MU-PRA Methodology and Implications on QHO: Summary of NRC Grant Findings

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Acknowledgements

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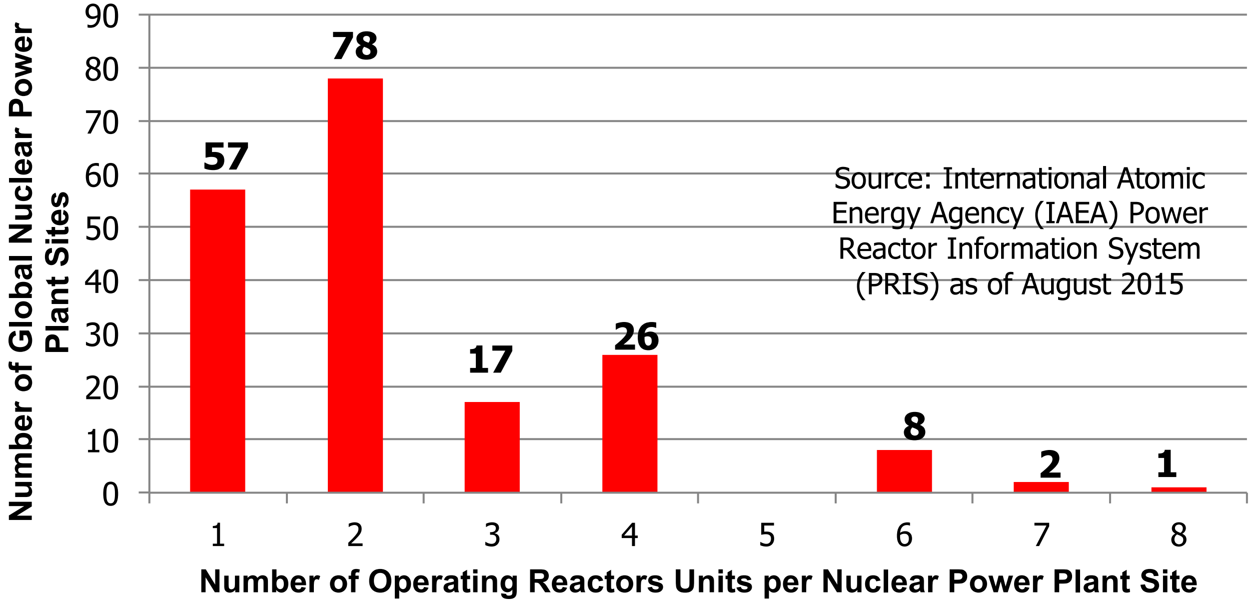
Topics Covered

- Why MU-MUPRA?
- MU-PRA Risk Metrics
- Unit-to-Unit Dependency Modeling
- MU-PRA Methodology
- A Simple Seismic PRA and Impact of MU-PRA
- Implications of MU-PRA on USNRC Safety Goals (QHOs)
- Experimental-Based (non-Parametric) Dependency Modeling
- Conclusions and Future Directions

Multi-Unit US and Global NPP Sites



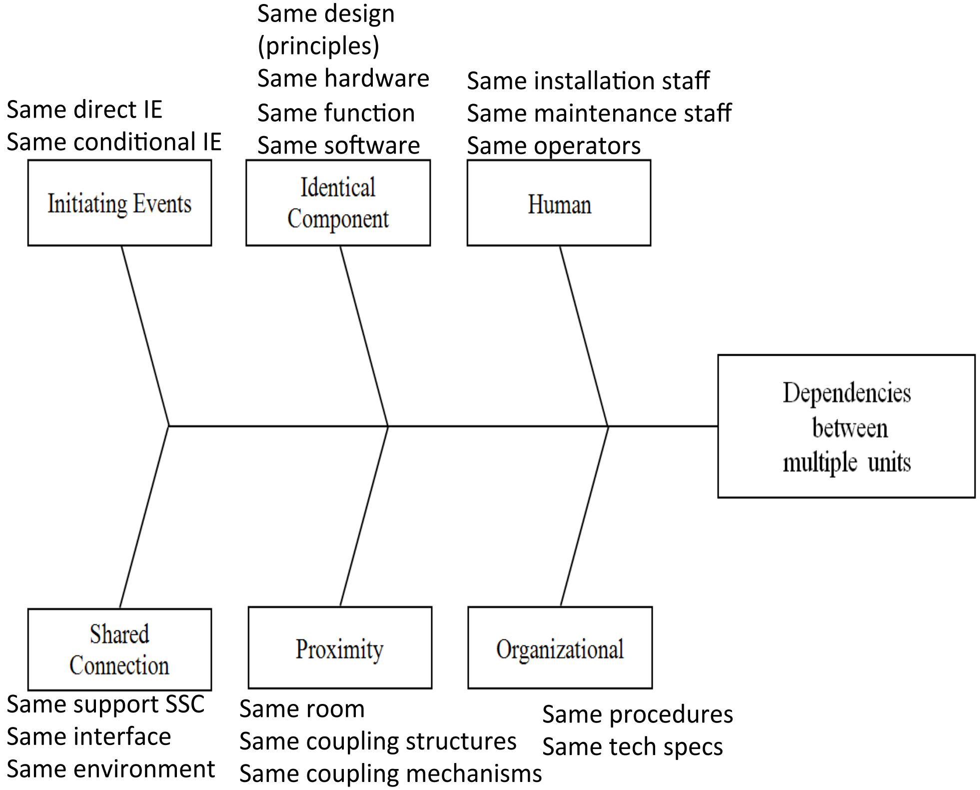
There are Major New Initiatives by IAEA.

