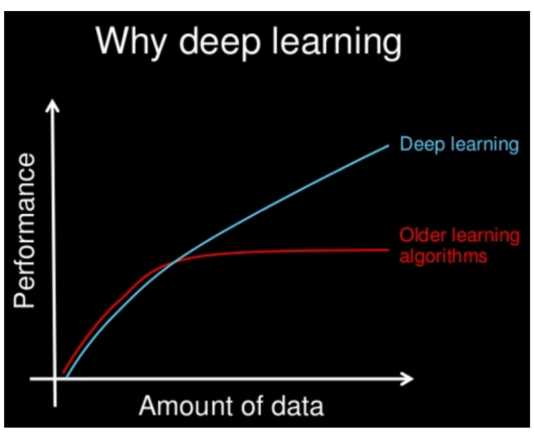
https://doi.org/10.1016/j.ymssp.2017.11.016

DEEP LEARNING BASED PHM
in collabotation with Sergio Cofré

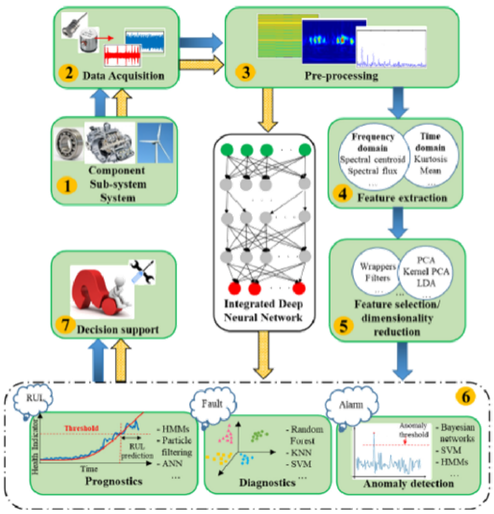
MASSIVE AND MULTIDIMENSIONAL DATA – BIG MACHINERY DATA ENABLERS



DEEP LEARNING – WHY?



DEEP LEARNING BASED PHM

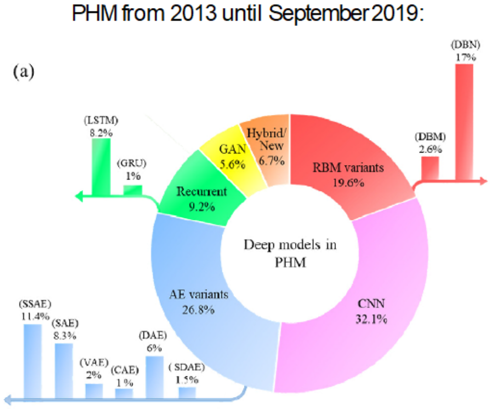


[From DOI 10.1016/j.measurement.2020.107929

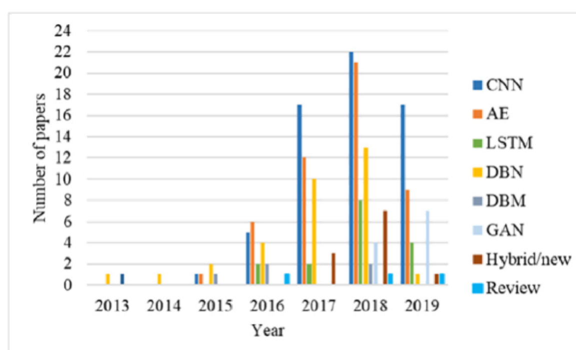
- DL has no explicit information on the system under study:
  - Models are bound to the quality of the available data
  - Interpreting its results can be challenging
- DL models are more flexible than ML models:
  - Allows us to compact steps on a PHM framework
- DL has caught the most research attention in the last few years

PUBLICATIONS: DEEP LEARNING IN PHM

The density of various deep learning architectures in PHM from 2013 until September 2019:



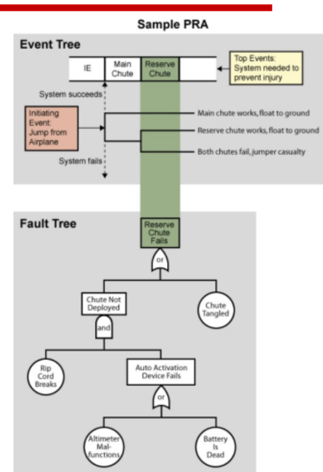
Breakdown of the papers in the year of publication:



WHEN PHM MEETS PRA
in collaboration with Taotao Zhou

LIMITATIONS OF CURRENT PRA

- PRA is static due to the nature of event tree/fault tree
- Built from generic operational experience and hence not specific to component condition
- Suffer from the parametric assumption characterized by some static parameters
- Depend on statistic analysis given limited number of failure observations
- Treat failures fully random with no degradation effects (assumption of constant failure rate)



https://www.nrc.gov/about-nrc/regulatory/risk-informed/pra.html

PHM BENEFITS TO PRA

- Complement the data scarcity by exploiting sensor monitoring data
- More realistic risk insights and alleviate the conservatism
- Enhance confidence and increase persuasiveness
- Enable diagnostic and prognostic capability in support of decision-making
- Allows for on-line risk monitoring and decision making

