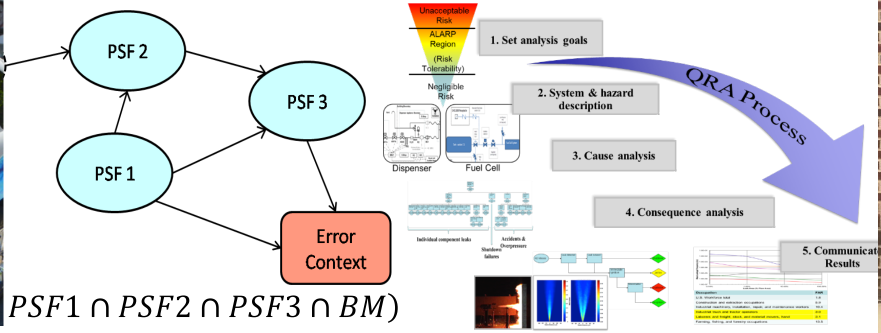


$PSF1 \cap PSF2 \cap PSF3 \cap BM)$

# Overview of UMD’s Systems Risk and Reliability Analysis (SyRRA) Lab

**Katrina Groth** (kgroth@umd.edu) (http://syrra.umd.edu)
Assistant Professor, Mechanical Engineering (http://enme.umd.edu)
Associate Director for Research & Outreach, Center for Risk and Reliability (http://crr.umd.edu)
University of Maryland

SYRRA

# Katrina M. Groth

Assistant Professor
Mechanical Engineering
University of Maryland

*Risk assessment, system safety, reliability engineering, energy, human reliability analysis, complex engineering systems*

CENTER FOR
RISK AND RELIABILITY

SYRRA

Systems Risk and Reliability Analysis Laboratory
[http://syrra.umd.edu](http://syrra.umd.edu)

## Current research

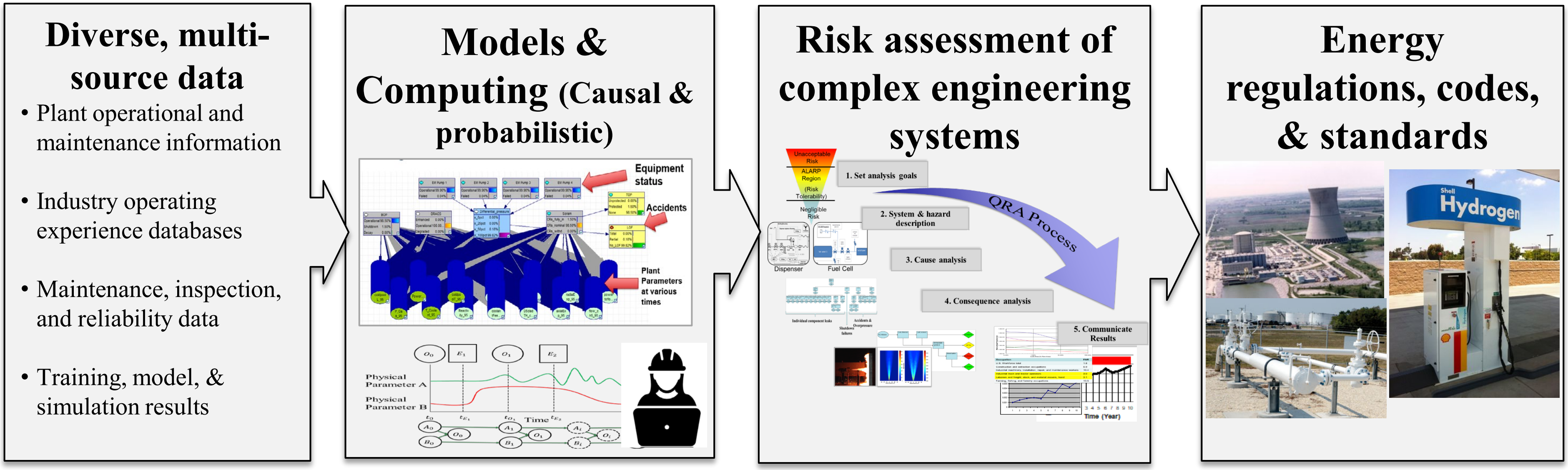
- Risk-informed PHM for complex engineering systems
- Risk & reliability approaches for on-site hydrogen storage
- Data- and model-informed nuclear human reliability analysis (HRA)
- Third party damage modeling for pipeline integrity
- Risk assessment frameworks for autonomous vehicles

A. JAMES CLARK
SCHOOL OF ENGINEERING

# SyRRA: Safety, risk and reliability engineering research for complex engineering systems

Rigorous basic & applied research into risk assessment and decision making under uncertainty

- Novel engineering research at the intersection of energy technologies, complex engineering systems, & risk and reliability
- For complex systems: Human + machine + environment + physical phenomena + AI
- Informed by models, engineering expertise, and data, (Not “just” data)



**Diverse, multi-source data**

- Plant operational and maintenance information
- Industry operating experience databases
- Maintenance, inspection, and reliability data
- Training, model, & simulation results

**Models & Computing (Causal & probabilistic)**

**Risk assessment of complex engineering systems**

**Energy regulations, codes, & standards**

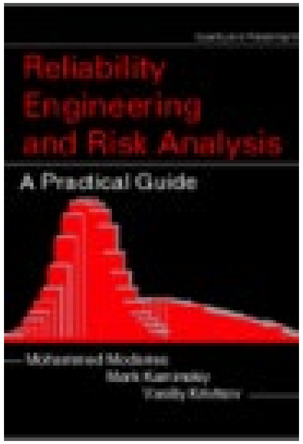
# Active research in the SyRRA lab

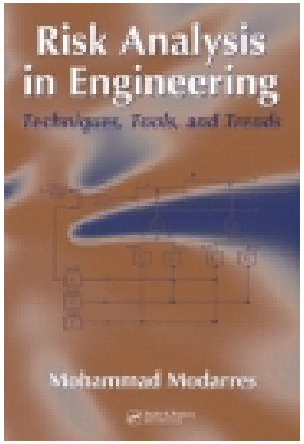
- Defining a PHM approach for complex engineering systems
- Constructing adaptive time models for risk-informed diagnostic support
- Developing novel risk & reliability approaches for hydrogen storage (LH2) & hydrogen fueling stations
- Data-informed Human Reliability Analysis (HRA)
- Third party damage modeling for pipeline integrity using causal models & field data
- Risk assessment frameworks for autonomous vehicles

In 2021: Open Post-doc, Ph.D. positions
- Computing/software for PRA
- Human reliability modeling for external hazards at NPPs

# Reliability Engineering program (ENRE) & Center for Risk And Reliability (CRR)

- #1 Reliability Engineering degree program in the U.S., #2 internationally (Microsoft Academic Rankings, 2020)
  - Housed within UMD's Mechanical Engineering Department
  - Offers M.S., M.Eng., and Ph.D. degrees – over 450 graduates since 1990.
- CRR: An umbrella organization for risk and reliability research at UMD's Clark School of Engineering.
  - ~15 core faculty; expertise spanning: reliability and risk ranging from microelectronics, to complex systems, human, hardware, software for a wide range of technologies. [http://crr.umd.edu](http://crr.umd.edu)





# Context on research with academic partners

- Core Goals of CRR:
  - Perform cutting edge research in safety, risk and reliability engineering of complex socio-technical engineering systems.
  - Educate the next generation of engineers & decision-makers.
  - Build a world-class center of excellence in risk and reliability.

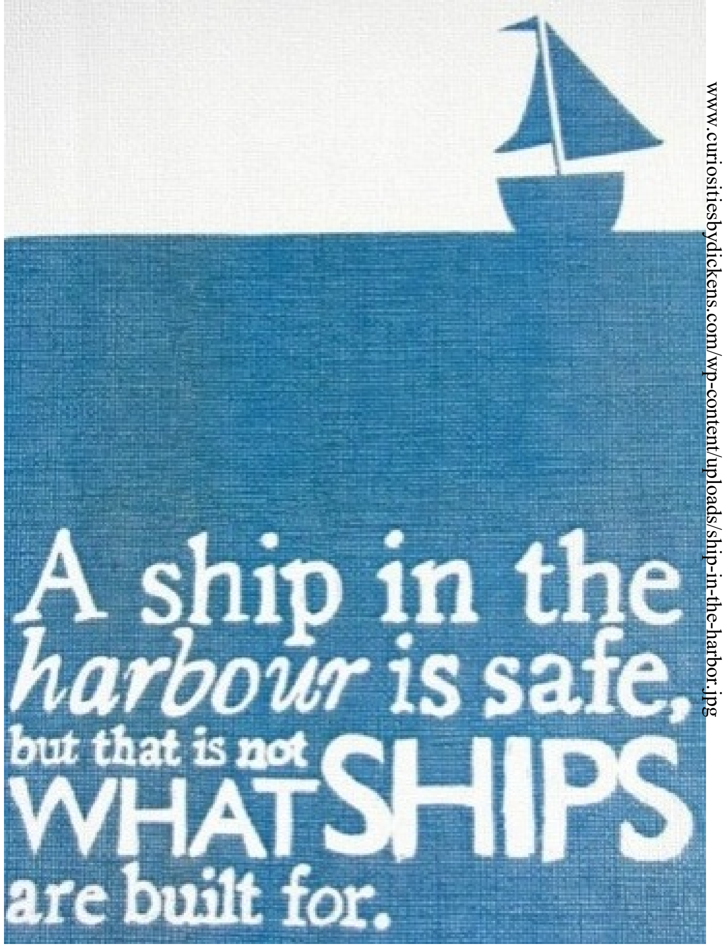
- Products of R1 “High research activity” universities:
  - Students - M.S. and Ph.D.
  - Journal papers in high-impact venues
  - Basic & applied research with visibility & impact
  - Connection to broader societal benefits