MU-PRA Development:

- CANADA
- S. KOREA
- FRANCE

Why MU-PRA? : Unit-to-Unit Dependencies are significant

- Schroer (Dennis) used a fishbone categorization to group LERs affecting multi-units at the U.S. sites



IMPORTANT FINDINGS

- 9% of ALL LERs reported affected two or more units
- Most involving Organizational and Shared Connection types of dependencies

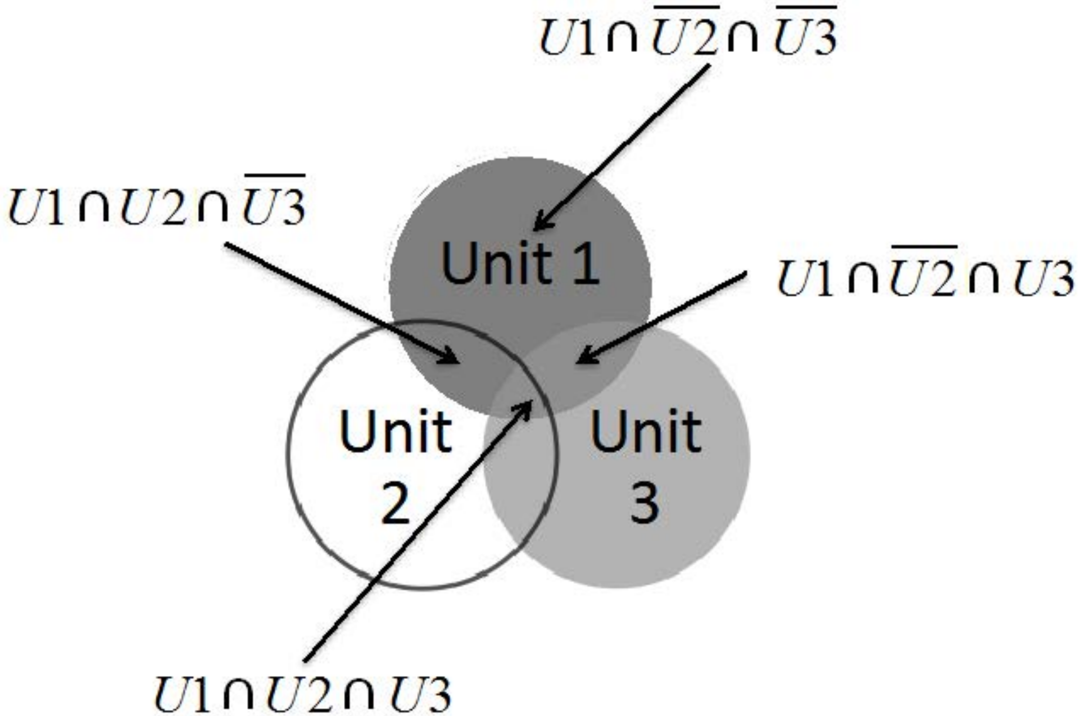
Source: Schroer, S. An Event Classification Schema For Considering Site Risk In A Multi-Unit Nuclear Power Plant Probabilistic Risk Assessment, University of Maryland, Master of Science Thesis in Reliability Engineering, 2012.

Multi-Unit CDF Metrics

- Three Possible MU-CDF Definitions:
  - CDF of one unit including consideration of all states of the other units (*marginal CDF Definition*)*
  - *Frequency of at least one or more core damages (total Site CDF Definition)*
  - *CDF for multiple core damages (concurrent CDF Definition)*