INTEGRATION OF PHM WITH PRA: BRIEF REVIEW

- Industrial community
  - Pacific Northwest National Laboratory (PNNL):
    - Proposed enhanced risk monitor (ERM) framework that incorporates time-dependent failure probabilities from PHM systems to dynamically update the risk metric
  - Oak Ridge National Laboratory (ORNL):
    - Adopted the ERM framework that provides the diagnostic and prognostic information through the decision-making support
  - Idaho National Laboratory (INL):
    - Developed a dynamic PRA that integrates plant component health using an exponential degradation model based on vibration monitoring data

Ramuhalli, Pradeep, Evelyn H. Hirt, Arun Veeramany, Christopher A. Bonebrake, William J. Ivans, Garill A. Coles, Jamie B. Coble et al. Prototypic Enhanced Risk Monitor Framework and Evaluation-Advanced Reactor Technology Milestone: M3AT-15PN2301054. No. PNNL--24712. Pacific Northwest National Lab.(PNNL), Richland, WA (United States), 2015.
Muhlheim, Michael David, Randy Belles, and Richard S. Denning. Integrated Risk-Informed Decision-Making for an ALMR PRISM. No. ORNL/SR-2016/211. Oak Ridge National Laboratory (ORNL), Oak Ridge, TN (United States), 2016.
Yadav, V., Agarwal, V., Gribok, A. V., & Smith, C.L. Modelling Component Failure Rates Utilizing Sensor-Based Degradation Data, Proceedings of Probabilistic Safety Assessment & Management conference (PSAM-14), 16-21 September 2018, Los Angeles, CA.
Vaibhav Yadav, Vivek Agarwal, Andrei V. Gribok, and Curtis L. Smith. "Dynamic PRA with component aging and degradation modeled utilizing plant risk monitoring data." Proceedings of the 2017 International Topical Meeting on Probabilistic Safety Assessment and Analysis (PSA2017), Pittsburgh, Pennsylvania, September, 2017.

INTEGRATION OF PHM WITH PRA: BRIEF REVIEW

- Academic community
  - Review articles on the role of PHM in support of PRA:
    - Varde and Pecht (2012) reviewed the state-of-art technologies in PHM and discussed the concept of an integrated risk-based approach to improve safety and operational performance. No case study or numerical example
    - Paltrinieri, Comfort and Reniers (2019) discussed the application of machine learning to learn relevant data for risk assessment. Presented a toy example of wellhead damage using deep neural network
    - Moradi and Groth (2020) discussed the general steps respectively in PRA and PHM and reviewed the literature on the integration of PRA and PHM. No case study or numerical example was presented

Varde, P.V., and Michael G.Pecht. "Role of prognostics in support of integrated risk-based engineering in nuclear power plant safety." International Journal of Prognostics and Health Management Volume 3 (color) (2012): 59.
Paltrinieri, N., Comfort, L., & Reniers, G.(2019). Learning about risk: Machine learning for risk assessment. Safety science, 118, 475-486.
Moradi, R., & Groth, K.M. (2020). Modernizing risk assessment: A systematic integration of PRA and PHM techniques. Reliability Engineering & System Safety, 107194.

INTEGRATION OF PHM WITH PRA: BRIEF REVIEW

- Academic community
  - Methodological development with focus on active components:
    - Zhou, Droguett and Modarres (2020) developed a time-dependent CCF model by integrating degradation states of components inferred from multi-sensor data and demonstrated using a real experimental studies of three centrifugal pumps
    - Ruiz-Tagle, Moradi, Groth and Droguett (2020) proposed a method that integrates logic-based and deep learning models dealing with streaming data and demonstrated using a real-world mining rock crusher system

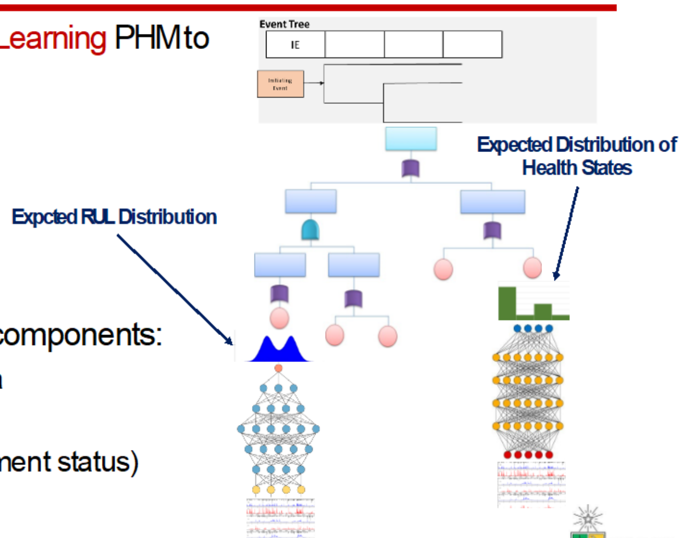
Ruiz-Tagle, Andres & Moradi, Ramin & Groth, Katrina & Droguett, Enrique. Towards a Framework for Risk Monitoring of Complex Engineering Systems with Online Operation Data: A Deep Learning Based Solution, Proceedings of the 30th European Safety and Reliability Conference and the 15th Probabilistic Safety Assessment and Management Conference, Venice, Italy, 1-6 November 2020.
T. Zhou, E. Droguett, M. Modarres, A Common Cause Failure Model for Components Under Age-Related Degradation, Reliability Engineering and System Safety J., vol. 195 (2020), https://doi.org/10.1016/j.ress.2019.106699.