# Why study risk & reliability?

- 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.
- Engineers create transformative technologies …but the engineering doesn't end when the product is delivered or the lights come on.
- Systems can be engineered for safety & reliability
- Engineers need insight into how to prevent, mitigate, and recover from system failures, accidents

# Reliability engineering supports decision-making

- A process **to explore priorities,** to **build consensus**, **to encourage discourse** among interested parties, **to build a common basis for safety discussions**
- By building an understanding of:
  - What the system is supposed to do (performance)
  - The sources, causes, and likelihood of failures (physics based, human, computational, etc.)
  - Strategies to reduce failure (e.g., design, operation, maintenance)



www.curiositiesbydickens.com/wp-content/uploads/ship-in-the-harbor.jpg

# Said another way: Quantitative Risk Assessment

**Risk** = "the potential for loss" (more specifically, "uncertainty about the potential for and severity of loss(es)"

### Risk Analysis

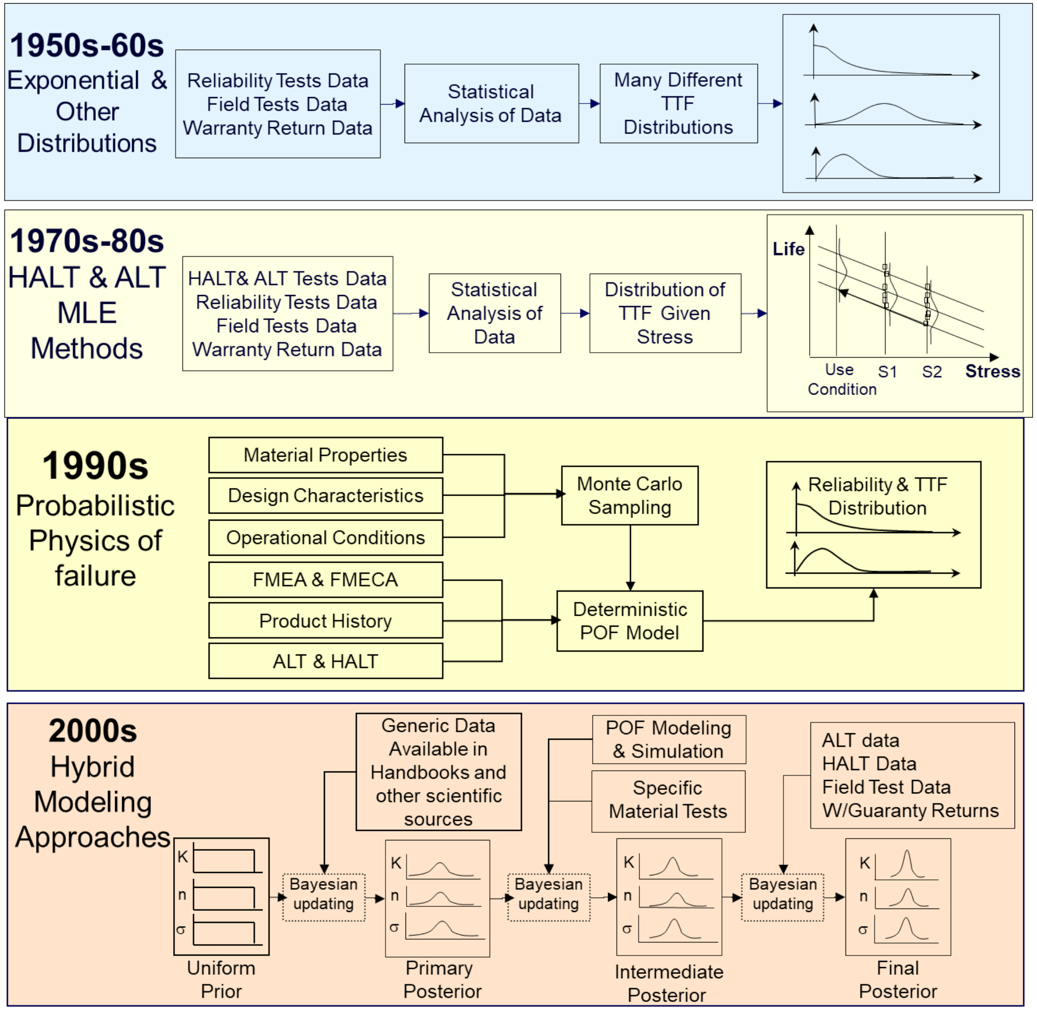
- A process used to identify and characterize risk in a system
  - What could go wrong?
  - How likely is it?
  - What are the consequences?

+

### Risk Management

- Provide inputs to decision makers on:
  - Sources of risk
  - Strategies to reduce risk
  - Priorities

# The field safety, risk & reliability is rapidly changing



**1950s-60s**
Exponential & Other Distributions

Reliability Tests Data
Field Tests Data
Warranty Return Data

Statistical Analysis of Data

Many Different TTF Distributions

**1970s-80s**
HALT & ALT MLE Methods

HALT& ALT Tests Data
Reliability Tests Data
Field Tests Data
Warranty Return Data

Statistical Analysis of Data

Distribution of TTF Given Stress

**1990s**
Probabilistic Physics of failure

Material Properties
Design Characteristics
Operational Conditions
FMEA & FMECA
Product History
ALT & HALT

Monte Carlo Sampling

Deterministic POF Model

Reliability & TTF Distribution

**2000s**
Hybrid Modeling Approaches

Generic Data Available in Handbooks and other scientific sources

POF Modeling & Simulation

Specific Material Tests

ALT data
HALT Data
Field Test Data
W/Guaranty Returns

Uniform Prior

Bayesian updating

Primary Posterior

Bayesian updating

Intermediate Posterior

Bayesian updating

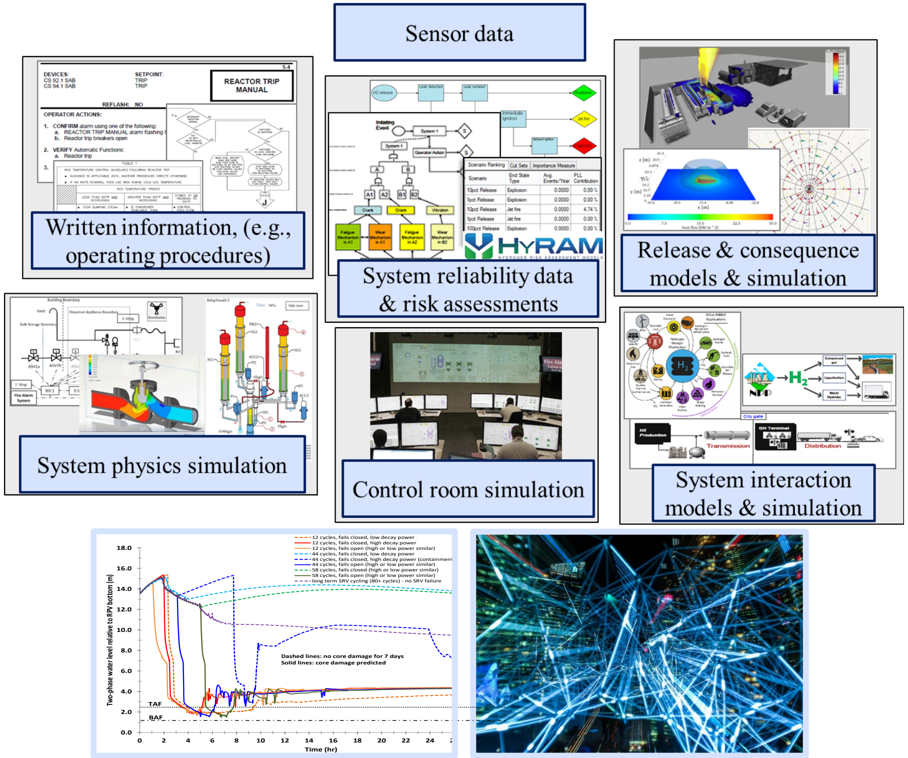
Final Posterior

## 2010's and beyond…

- Prognostics, Systems health management;
- Causality + statistical models
- Heterogeneous data, big data, sparse data,
- Machine learning, artificial intelligence, simulation
- Complex systems; systems of systems;

# Motivating questions: New data & computing motivate new questions for risk analysis

- We have more data, in more formats, at more scales, than ever before.
- Recent advances in computer science & causality offer new opportunities for many fields
  - Machine learning, Big data, Data science/analytics
  - Causal modeling



- **How can we use this to make systems safer?**
- **And how do we do it without overwhelming decision makers?**

# Motivating questions:

How can we use this data & engineering knowledge to make systems safer & more resilient? (Despite our uncertainty)

And how do we do it without overwhelming decision makers?

# And we approach this in a Bayesian way

Judea Pearl says:

> "Bayes means:
> (1) using knowledge we possess prior to obtaining data,
> (2) encoding such knowledge in the language of probabilities
> (3) combining those probabilities with data and
> (4) accepting the combined results as a basis for decision making and performance evaluation."

Judea Pearl, "Bayesianism and causality, or, why I am only a half-Bayesian" *Foundations of Bayesianism,* **2001**, *24*, 19-34

# Research sponsors

NSF

U.S.NRC
United States Nuclear Regulatory Commission
*Protecting People and the Environment*

ASME
SETTING THE STANDARD

NREL
NATIONAL RENEWABLE ENERGY LABORATORY

gti®

PHMSA
Pipeline and Hazardous Materials Safety Administration

DEPARTMENT OF ENERGY · UNITED STATES OF AMERICA

Sandia National Laboratories

INL Idaho National Laboratory

# Scholarship & Fellowships

## Rockwell Collins Fellowship

- Awarded annually to one graduate student in the field of reliability engineering on the basis of scholastic achievement, research contributions, publications, or extra-curricular activities with demonstrated contributions to the field.