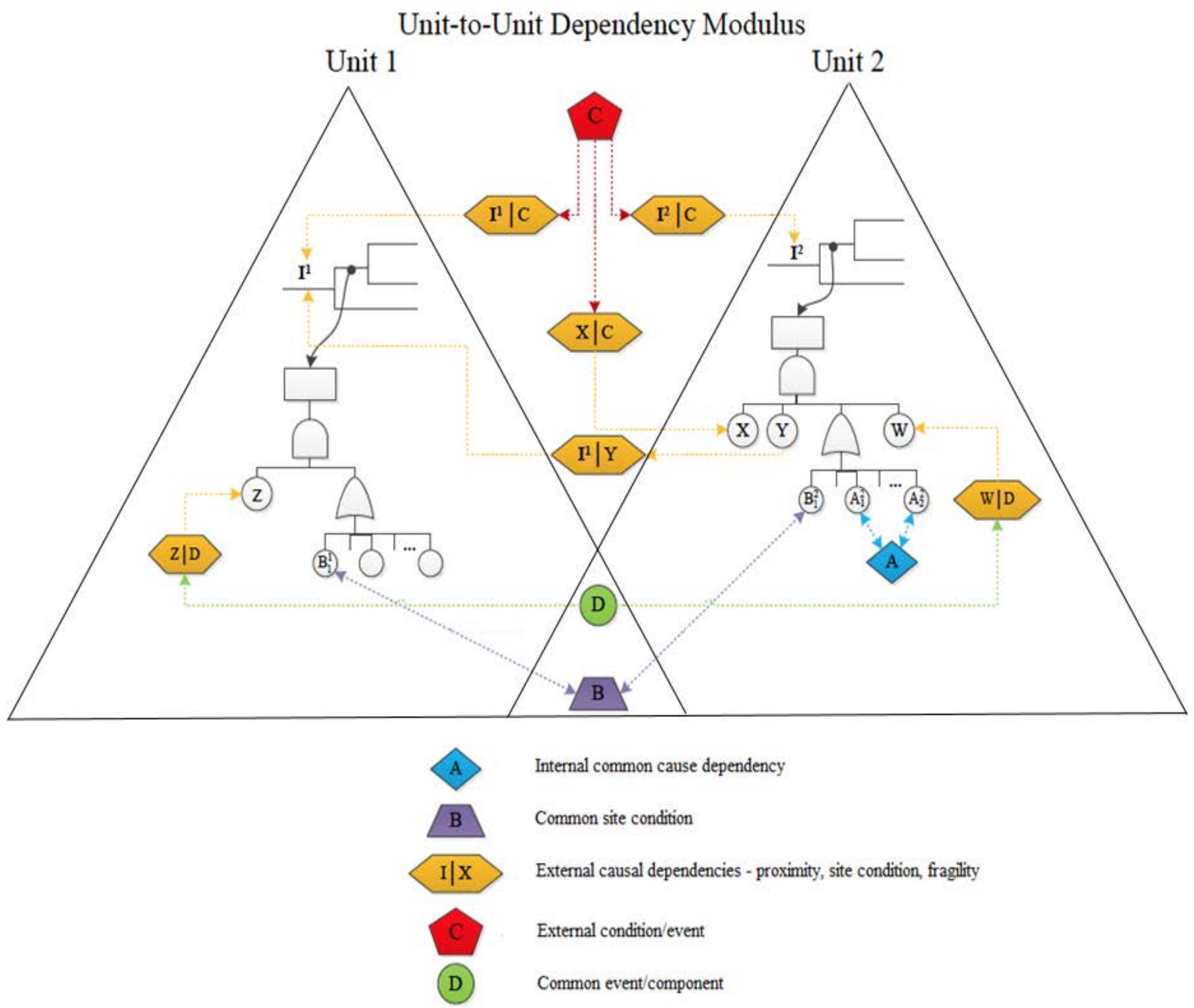
* Single unit PRAs include scenarios exclusive to one unit, assuming others will be unaffected

Multi-Unit CDF Metrics (Cont.)



A multi-unit PRA (MUPRA) analysis for any of the proposed CDF metric requires assessment of the inter- and intra-unit dependencies

Dependent Failures in Multi-Units: The Critical Element of a Successful MU-PRA



Classes of Dependencies:

- **Parametric**
- **Causal**

Estimating Dependent Failure Probabilities in MUPRA

Identical and Causal (dissimilar dependent events)

Dependent Failure Methods Proposed or Used:

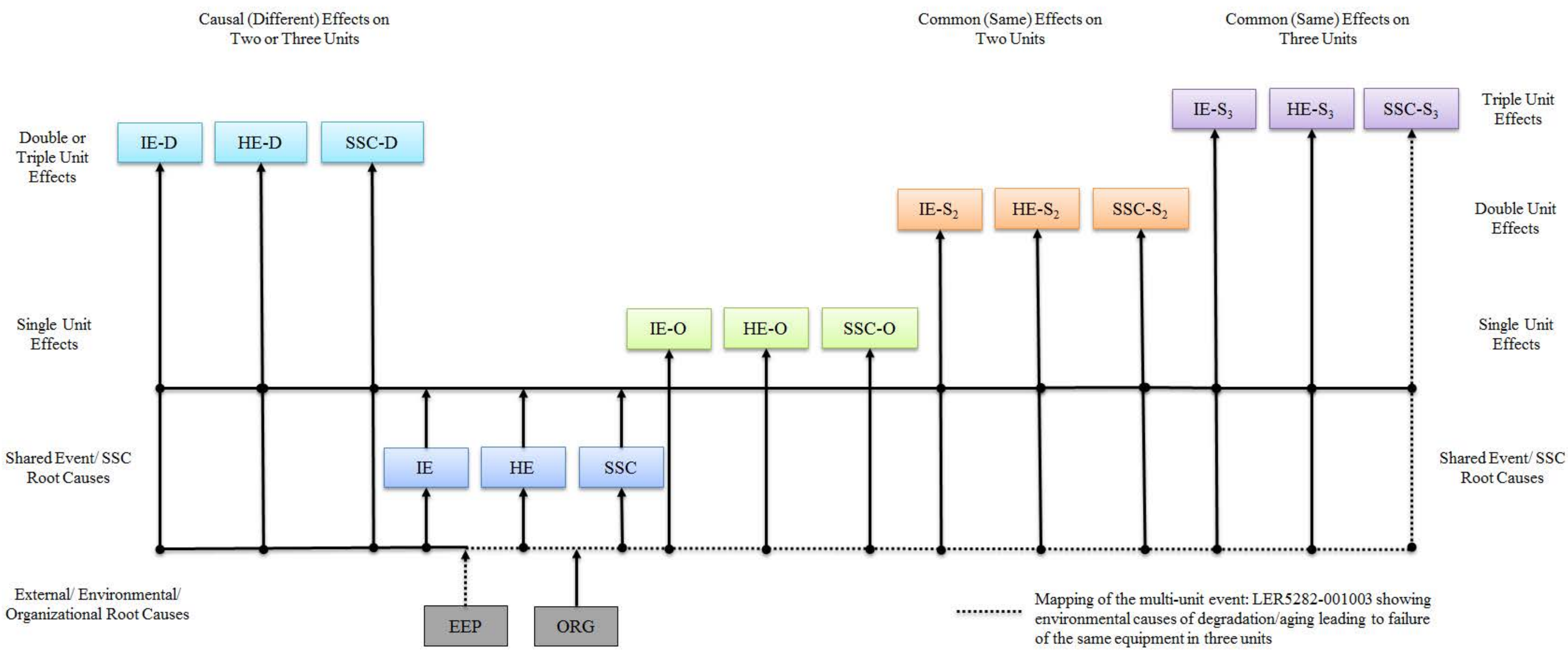
- Parametric
- Probabilistic Physics-of-Failure
- Bayesian Networks