SOME RESEARCH GAPS

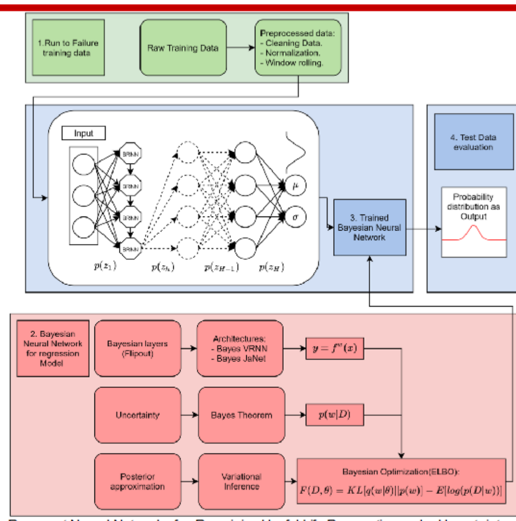
- All focus on hardware failures
- No sufficient discussions on prognostic perspective
- Sporadic ad hoc approaches exist in integrating component health condition, but no systematic methodology has been established
- No real case study exists
- Leverage on multi-sensor data
- Scalability: Big Machinery Data Paradigm
- Autonomous risk-based decision making

PROPOSAL: GENERAL FRAMEWORK

- Integration of Bayesian Deep Learning PHM to PRA regarding various tasks:
  - Event characterization
  - Causality reasoning
  - Decision-making support
- Integrate health condition of components:
  - Multi-sensor monitoring data
  - Expert opinion
  - Categorical data (e.g., equipment status)
  - Inspection data

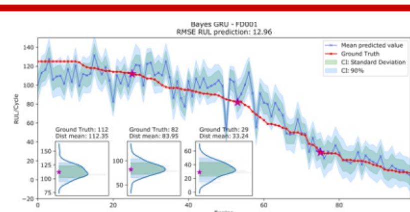


BAYESIAN DEEP LEARNING FOR RUL PROGNOSTICS UNDER UNCERTAINTY

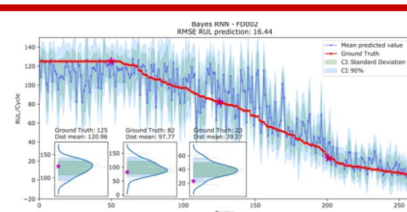


J.Caceres, E. Lopez Droguett, T.Zhou. Bayesian Recurrent Neural Networks for Remaining Useful Life Prognostics under Uncertainty. Structural Control & Health Monitoring, under review.

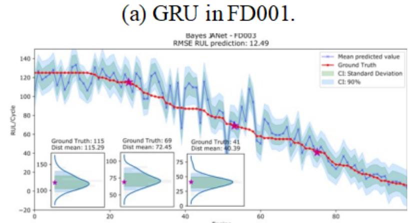
BAYESIAN DEEP LEARNING FOR RUL PROGNOSTICS UNDER UNCERTAINTY



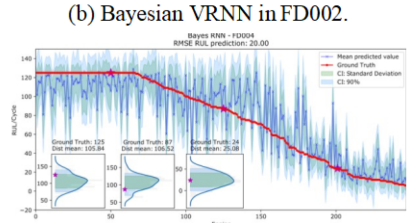
(a) GRU in FD001.



(b) Bayesian VRNN in FD002.



(c) Bayesian JANET in FD003.

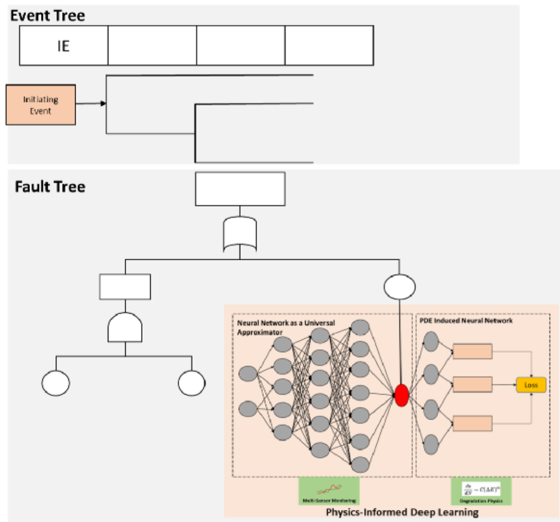


(d) Bayesian VRNN in FD004.