## C. Raymond Knight Fellowship

- Awarded annually to graduate students studying reliability engineering on the basis of merit.

## Willie M. Webb Scholarship

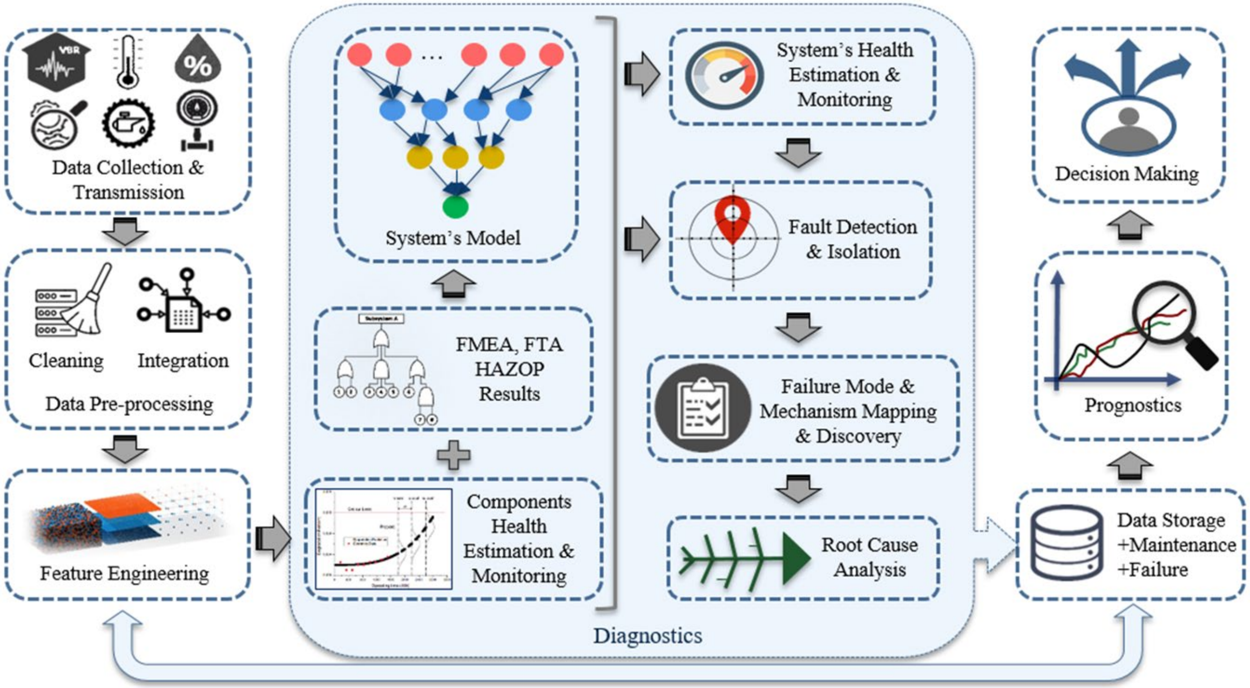
- Awards annually to women or minorities pursuing Reliability Engineering degrees at the University of Maryland, based on merit, future promise, and contributions to the field.

## Marvin Roush Fellowship

- Recognizes the pioneering contributions of Dr. Roush, who helped establish the Reliability Engineering educational program in 1991.

# Active research: PACES, a PHM approach for complex engineering systems

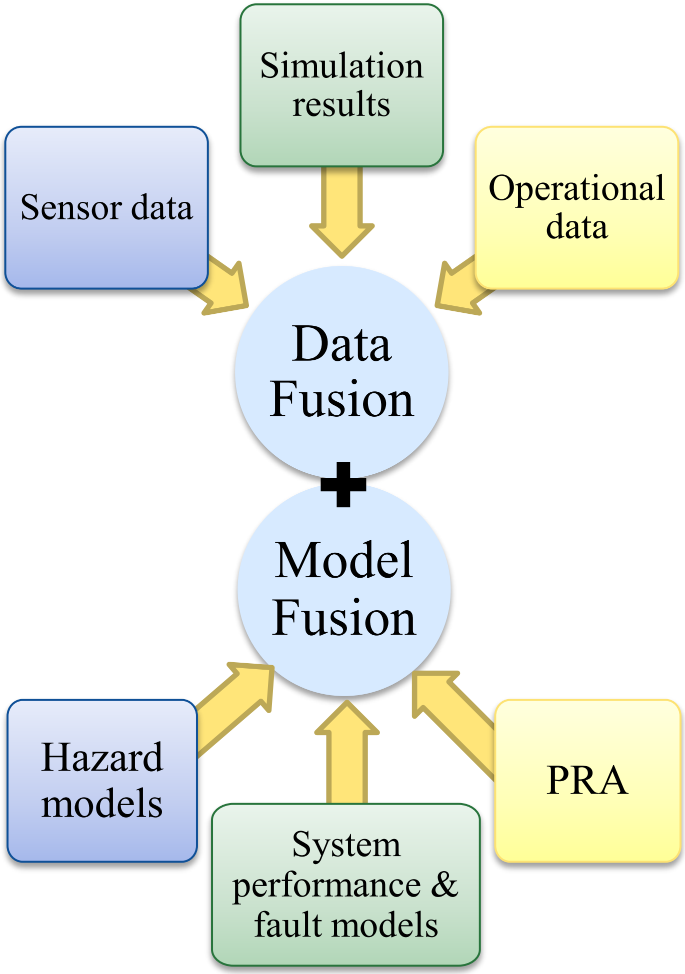
- **Research Objective**: Create a framework which enables active risk assessment, management for complex systems by combining concepts from PRA, PHM to fuse data from multiple sources (e.g., sensors, operational records, maintenance logs, system configuration) at multiple scales
- **Goal**: Put the power of many data into the hands of decision makers to improve monitoring, diagnosis & response planning



# Active Research: Leveraging big data in NPPs requires a defined strategy

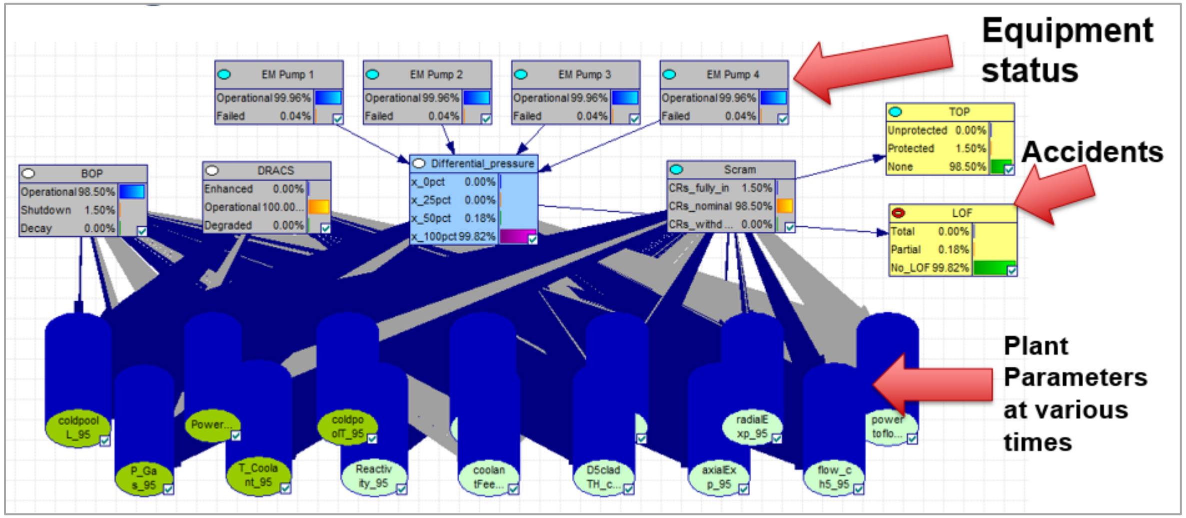
To use big data in NPP operations, we need to:

1. **Define** the types of relevant data & information
2. **Process** disparate plant data streams in near-real time for a variety of problems
3. **Integrate data** streams with existing engineering knowledge & models
4. **Transform** complex integrated data into useful information needed by decision makers



# “Smart Procedures”: Dynamic risk-informed diagnostic support for severe accidents

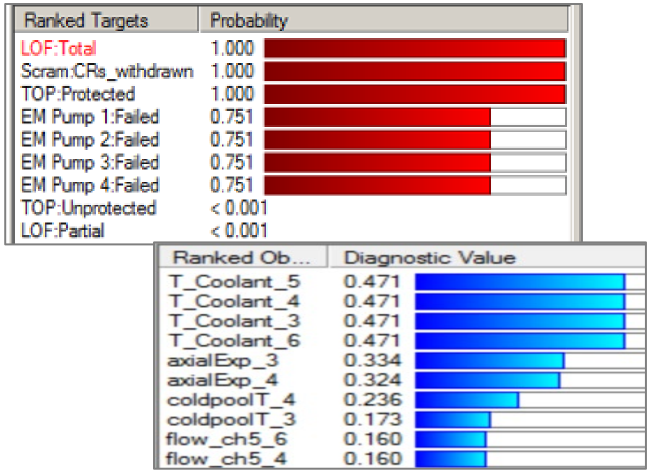
- Proof-of-principle studies demonstrated possibilities for supporting diagnosis using reactor simulation, PRA
  - Handles uncertainty (e.g., partial information) - But **not a “<u>silver bullet</u>”**
  - Preliminary insights match expectations
    - Redundancy between power/reactivity
    - High diagnostic value for T_coolant