Parametric Assessment of Conditional Probability of Failures

- Parametric analysis of MU dependencies
- LER Data of 2000-2011 of multi-unit sites categorized by their root-causes and effects
- Detailed Excel File of the LER Analysis Developed

Event Description	Number of Events, N, for 2- or 3-Unit Sites	Number of Events, N, 3-Unit Sites
Initiating Events	728	134
Component Failure / Degradation	1390	221
Human Error	341	45
Total	2459	400

Parametric Assessment of Conditional Probability of Failures (Cont.)



Parametric Assessment of Conditional Probability of Failures (Cont.)

Events Categorization, j (identified for either i=2 for events involving 2 units, or i=3 for events involving 3 units)	Number of occurrences of type j events involving i units, n_{ij}, reported by Schroer[20]	Point estimate of the probability of the event, $\hat{p}_{ij}$	The 95% posterior Bayesian interval within which the true p_{ij} resides
Identical Human Error Event (2 Units)	11	0.032	(1.7E-0.2; 5.5E-02)
Identical Human Error Event (3 Units)	1	0.022	(2.4E-03; 9.9E-02)
Human Error Event in One Unit Causes Different Human Errors in Other Unit(s) $(HE_x\|HE_y)$	0	0	(1.4E-06; 7.3E-03)
Identical Component Failure/Degradation Event (2 Units)	39	0.028	(2.0E-02; 3.8E-02)
Identical Component Failure/Degradation Event (3 Units)	2	0.009	(1.9E-03; 2.9E-02)
Identical Initiating Event (2 Units)	23	0.032	(2.1E-02; 4.6E-02)
Identical Initiating Event (3 Units)	2	0.015	(3.1E-03; 4.7E-02)
Initiating Events in One Unit Causes Different Initiating Event in Other Unit(s) $(IE_x\|IE_y)$	7	0.010	(4.3E-03; 1.9E-02)
Component Failure/Degradation in One Unit Causes Initiating Event in Other Unit(s): $(C_x\|I_y)$	8	0.011	(5.2E-03; 2.1E-02)
Component Failure/Degradation in One Unit Causes Different Component Failure/Degradation in Other Unit(s): $(C_x\|C_y)$	24	0.017	(1.1E-02; 2.5E-02)
Initiating Event in One Unit Causes Component Failure/Degradation in Other Units: $(IE_x\|C_y)$	1	0.001	(1.5E-04; 6.4E-03)

- Site-to-Site variations also evaluated
- Bayesian estimate of conditional dependent failure probabilities
- LER data used as evidence with uninformative priors

$$\hat{p}_{ij} = \frac{n_{ij}}{N}$$

where $\boldsymbol{n_{ij}}$ is the total number of observed events of type j (such as initiating event) involving occurrences in i reactor units (i= 2, or 3 in U.S.) due to the total number of LER events of type-j events observed in N total events that occurred in the MU sites.

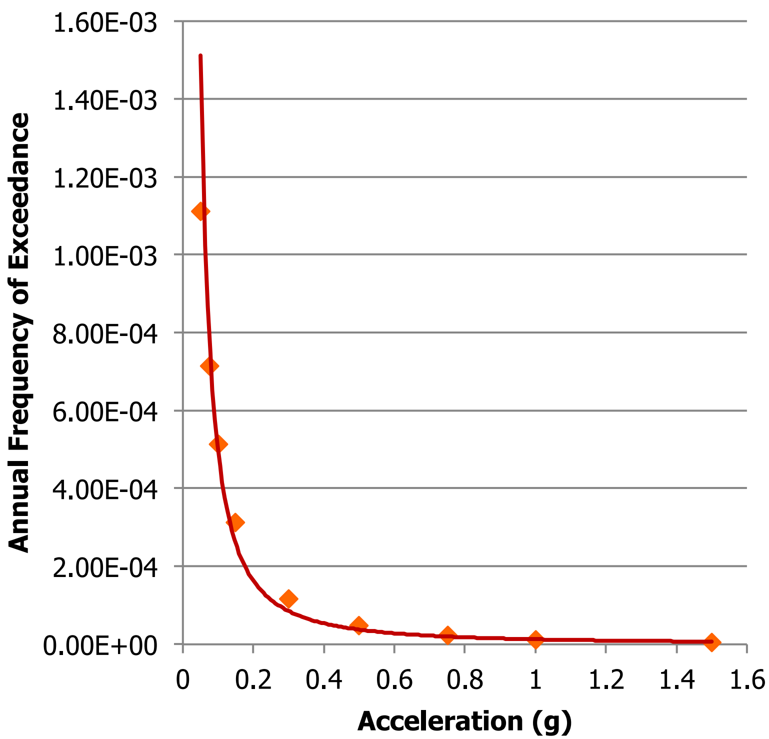
Case Study:
A Simple MU Seismic PRA of Advanced Reactor Units