Comparison between the real RUL and RUL predictions from Bayesian RNNs for C-MAPSS

PHYSICS INFORMED DEEP LEARNING FOR RUL OF PASSIVE OR ACTIVE COMPONENTS

- Integrate the health condition of passive or active components by fusing multi-sensor monitoring data and physics-based information



PHYSICS INFORMED DEEP LEARNING FOR RUL OF PASSIVE OR ACTIVE COMPONENTS

- Consider an unknown function $u(z)$ and its derivatives

- PDE can be written as:

$$u_t = g(z, u, u', u'', \ldots) \rightarrow u_t - g(u, u', u'', \ldots) = 0$$

- The unknown function u and the right-hand side can be given as NN:

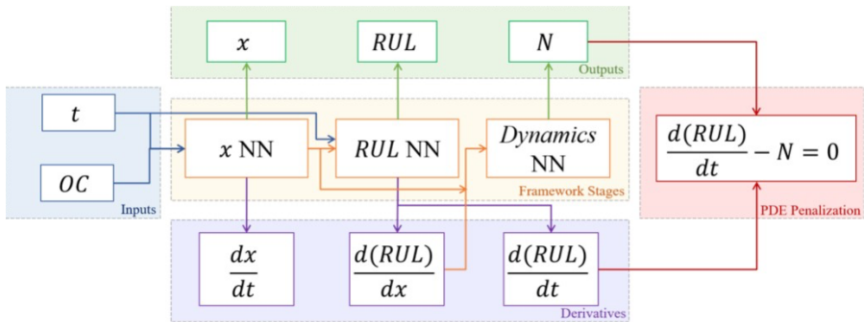
$$f := u_t - NN(z, u, u', \ldots) = 0$$

- Cost function:

$$Cost = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 + \frac{1}{M}\sum_{j=1}^{M} f^2$$

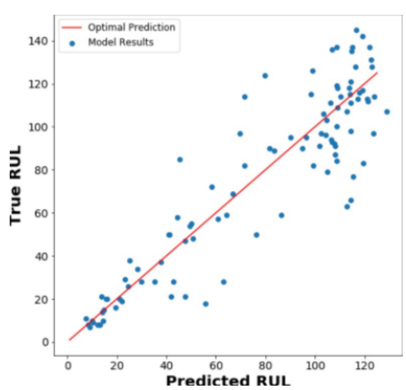
PHYSICS INFORMED DEEP LEARNING FOR RUL OF PASSIVE OR ACTIVE COMPONENTS

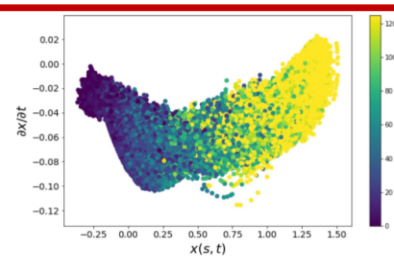
- Uncovering the underlying physics of degrading system behavior:



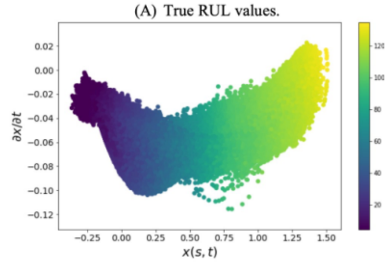
S. Cofré, E. Lopez Droguett, M. Modarres. Uncovering the Underlying Physics of Degrading System Behavior through a Deep Neural Network Framework: The Case of RUL Prognosis. ASME Conference, 2020.

PHYSICS INFORMED DEEP LEARNING FOR RUL OF PASSIVE OR ACTIVE COMPONENTS





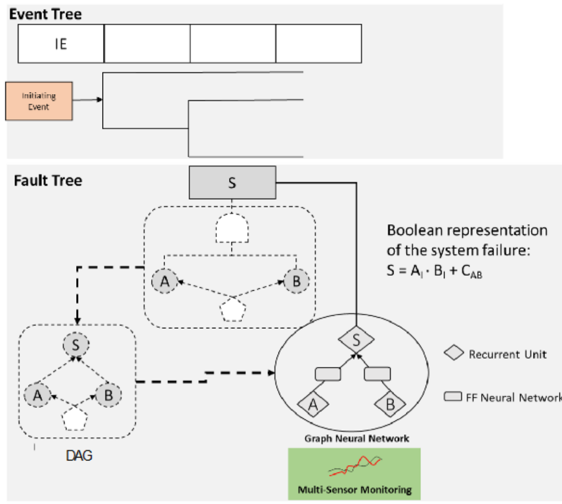
(A) True RUL values.



(B) Predicted RUL values.