**Equipment status**

**Accidents**

**Plant Parameters at various times**

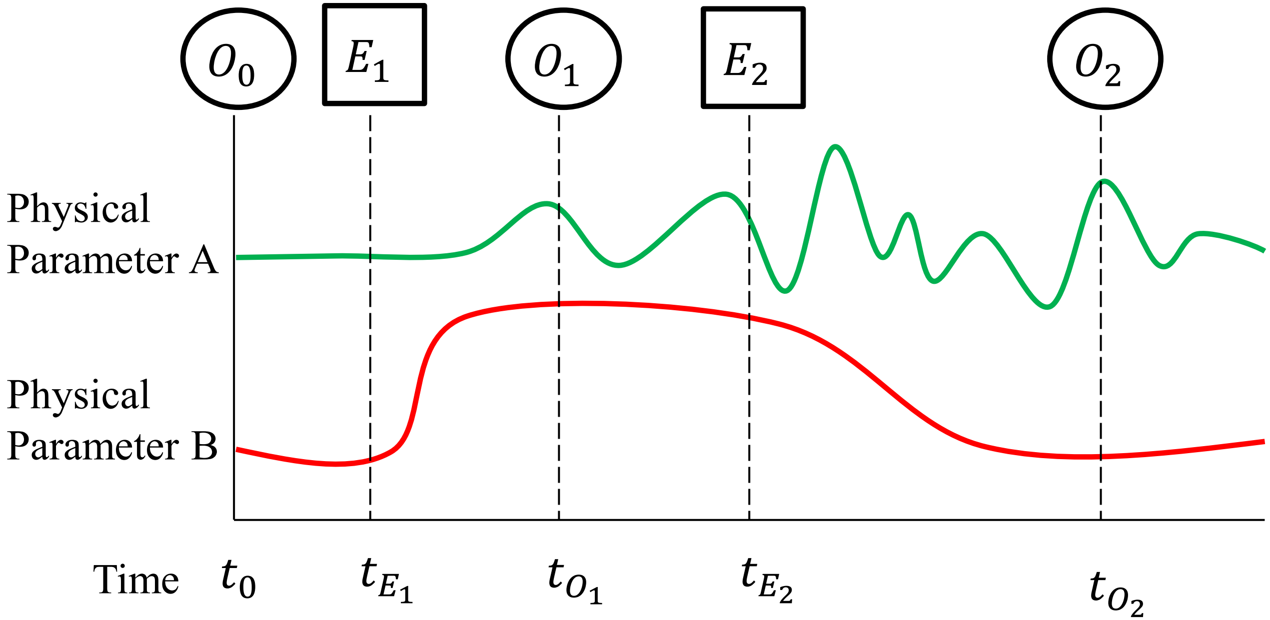


| Ranked Targets | Probability |
|---|---|
| LOF:Total | 1.000 |
| Scram:CRs_withdrawn | 1.000 |
| TOP:Protected | 1.000 |
| EM Pump 1:Failed | 0.751 |
| EM Pump 2:Failed | 0.751 |
| EM Pump 3:Failed | 0.751 |
| EM Pump 4:Failed | 0.751 |
| TOP:Unprotected | < 0.001 |
| LOF:Partial | < 0.001 |

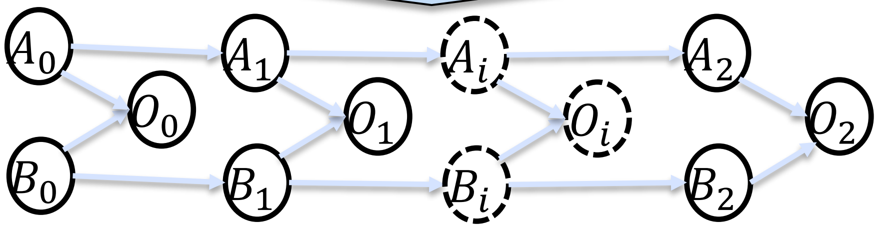
| Ranked Ob... | Diagnostic Value |
|---|---|
| T_Coolant_5 | 0.471 |
| T_Coolant_4 | 0.471 |
| T_Coolant_3 | 0.471 |
| T_Coolant_6 | 0.471 |
| axialExp_3 | 0.334 |
| axialExp_4 | 0.324 |
| coldpoolT_4 | 0.236 |
| coldpoolT_3 | 0.173 |
| flow_ch5_6 | 0.160 |
| flow_ch5_4 | 0.160 |

Groth KM, Denman MR, Jones TB, Darling MC, Luger GF. Building and using dynamic risk-informed diagnosis procedures for complex system accidents. *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability*. 2019.
Darling MC, Luger GF, Jones TB, Denman MR, Groth KM. Intelligent Modeling for Nuclear Power Plant Accident Management. *International Journal of Artificial Intelligence Tools*. 2018;27(2).

# Active Research: Constructing more adaptive models for diagnosis in complex systems



Conversion of real/simulated data into predictive models



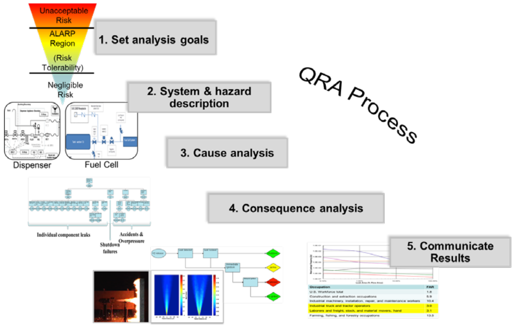
**Impact:** Enabling risk-informed diagnosis support by:

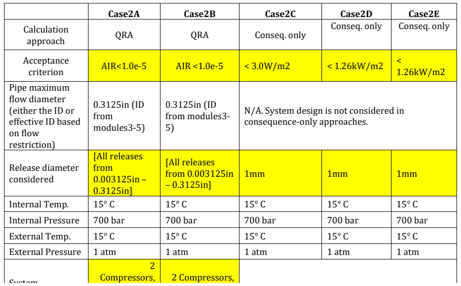
- Reducing model redundancy
- Minimizing computational requirements
- Incorporating necessary system information

# Hydrogen risk & safety research

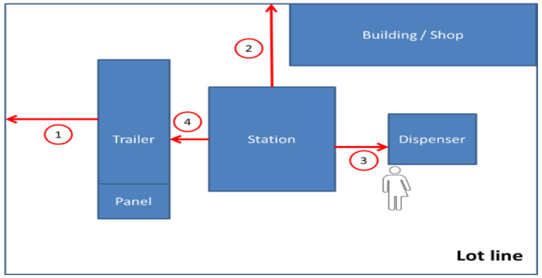
## Developed safety tools & international codes for H2 infrastructure through quantitative risk assessment

- **HyRAM**: Spearheaded development of first-of-kind integration platform for hydrogen safety models & data
  - Built to put safety R&D into the hands of industry experts
- **Subtask leader (Appendix A) of ISO 19880-1** *Hydrogen Fueling Stations*: Developed consensus approach for defining specific mitigations (e.g., safety distances) using HyRAM + regional requirements from teams in US, UK, Japan, Germany, France





| | Case2A | Case2B | Case2C | Case2D | Case2E |
|---|---|---|---|---|---|
| Calculation approach | QRA | QRA | Conseq. only | Conseq. only | Conseq. only |
| Acceptance criterion | AIR<1.0e-5 | AIR <1.0e-5 | < 3.0W/m2 | < 1.26kW/m2 | < 1.26kW/m2 |
| Pipe maximum flow diameter (either the ID or effective ID based on flow restriction) | 0.3125in (ID from modules3-5) | 0.3125in (ID from modules3-5) | N/A. System design is not considered in consequence-only approaches. | | |
| Release diameter considered | [All releases from 0.003125in – 0.3125in] | [All releases from 0.003125in – 0.3125in] | 1mm | 1mm | 1mm |
| Internal Temp. | 15° C | 15° C | 15° C | 15° C | 15° C |
| Internal Pressure | 700 bar | 700 bar | 700 bar | 700 bar | 700 bar |
| External Temp. | 15° C | 15° C | 15° C | 15° C | 15° C |
| External Pressure | 1 atm | 1 atm | 1 atm | 1 atm | 1 atm |
| System | 2 Compressors, | 2 Compressors, | | | |



# HyRAM: Making hydrogen safety science accessible through computational tools

HYRAM
HYDROGEN RISK ASSESSMENT MODELS

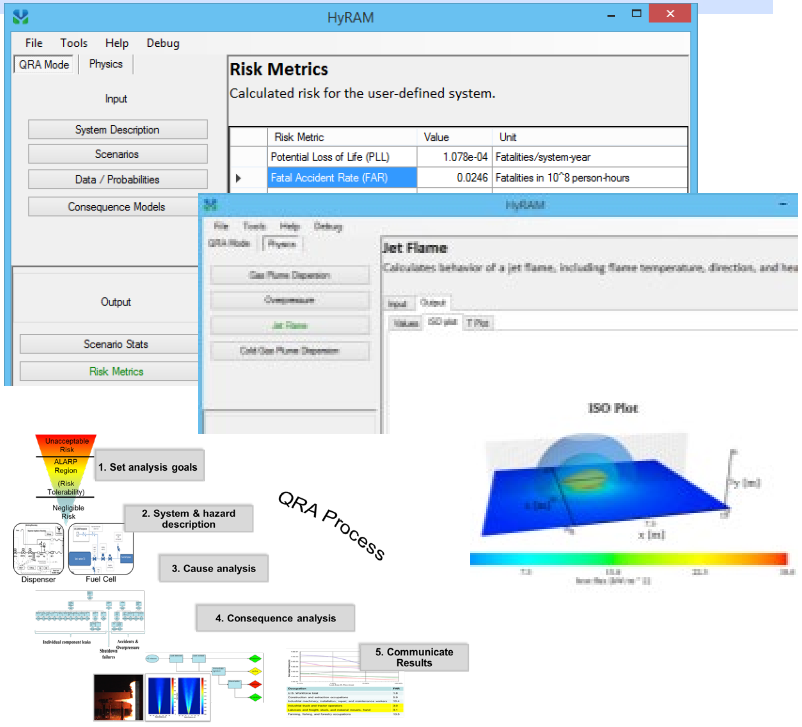
**First-of-its-kind integration platform** for state-of-the-art hydrogen safety models & data - **built to put the R&D into the hands of industry safety experts**