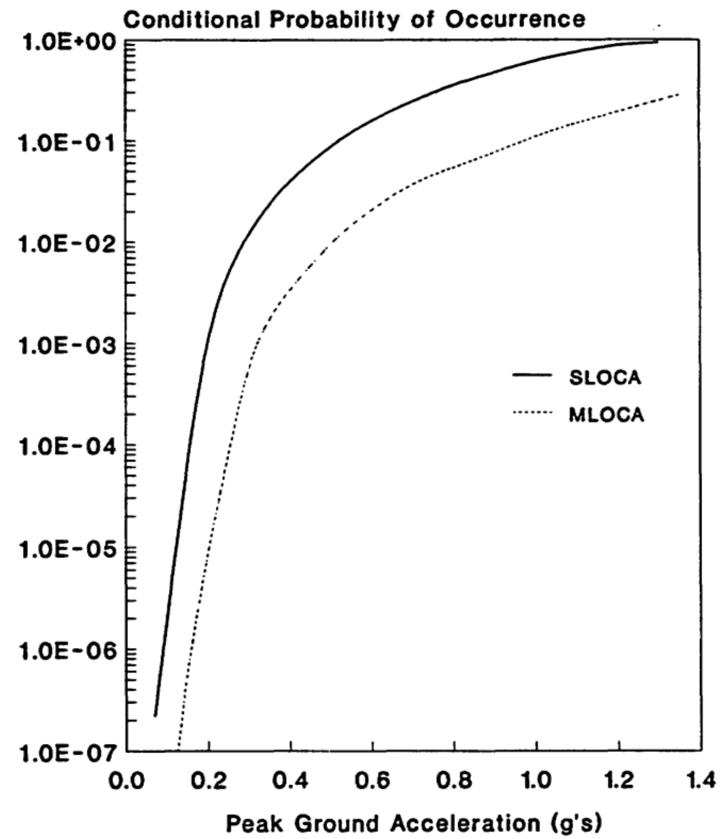
Objective and Methodology

- **Objectives**
  - Hypothetical site consisting of two advanced reactor units
  - Seismically induced small LOCA
  - Identify the MU-CD scenarios due to internal events with seismic IE
- **Methodology: parametrical-based using SAPHIRE.**
  - Use MU dependent events from the 2000-2011 LERs
  - Seismic IE with equally-correlated assumption between SSC capacities

- **Risk Metrics**
  - Site CDF (i.e., at least one CD)
  - Multi-Unit CDF (i.e., concurrent CDs)
  - Marginal Single-Unit CDF