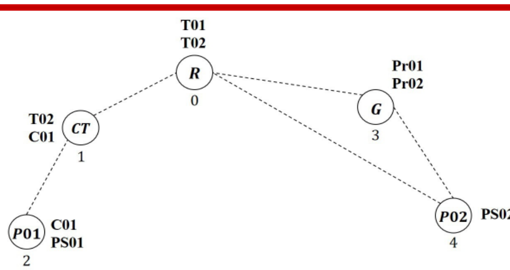
GEOMETRIC DEEP LEARNING FOR COMMON CAUSE DEPENDENCIES

- Graph Neural Network to address common cause dependencies among components
- System Level and Systems of Systems PHM



GEOMETRIC DEEP LEARNING FOR COMMON CAUSE DEPENDENCIES

- Graph:



Adjacency matrix (A):

$$A_! = \begin{pmatrix} 0 & 1 & 0 & 1 & 1 \\ 1 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 1 & 0 \end{pmatrix}$$

Feature matrix (X):

$$X_! = \begin{pmatrix} S_{\text{"\#\$!}} & S_{\text{"\#\%!}} & 0 & 0 & 0 & 0 & 0 \\ 0 & S_{\text{"\#\%!}} & S_{\text{\&\#\$!}} & 0 & 0 & 0 & 0 \\ 0 & 0 & S_{\text{\&\#\$!}} & 0 & 0 & S_{\text{'\#\$!}} & 0 \\ 0 & 0 & 0 & S_{\text{'(\#\$!}} & S_{\text{'(\#\%!}} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & S_{\text{\#\%!}} \end{pmatrix}$$

A. Ruiz-Tagle, E. Lopez Droguett. System-Level Prognostics and Health Management: A Graph Convolutional Network Based Framework. Journal of Risk and Reliability, 2020.

GEOMETRIC DEEP LEARNING FOR COMMON CAUSE DEPENDENCIES

$$A = \begin{pmatrix} 1 & 1 & 0 & 1 & 1 \\ 1 & 1 & 1 & 0 & 0 \\ 0 & 1 & 1 & 0 & 0 \\ 1 & 0 & 0 & 1 & 1 \\ 1 & 0 & 0 & 1 & 1 \end{pmatrix}$$

	Reboiler (node 0)	Condensate Tank (node 1)	M014 pump (node 2)	Generator (node 3)	M015 pump (node 4)
Reboiler (node 0)	0.55 ± 0.15				
Condensate Tank (node 1)	0.46 ± 0.06	0.70 ± 0.06			
M014 pump (node 2)	0.02 ± 0.03	0.55 ± 0.16	1.00 ± 0.00		
Generator (node 3)	0.45 ± 0.05	0.22 ± 0.05	0.06 ± 0.09	0.59 ± 0.04	
M015 pump (node 4)	0.45 ± 0.05	0.22 ± 0.05	0.06 ± 0.09	0.59 ± 0.04	0.59 ± 0.04

Computed IM compared with the original !

GEOMETRIC DEEP LEARNING FOR COMMON CAUSE DEPENDENCIES

$$A = \begin{pmatrix} 1 & 1 & 0 & 1 & 1 \\ 1 & 1 & 1 & 0 & 0 \\ 0 & 1 & 1 & 0 & 0 \\ 1 & 0 & 0 & 1 & 1 \\ 1 & 0 & 0 & 1 & 1 \end{pmatrix}$$

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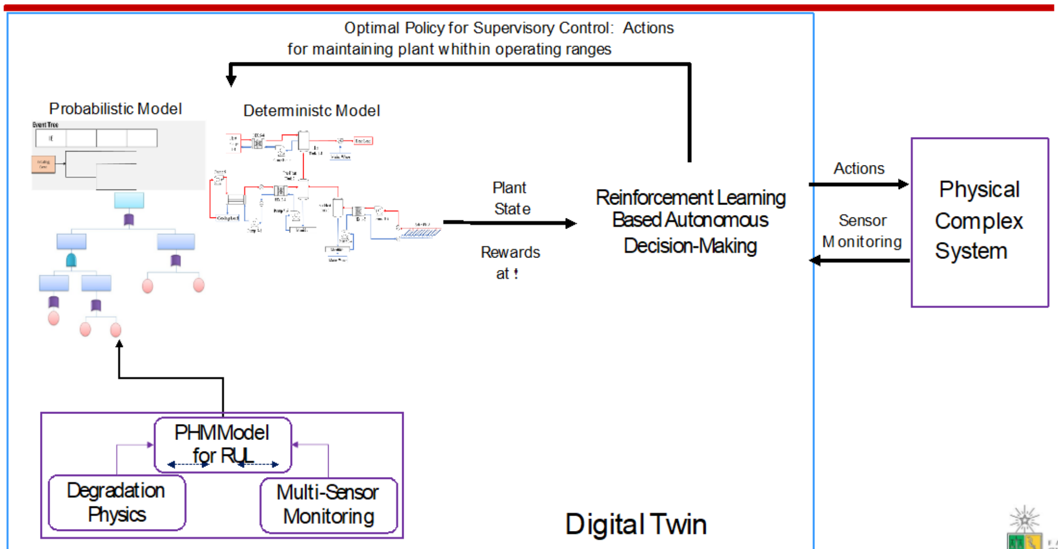
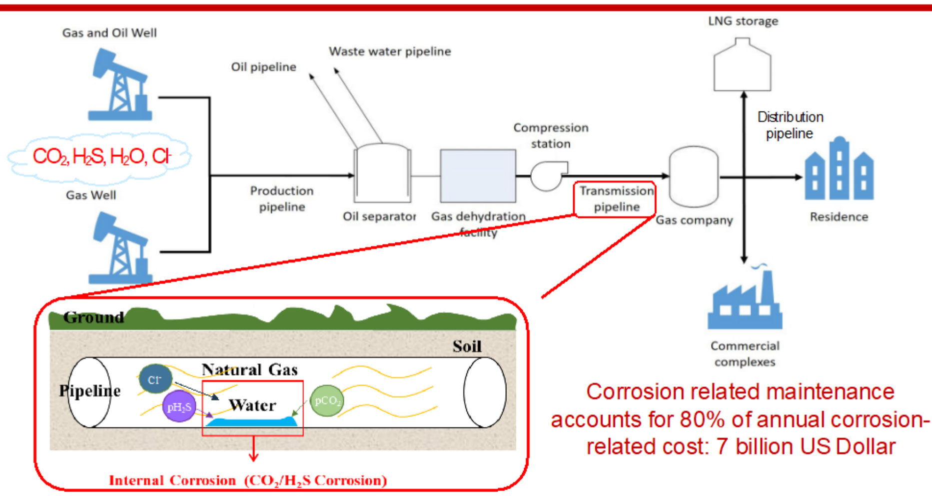
Computed IM compared with the original !