**Core functionality:**

- Quantitative risk assessment (QRA) methodology
- Frequency & probability data for hydrogen component failures
- Fast-running models of hydrogen gas and flame behaviors

**Key features:**

- GUI & Mathematics Middleware
- Documented approach, models, algorithms
- Flexible and expandable framework; supported by active R&D



**Risk Metrics**

Calculated risk for the user-defined system.

| Risk Metric | Value | Unit |
|---|---|---|
| Potential Loss of Life (PLL) | 1.078e-04 | Fatalities/system-year |
| Fatal Accident Rate (FAR) | 0.0246 | Fatalities in 10^8 person-hours |

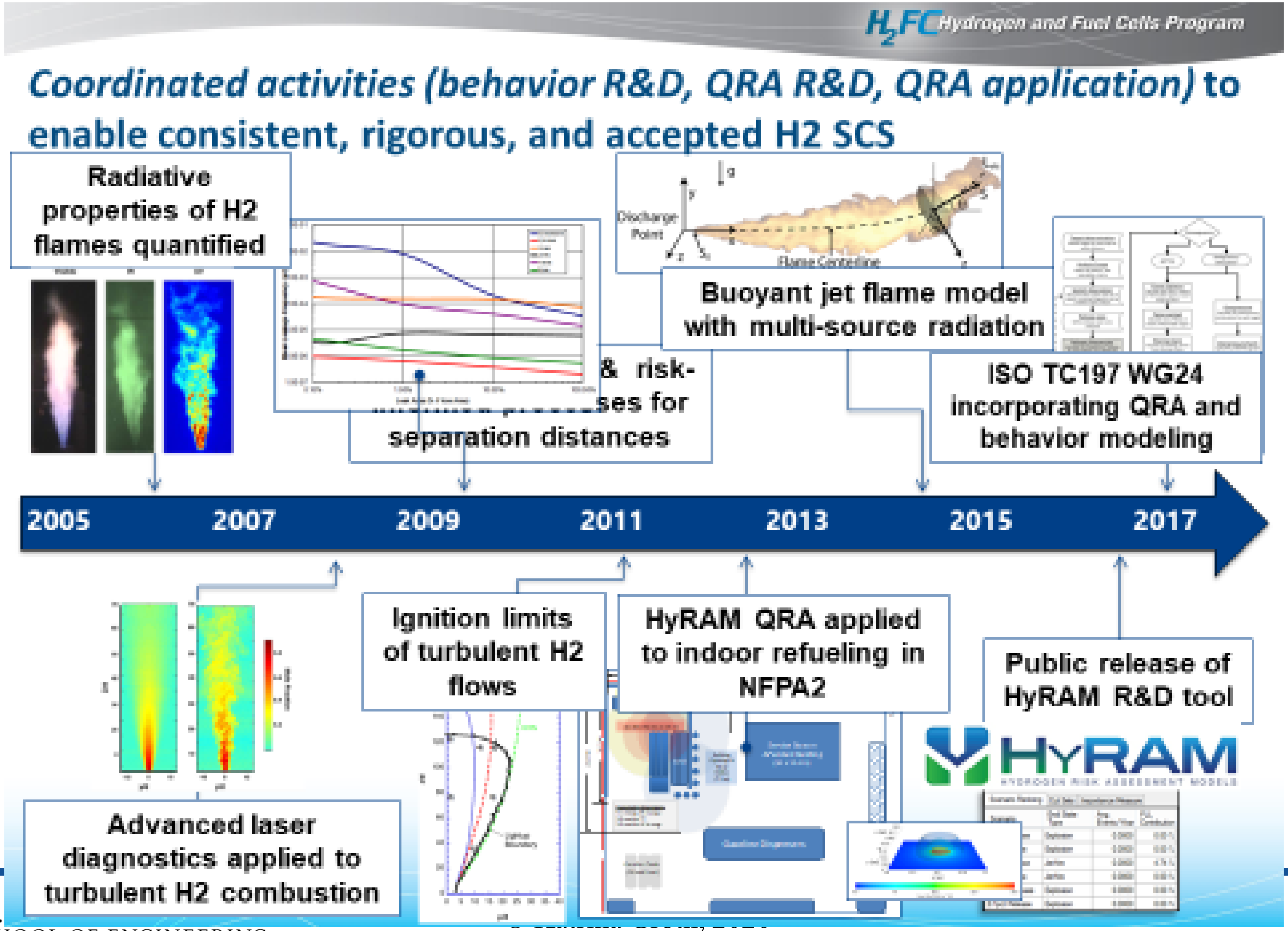
**Jet Flame**

Calculates behavior of a jet flame, including flame temperature, direction, and hea

1. Set analysis goals
2. System & hazard description
3. Cause analysis
4. Consequence analysis
5. Communicate Results

**Free at http://hyram.sandia.gov**

# Enabling Hydrogen infrastructure safety with QRA & data integration



**Coordinated activities (behavior R&D, QRA R&D, QRA application) to enable consistent, rigorous, and accepted H2 SCS**

Radiative properties of H2 flames quantified

& risk-
ses for
separation distances

Buoyant jet flame model with multi-source radiation

ISO TC197 WG24 incorporating QRA and behavior modeling

Advanced laser diagnostics applied to turbulent H2 combustion

Ignition limits of turbulent H2 flows

HyRAM QRA applied to indoor refueling in NFPA2

Public release of HyRAM R&D tool

# Using quality QRA to harmonize safety distances: ISO19880-1 Annex A

- **International agreement on approach, safety examples**
  - Sub-team: US, UK, Japan, Germany, France – all agreed to the approach; brought regional choices & assumptions
  - All calculations using HyRAM tool
- **Impact:**
  - US benefits from harmonized NFPA-ISO approach;
  - Bonus value to EU: Reducing cross-border challenges
- **HyRAM directly enabled progress:**
  - Real-time use of HyRAM was a key reason for coming to consensus;
    - Several collaborators brought their own tools, results, data (some proprietary); Results generally agreed once we were able to make assumptions/choices clear and use those directly in the calculations;
  - Collaborators HyRAM usability, speed combined with methodology flexibility and transparency, as ***more beneficial to permitting than the resulting distances.***

| | Case2A | Case2B | Case2C | Case2D | Case2E |
|---|---|---|---|---|---|
| Calculation approach | QRA | QRA | Conseq. only | Conseq. only | Conseq. only |
| Acceptance criterion | AIR<1.0e-5 | AIR <1.0e-5 | < 3.0W/m2 | < 1.26kW/m2 | < 1.26kW/m2 |
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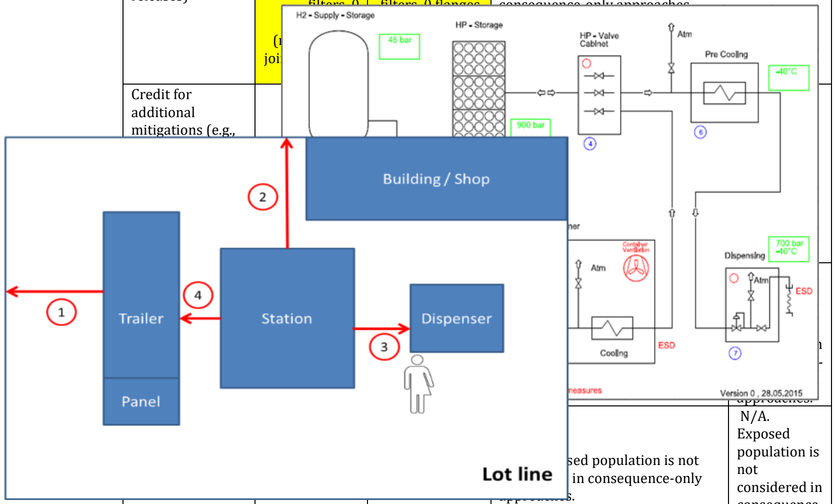
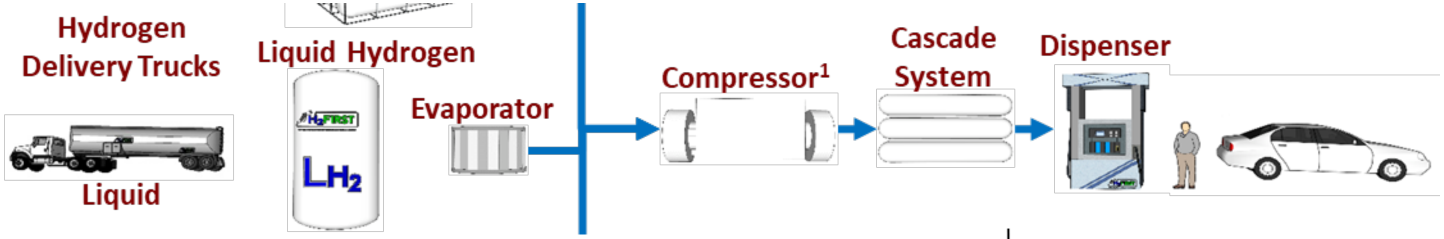
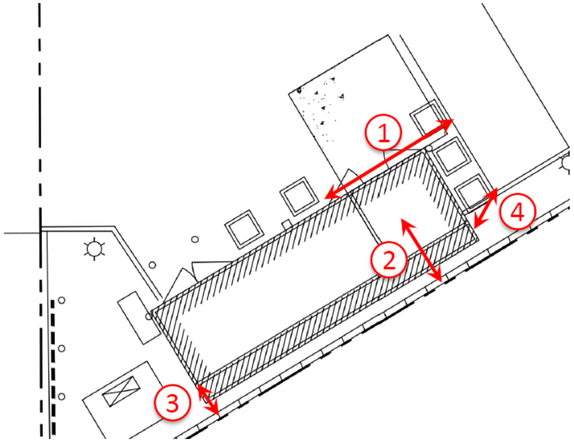
| Release diameter considered | [All releases from 0.003125in – 0.3125in] | [All releases from 0.003125in – 0.3125in] | 1mm | 1mm | 1mm |
| Internal Temp. | 15° C | 15° C | 15° C | 15° C | 15° C |
| Internal Pressure | 700 bar | 700 bar | 700 bar | 700 bar | 700 bar |
| External Temp. | 15° C | 15° C | 15° C | 15° C | 15° C |
| External Pressure | 1 atm | 1 atm | 1 atm | 1 atm | 1 atm |
| System configuration (sources of releases) | 2 Compressors, 40 Cylinders, 20 Valves, 8 Instruments, 0 filters, 0 (r joi | 2 Compressors, 48 Cylinders, 32 Valves, 12 Instruments, 0 filters, 0 flanges, | N/A. System design is not considered in consequence-only approaches. | | |
| Credit for additional mitigations (e.g., | | | | | approaches. |
| | | | sed population is not in consequence-only approaches. | | N/A. Exposed population is not considered in consequence-only approaches. |
| Illustrative examples of Calculated safety distance | **1m** | **2.5m** | **4.5m** | **5.5m** | **2.75 m** |