Seismic Hazard Curve and Initiating Event Frequency

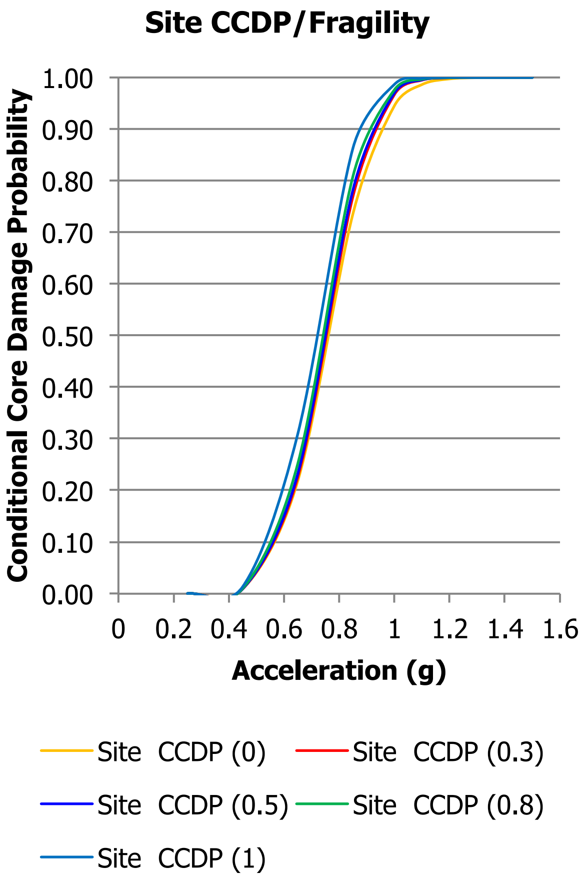


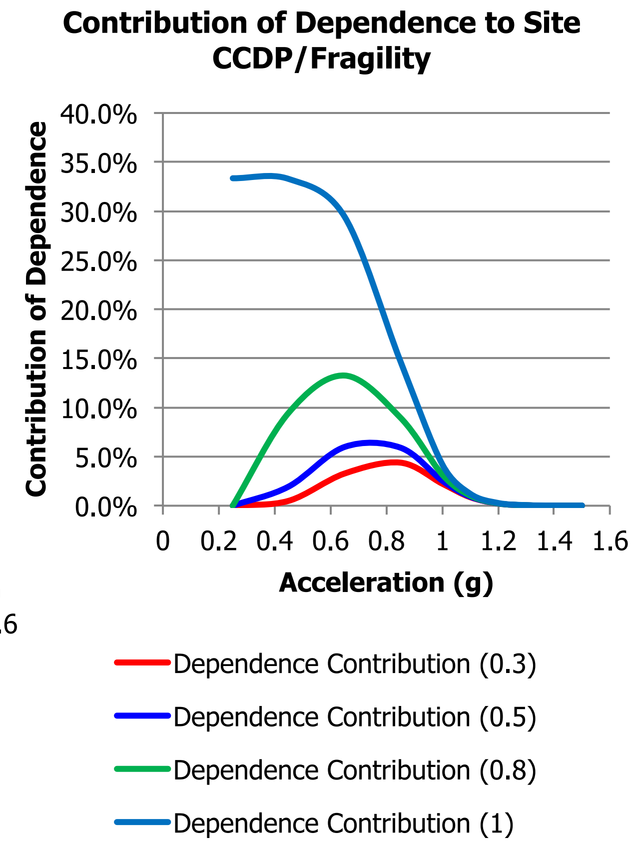


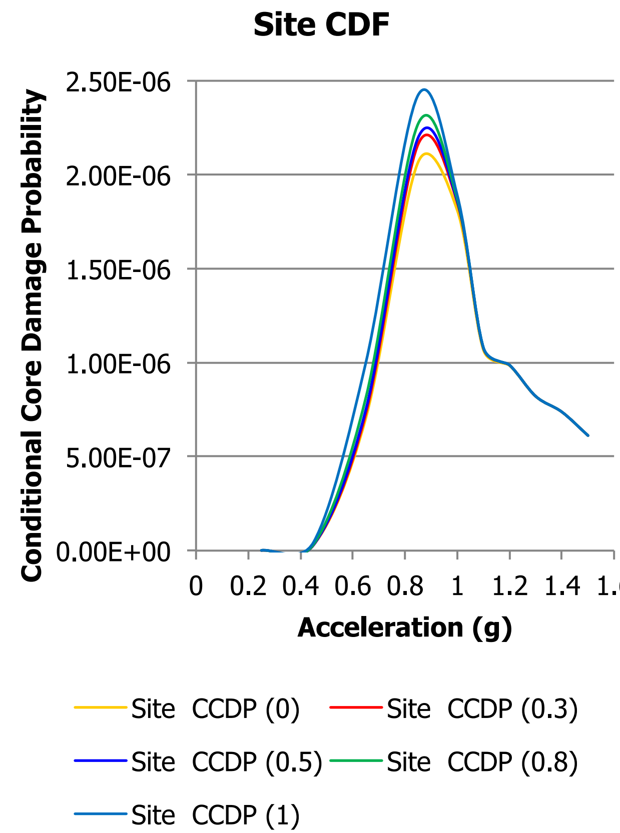
NUREG/CR-4840, November 1990

- The Frequency of Seismically induced SLOCA
  - Annual frequency exceedance (e.g., 4.78E-5 for PGA=0.5g)
  - Conditional probability of SLOCA (e.g., 0.089 for PGA=0.5g)
  - Frequency of seismic-induce SLOCA (e.g., 4.25E-6 for PGA=0.5g)

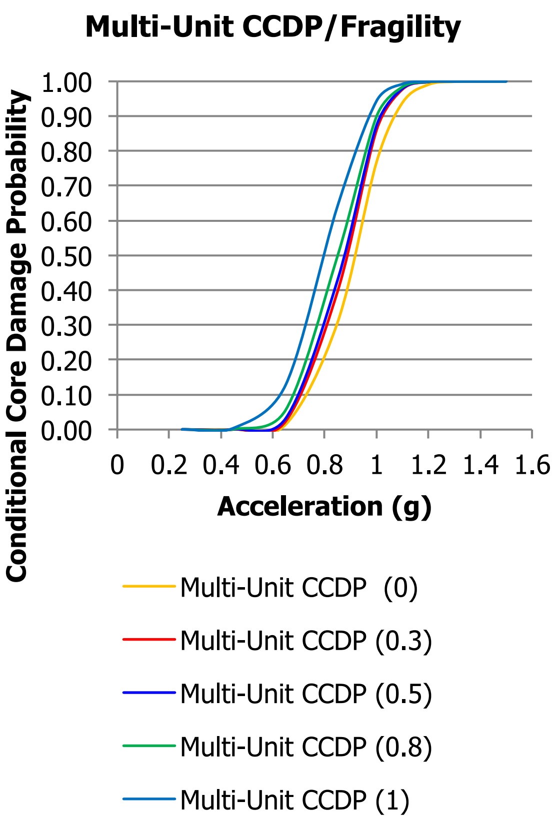
Preliminary Case Study Results (Seismic Event) – Site CDF