TOWARDS A DIGITAL TWIN FOR RISK INFORMED DECISION MAKING

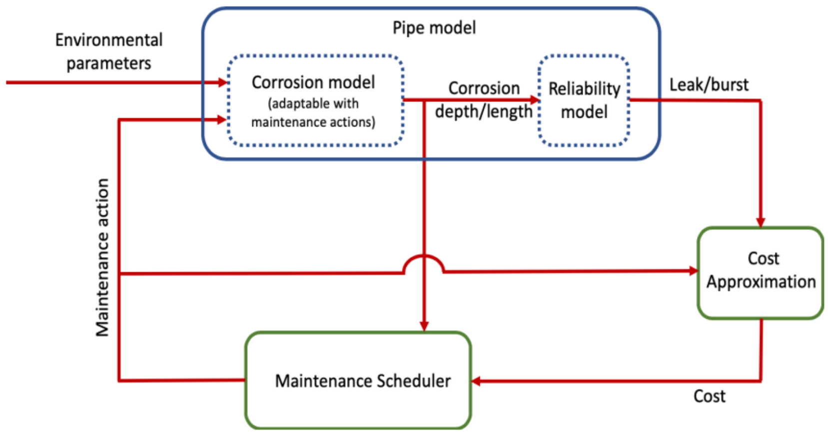


REINFORCEMENT LEARNING AUTONOMOUS DECISION-MAKING



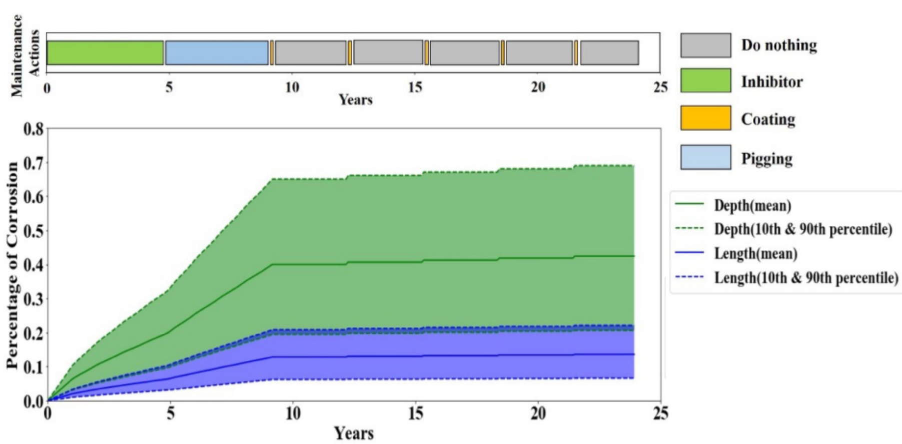
C. Correa, E. Lopez Droguett, J. M. Cardemil. Operation Scheduling in a Solar Thermal System: A Reinforcement Learning-Based Framework. Applied Energy, 2020.
Z. Mahmoodzadeh, K. Wu, E. Lopez Droguett, A. Mosleh. Condition-Based Maintenance with Reinforcement Learning for Dry Gas Pipeline Subject to Internal Corrosion, Sensors, under review.