# Active research: Development of PHM capabilities for LH2 station w/on site storage

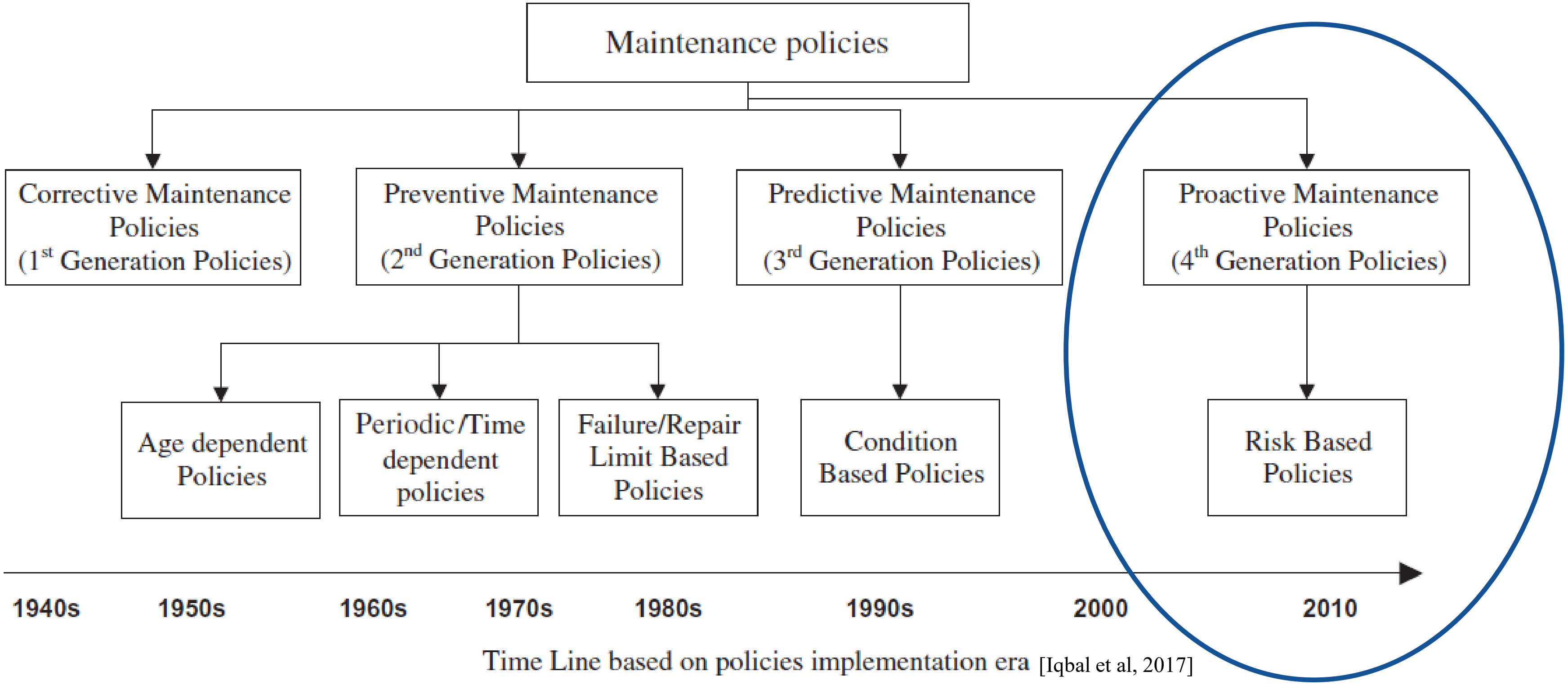


- **Objective**: Develop scientific methods for LH safety distance requirements in safety codes and standards (e.g., NFPA 2)
- **Approach**: Develop LH2 PHM and reliability models
    - Failure mode identification of selected design.
    - Scenario development for LH2 releases
    - Python-based PHM framework for prediction of reliability metrics (e.g., component life, fault diagnosis, maintenance schedules)
- **Impact**: Reduce safety distances that limit development of urban markets.



| Number | Exposure | Prescribed Distance | Actual Distance |
|---|---|---|---|
| 1 | LH2 delivery connection to parked cars | 25 feet | 10.6 feet |
| 2 | LH2 distance to overhead wires | 25 feet | 10 feet |
| 3 | GH2 distance to lot lines | 17 feet | 3.3 feet |
| 4 | GH2 distance to parked cars | 8 feet | 5.1 feet |

# Active research: Defining a risk informed, data-driven maintenance policy



Maintenance policies

Corrective Maintenance Policies (1st Generation Policies)

Preventive Maintenance Policies (2nd Generation Policies)

Predictive Maintenance Policies (3rd Generation Policies)

Proactive Maintenance Policies (4th Generation Policies)

Age dependent Policies

Periodic/Time dependent policies

Failure/Repair Limit Based Policies

Condition Based Policies

Risk Based Policies

1940s

1950s

1960s

1970s

1980s

1990s

2000

2010

Time Line based on policies implementation era [Iqbal et al, 2017]

Estimation of **probability of failure** with a high confidence level plays an important role in maintenance optimization.

Different **failure modes & sequences** must be investigated and consequences based on the historical data or physical modeling

# Active research: Developed a hybrid (data + physics) corrosion degradation model for pipeline Prognostic and Health Management

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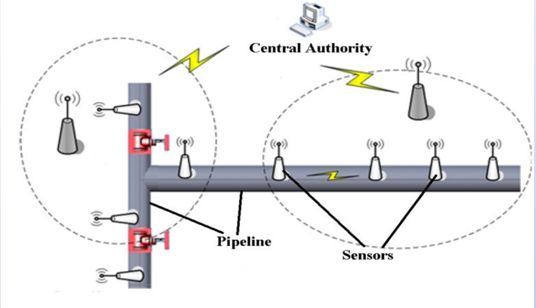

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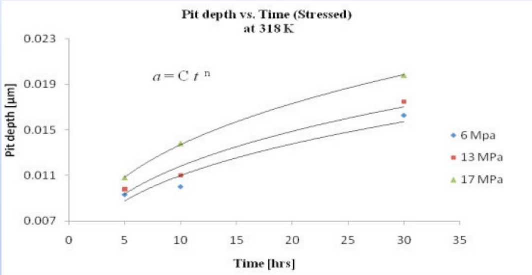
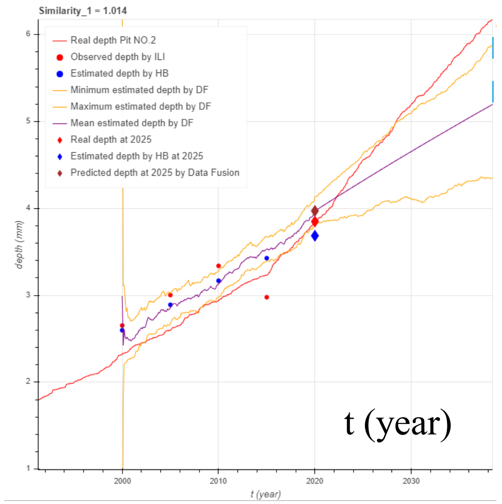
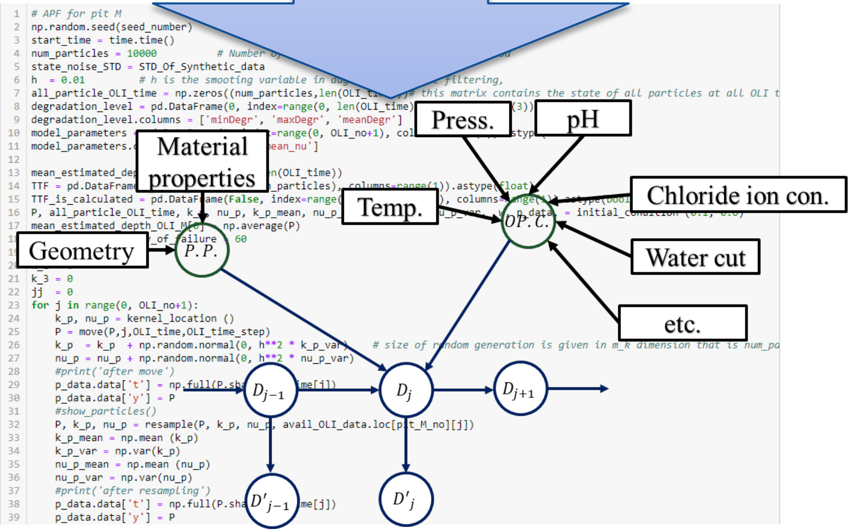
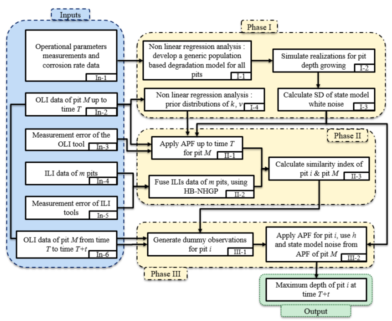