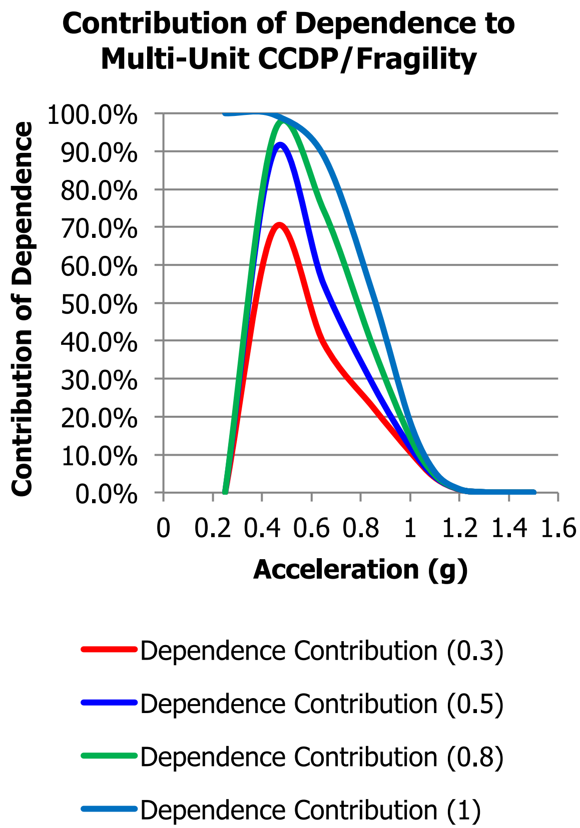


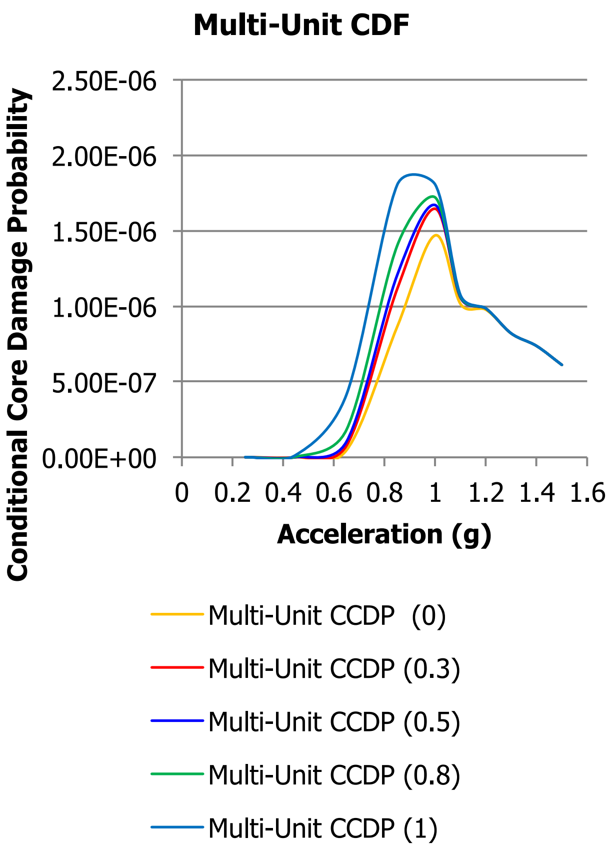




Preliminary Case Study Results (Seismic Event) – Concurrent CDF

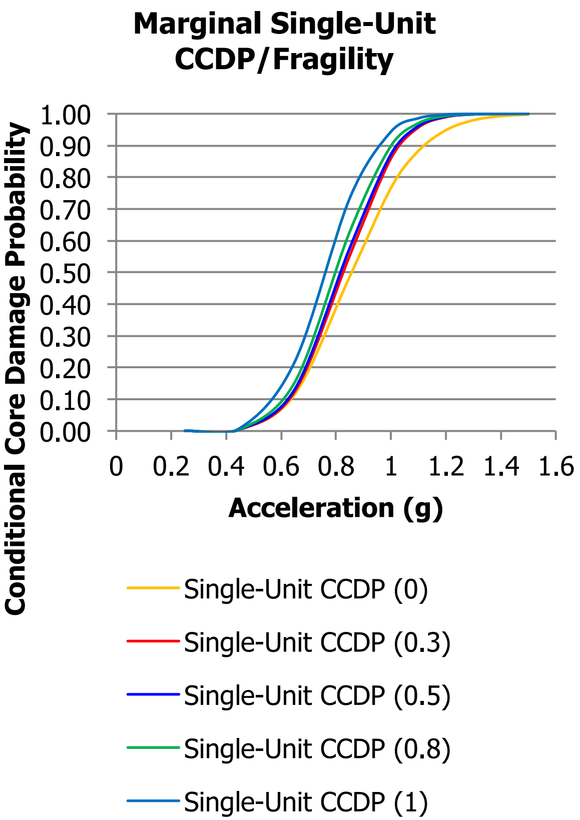


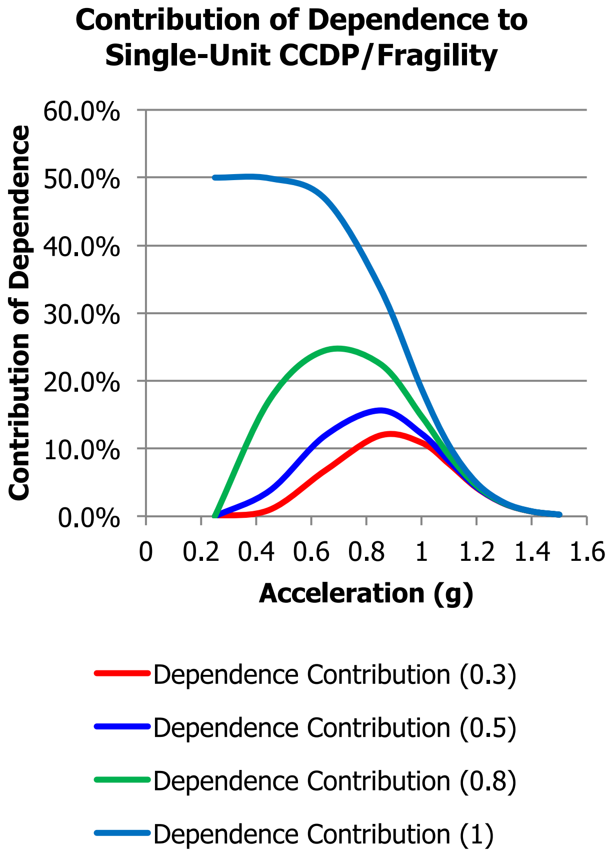


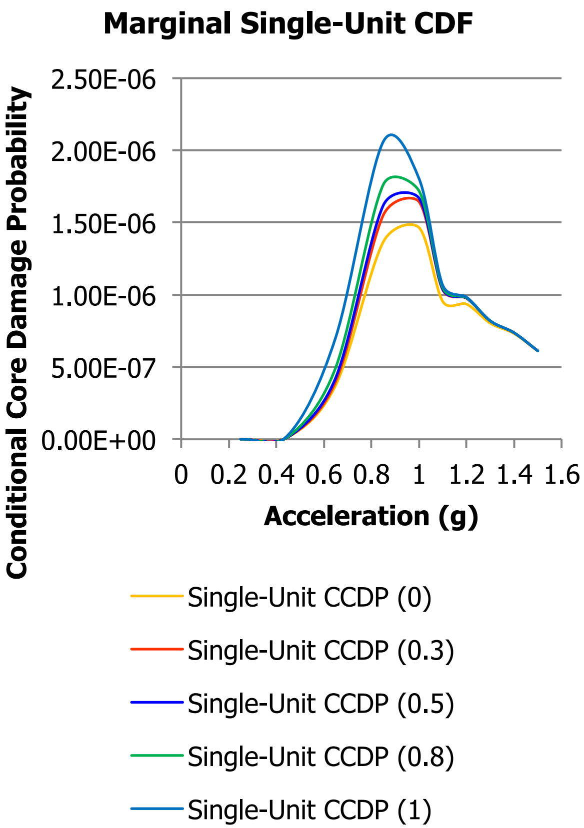