REINFORCEMENT LEARNING AUTONOMOUS DECISION-MAKING



- **Autonomous decision maker with smart condition-based maintenance scheduler via Reinforcement Learning**

REINFORCEMENT LEARNING AUTONOMOUS DECISION-MAKING

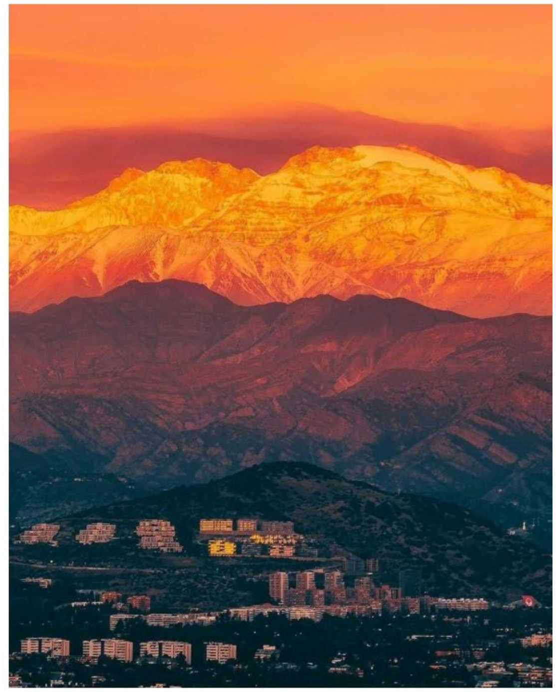


Thank You

Enrique Lopez Droguett

elopezdroguett@ing.uchile.cl

UNIVERSIDAD DE CHILE



8. Breakout group outputs

What is the relationship between PRA & PHM? How can they synergize?

- Breakout group 1 (Curtis Smith, Pradeep Ramuhalli, Ramin Moradi, Richard Laudenat)
    - Need for commercial engineering tools to have attributes of PRA & PHM
    - Need to resolve/connect across the two different levels of abstraction between PHM & PRA
    - Passive vs. active component level
    - Chance to do dependency analysis and to bring in model-based engineering; engineering insights vs. "PRA insights" (temperature margins instead of failure probabilities)

- Breakout group 2 (Askin Guler Yigitoglu, Camila Correa Jullian, Fernando Ferrante, Mihai Diaconeasa, Roger Boyer)
    - PRA Failure logic and PHM logic
    - Assessment of how system performs
    - Combine data acquisition with failure history
    - Scale: PRA tends to be higher level than PHM
        - PRA models to level of data (surrogate/generic
        - PHM utilizes real time (plant specific) data based on the sensors
    - Safety (PRA) versus performance (PHM)
    - PRA is top down approach, PHM based on available sensor data to assess the system health
    - PRA is constant failure rate, while PHM needs to account for degraded states
    - PRA tools are more mature? Vs PHM tools are customized to the design/system/plant being assessed, both are modeled for their specific application
    - PHM helps with early detection (precursor)

- Breakout group 3 (Austin Lewis, Enrique Lopez Droguett, Michael Azarian, Sergio Cofre, Yuanchang Chen)
    - Challenges
        - Difficulty in obtaining training data & the need for failure data to apply PHM, deep learning techniques; adequacy of physical models
        - PRA assumptions of constant failure rate; vs. PHM modeling of more realistic failure/degradation behavior
        - Interactions between degrading components; and the influence on the overall system; complexity of component degradation at different rates
        - Scalability to very complex systems;
        - Lack of a common language between PHM and PRA creates barriers to working together & bridging the divide

- Breakout group 4 (Daniel Nunez, Linyu Lin, Masoud Pourali, Mohammad Pourgol-Mohammad, Stephen Thomas)
    - Experiences with tools for PRA and PHM from different industrial/application perspectives
    - Commercial PHM tool availability
    - Difficulty adding sensoring/monitoring large scale complex systems & existing plants
    - Meaning of RUL & need for tools in a healthcare context; autonomous vehicle contexts
    - Newness & novelty create accessibility challenges; need for more education & introductory materials

- Breakout group 5 (Vivek Agarwal, Andres Ruiz-Tagle Palazuelos, Jose Celeya, Mohammad Modarres, Bob Youngblood)
    - (Need for) Interpretability as we try to integrate both – necessary in higher consequence industries, may be less necessary in lower consequence applications.
    - Higher interpretability for physics based models and for PRA models vs. the (lower interpretability of) data driven techniques.
    - Need to integrate physical models and PRA models is a key aspect of achieving this integration & has explanatory value
    - Need to define the level of interpretability required viz-a-viz context of the end user