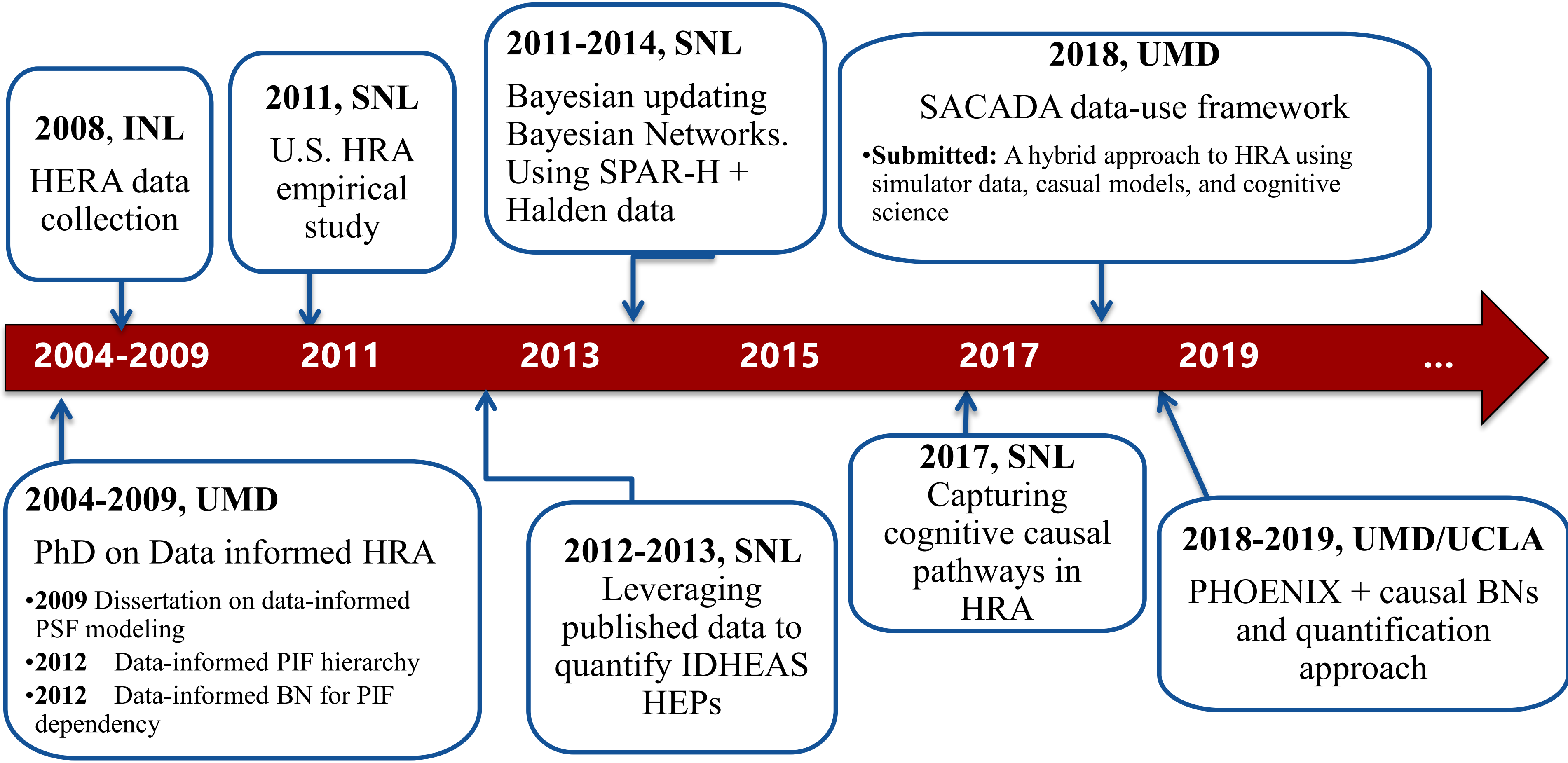


```
# APF for pit M
np.random.seed(seed_number)
start_time = time.time()
num_particles = 10000          # Number o
state_noise_STD = STD_Of_Synthetic_data
h  = 0.01          # h is the smooting variable in aug                    filtering,
all_particle_OLI_time = np.zeros((num_particles,len(OLI_ti    # this matrix contains the state of all particles at all OLI t
degradation_level = pd.DataFrame(0, index=range(0, len(OLI_time)              (3))
degradation_level.columns = ['minDegr', 'maxDegr', 'meanDegr']
model_parameters =                =range(0, OLI_no+1), col                styp
model_parameters.c                ean_nu']

mean_estimated_dep                n(OLI_time))
TTF = pd.DataFrame                _particles), columns=range(1)).astype(float)
TTF_is_calculated = pd.DataFrame(False, index=range(            ), columns=range(1)).astype(bool
P, all_particle_OLI_time, k_p, nu_p, k_p_mean, nu_p_            u_p_var,   p_data = initial_condition (0.1, 0.0)
mean_estimated_depth_OLI_M[0] = np.average(P)
                  _of_failure = 60


k_3 = 0
jj  = 0
for j in range(0, OLI_no+1):
    k_p, nu_p = kernel_location ()
    P = move(P,j,OLI_time,OLI_time_step)
    k_p  = k_p  + np.random.normal(0, h**2 * k_p_var)    # size of random generation is given in m_k dimension that is num_pa
    nu_p = nu_p + np.random.normal(0, h**2 * nu_p_var)
    #print('after move')
    p_data.data['t'] = np.full(P.sha             ime[j])
    p_data.data['y'] = P
    #show_particles()
    P, k_p, nu_p = resample(P, k_p, nu_p, avail_OLI_data.loc[pit_M_no][j])
    k_p_mean = np.mean (k_p)
    k_p_var = np.var(k_p)
    nu_p_mean = np.mean (nu_p)
    nu_p_var = np.var(nu_p)
    #print('after resampling')
    p_data.data['t'] = np.full(P.sha             me[j])
    p_data.data['y'] = P
```



## Application to maintenance policy planning

# Data-informed Human Reliability Analysis



**2008, INL**
HERA data collection

**2011, SNL**
U.S. HRA empirical study

**2011-2014, SNL**
Bayesian updating
Bayesian Networks.
Using SPAR-H + Halden data

**2018, UMD**
SACADA data-use framework
- **Submitted:** A hybrid approach to HRA using simulator data, casual models, and cognitive science

**2004-2009, UMD**
PhD on Data informed HRA
- **2009** Dissertation on data-informed PSF modeling
- **2012** Data-informed PIF hierarchy
- **2012** Data-informed BN for PIF dependency

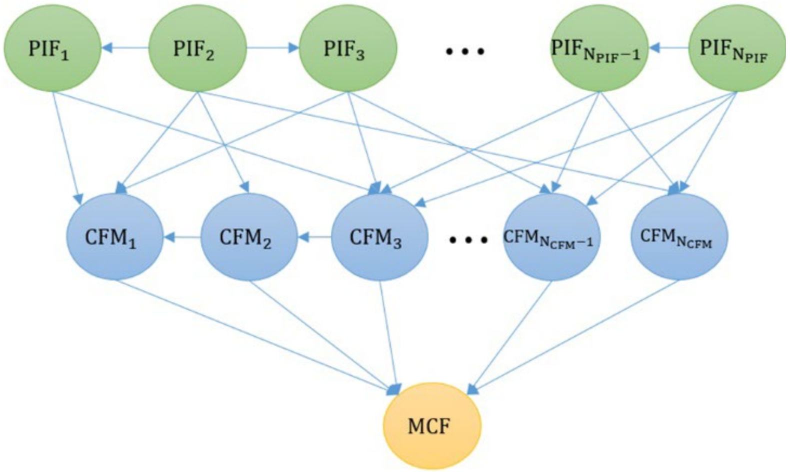
**2012-2013, SNL**
Leveraging published data to quantify IDHEAS HEPs

**2017, SNL**
Capturing cognitive causal pathways in HRA

**2018-2019, UMD/UCLA**
PHOENIX + causal BNs and quantification approach

# New: Defined a generalized set of HRA quantification elements for data fusion

- 3 **core types of variables**:
  - Performance influencing factors (PIFs)
  - Crew failure modes (CFM)
  - Macrocognitive functions (MCFs)

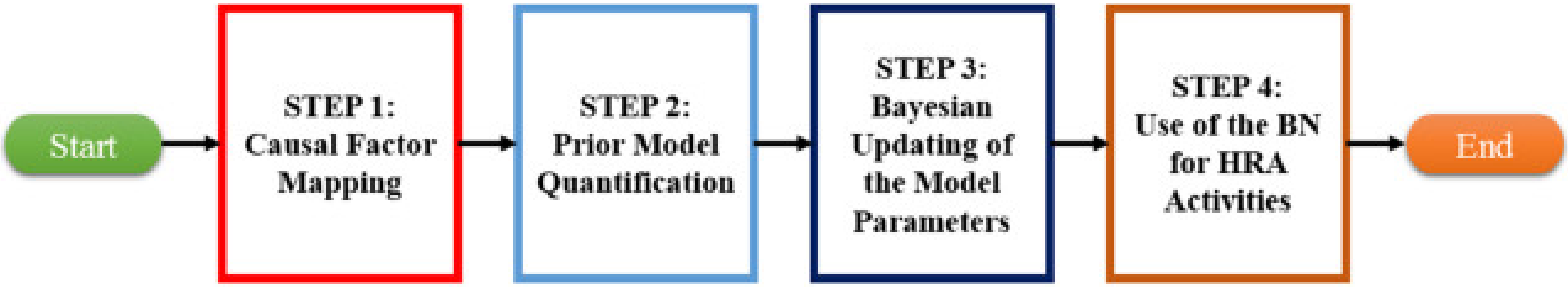


- **5 core types of probabilistic relationships** need to be quantified (4 of which involve dependency):

$$\Pr(PIF_x)$$
$$\Pr(PIF_x|pa(PIF_x))$$
$$\Pr(CFM_k|pa(CFM_k))$$
$$\Pr(MCF_i|pa(MCF_i))$$
$$\Pr(HFE|MCFs))$$

K. M. Groth, R. Smith, and R. Moradi, "A hybrid approach to HRA using simulator data, causal models, and cognitive science," Reliability Engineering and System Safety, vol. 191, Nov. 2019

# New: A hybrid approach to HRA quantification using simulator data, causal models, and cognitive science



- Step 1: Causal Factor Mapping (BN structure development)
  - Create a causal map of the relationship between the PIFs, CFMs, and MCFs using Bayesian Networks. (Groth 2012; Ekanem &Mosleh 2013; Zwirglmaier, Straub, Groth 2017)
  - Simplify BN structure using node reduction (Zwirglmaier, Straub, Groth 2017)
- Step 2: Prior model quantification (BN parameterization)
  - Map source variables to PIFs, CFMs, and MCFs taxonomy (Groth 2012)
  - Use expert elicitation, current HRA method, deterministic relationships to get priors
- Step 3: Bayesian update model parameters
  - Map data source variables to PIFs, CFMs, and MCFs taxonomy
  - Bayesian update specific conditional probability relationships using data source (Groth, Swiler, Smith 2014)
- Step 4: Use the BN for HRA activities

K. M. Groth, R. Smith, and R. Moradi, "A hybrid approach to HRA using simulator data, causal models, and cognitive science," Reliability Engineering and System Safety, vol. 191, Nov. 2019

# Active Research: Defining types of dependency between Human Failure Events in Human Reliability Analysis

- Developing the theoretical and mathematical foundations to model "Human Reliability Analysis dependency" between Human Failure Events (HFEs).
- Captures causation, not just correlation; Model & data informed
- Enables better human-machine teams, task allocation, risk assessment

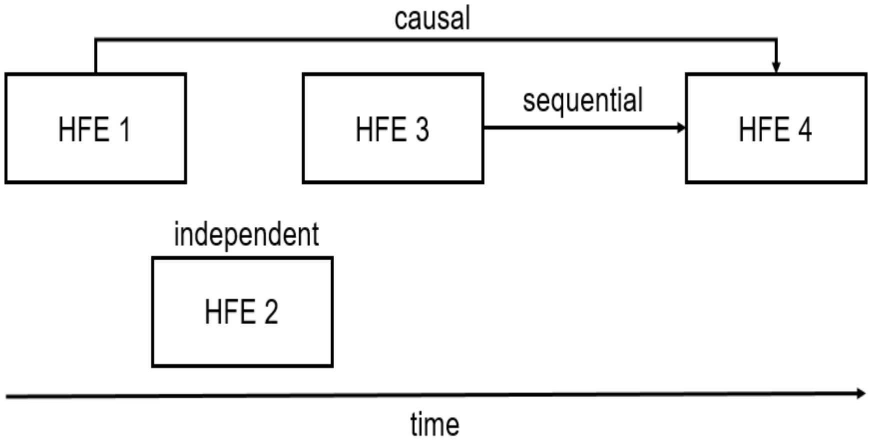
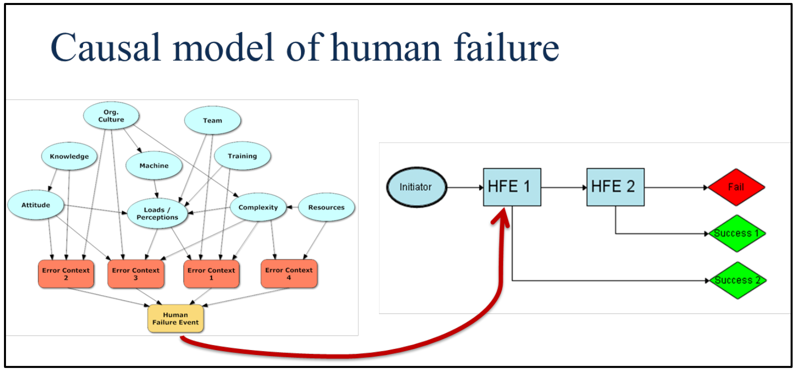


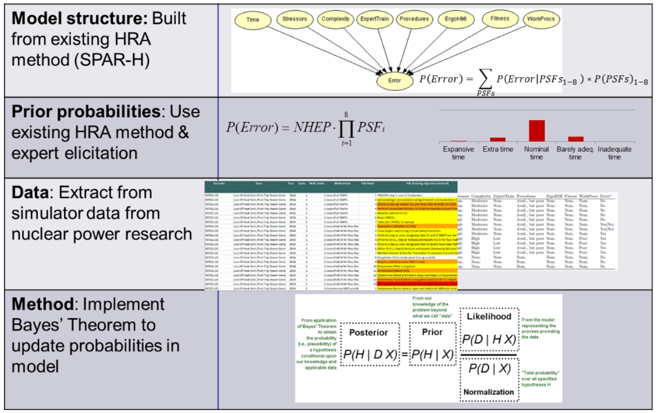
*Photo Source:* http://www.spokesman.com/stories/2017/jul/07/renewable-sources-of-electricity-outpace-nuclear-p/

# Active research: data-informed causal model of human reliability for nuclear power plant operators

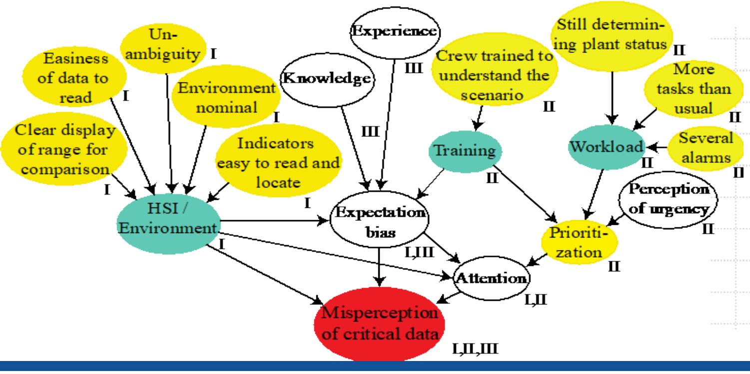
- PIF hierarchy + SACADA data + Cognitive Basis + DBNs
- Result: New paradigm for HRA.
  - Data-driven, science-based, dynamic, transparent, repeatable.

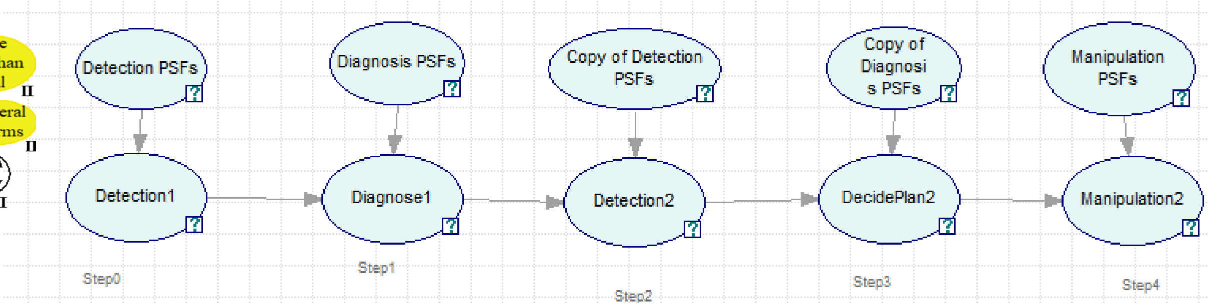


Causal model of human failure



| | |
|---|---|
| **Model structure:** Built from existing HRA method (SPAR-H) | $P(Error) = \sum_{PSFs} P(Error\|PSFs_{1-8}) * P(PSFs)_{1-8}$ |
| **Prior probabilities**: Use existing HRA method & expert elicitation | $P(Error) = NHEP \cdot \prod_{i=1}^{8} PSF_i$ |
| **Data**: Extract from simulator data from nuclear power research | |
| **Method**: Implement Bayes' Theorem to update probabilities in model | $P(H \| D X) = P(H \| X) \dfrac{P(D \| H X)}{P(D \| X)}$ |





# Summary

- **Objective**:
  - Conduct rigorous basic & applied research into risk assessment and decision making under uncertainty for complex engineering systems
  - Informed by models, engineering expertise, and data
  - Portfolio approach: Active research on PRA, PHM, HRA with direct impact on safety for hydrogen energy, oil and gas, transportation, and nuclear power
- **Results to date**:
  - XYZ journal & conference papers
  - 1 Ph.D., 2 MS degrees graduates as of 2020.
- **Next steps:**
  - Expanding capabilities & size of SyRRA lab, CRR
- **Impact**:
  - Research contributions to system safety, risk analysis, and reliability engineering
  - Educating a new generation of researchers & practitioners to think deeply about risk, reliability, and safety
  - Service to the global engineering community & UMD

SYRRA

A. JAMES CLARK
SCHOOL OF ENGINEERING