9. Registered Participants

Name	Organization
Katrina Groth	University of Maryland
Mohammad Modarres	University of Maryland
Mohammad Pourgol Mohamad	ASME-SERAD & University of Maryland
Richard Laudenat	ASME President 2019-2020
Fernando Ferrante	Electric Power Research Institute (EPRI)
Andrew Sowder	Electric Power Research Institute (EPRI)
Hamzeh Soltanali	Ferdowsi University of Mashhad (FUM)
Daniel Nunez	GE Healthcare
Abhinav Saxena	GE Research
Bob Youngblood	Idaho National Laboratory
Curtis Smith	Idaho National Laboratory
Vivek Agarwal	Idaho National Laboratory
Masoud Pourali	KimiaPower
Roger Boyer	NASA-JSC
Linyu Lin	North Carolina State University
Mihai A. Diaconeasa	North Carolina State University
William Buttner	NREL
Pradeep Ramuhalli	Oak Ridge National Laboratory
Askin Guler Yigitoglu	ORNL
Enrico Zio	Politecnico di Milano
Adam Williams	Sandia National Laboratories
Andrew J. Clark	Sandia National Laboratories
Jose Celaya	Schlumberger
Allan Luk	Seagate US LLC
Enrique Lopez Droguett	University of Chile
Michael Ma	University of Massachusetts Lowell
Michael Azarian	University of Maryland
Sergio Cofre	University of Maryland
Camila Correa Jullian	University of Maryland
Ramin Moradi	University of Maryland
Andres Ruiz-Tagle	University of Maryland
Stephen Thomas	University of Maryland
Taotao Zhou	University of Maryland
Jamie Coble	University of Tennessee-Knoxville
Yuanchang Chen	University of Texas at Dallas
Seyed A. Niknam	Western New England University
Jeffrey Lane	Zachry Nuclear Engineering

10. Zoom Chat log (Only includes chat sent to everyone)

From Jamie Coble (she/her/hers) to Everyone: 01:23 PM
I'm sorry that I have to miss much of this workshop. This is a topic I am very interested in from both the PHM and PRA sides, and I'm always interested in conversation to explore opportunities! I welcome anyone's thoughts or discussion.

From Vivek Agarwal to Everyone: 02:19 PM
How would incorporate uncertainty analysis across hardware, software, analytics and decision-making?
As data grows deep learning tends to perform better, correct. But do we really need large volume of data to develop digital twin
Big Data versus heterogeneous limited data

From Bob Youngblood to Everyone: 02:20 PM
Thanks for the truly interesting talks. Of course the present emphasis is on understanding what's going on with degradation. But given the emphasis on understanding the delta between nominal expectation and observation, two closely related applications suggest themselves. One is detecting anomalies (like precursors, but not necessarily near misses), and another is detecting cyber intrusion. Both of these are instances of your model of the world being somehow incomplete. The technologies Enrique mentioned might help address these…

From Vivek Agarwal to Everyone: 02:23 PM
Curtis: Are current PRA tools capable of integrating all the advancements in PHM to enable online risk monitoring? If not, what needs to be done?

From Daniel Núñez to Everyone: 02:25 PM
Question for Dr. López Droguett: if you have a complex system monitoring multiple sensors and failures (system stops). If that system is failing due to component quality changes driven by cost reduction (example: cheap sensors, PCB's with solder quality issues), do you think that can be a case of quality of data that can confuse a deep learning approach to monitor and learn system degradation? Is there an assumption of well design systems with high quality components so that we are only looking for wear out failures?

From Abhinav Saxena to Everyone: 02:29 PM
Comment: One challenge that i see in relying on data-driven approaches is that data collection from legacy systems (which most of these are) were designed with human-n-the-loop decision making, where a SME fills in the contextual gaps. Use of ML/DL methods fall short of filling such gaps resulting in large number of false alerts, etc. being able to take advantage of new are AI methods may require re-design of data collection. hence i see confluence of data-based and physics-based models is the only realistic path in the near future.

From Jose Celaya to Everyone: 02:51 PM
Thanks a lot for the team…

From Askin Guler Yigitoglu to Everyone: 02:55 PM
I would like add, beside PHM provides failure data input to the PRA, it can be also used to inform success criteria we used in fault trees to understand if degradation affect the performance of trains/redundancy.

From Curtis Smith to Everyone: 03:06 PM
@vivek question: Current PRA tools sort of are ready for PHM info. A middle calculation layer is created that manages the interface between sensor data and then prediction of failure that goes into the PRA model. This can be done and automated, but I am not aware of anyone who has automated this.

From Mihai Diaconeasa to Everyone: 03:08 PM
I agree, Curtis. An interface should be able to handle the transfer of information, but perhaps the exchange of information should go both ways.

From Curtis Smith to Everyone: 03:12 PM
@vivek "Big Data" : seems like we need a future workshop on "Is 'Reliability' Needed in a World of AI/ML?"

From Jose Celaya to Everyone: 03:16 PM
@ramin, it depends of what part of PHM problem you want to solve using deep learning as a building block… For anomaly detection, perhaps more sensor and more data can help.

From Jose Celaya to Everyone: 03:16 PM
But if you are after something as hard as RUL estimation, just having more sensors, does not enable a deep learning based solution.

From Sergio Manuel Ignacio Cofre to Everyone: 03:22 PM
Thank you Jose, that was a great insight

From Daniel Núñez to Everyone: 03:23 PM
Thank you José. That totally relates to what I'm seeing in complex healthcare imaging systems. The need to focus in one specific problem