Budnitz, R.J., G.S. Hardy, D.L. Moore and, M.K.Ravindra, Correlation of Seismic Performance in Similar SSCs Final Report Draft, Lawrence Berkeley National Laboratory, March 2015 (Under Review)

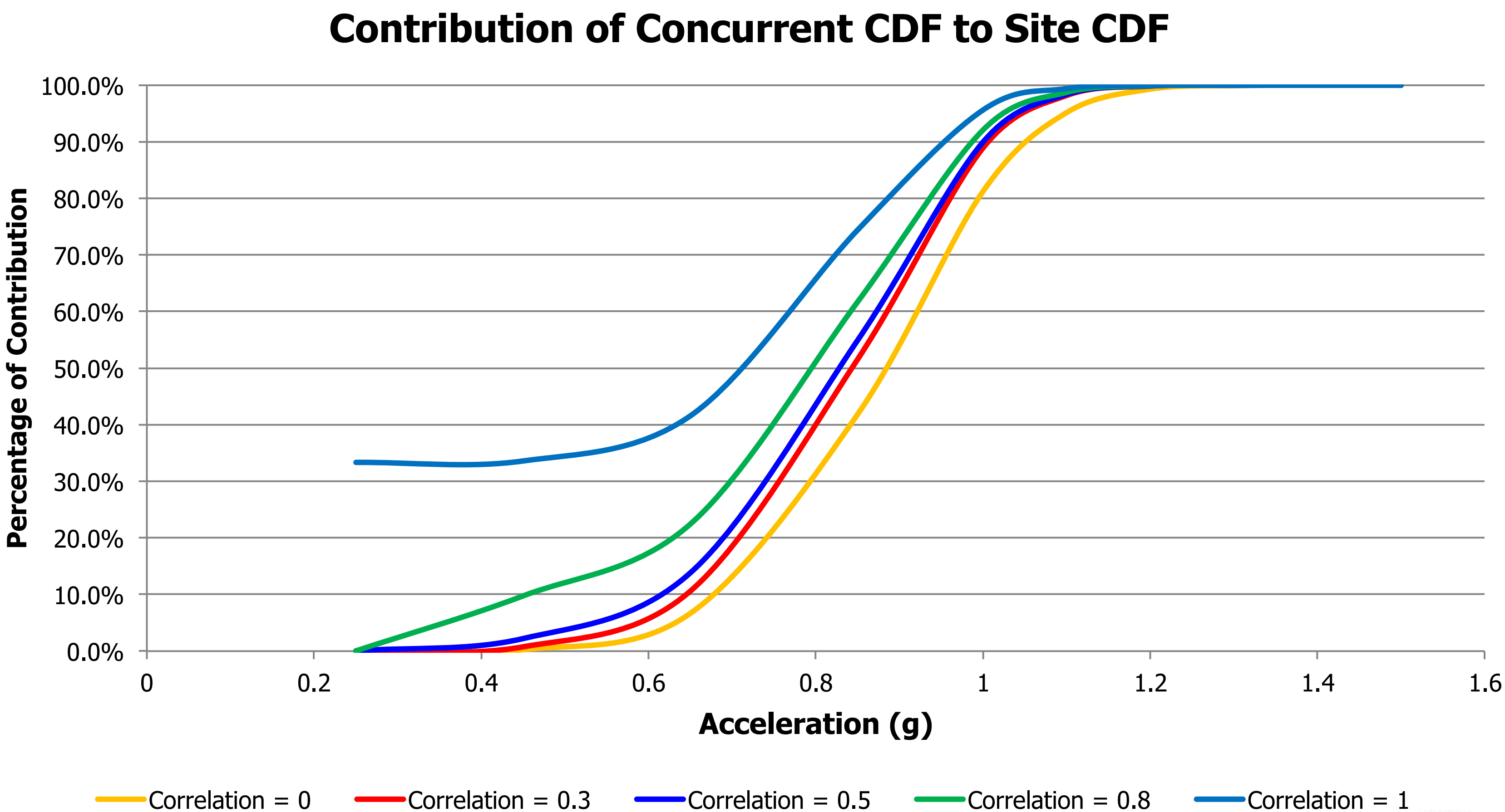
Preliminary Case Study Results (Seismic Event) – Marginal CDF







Preliminary Case Study Results (Seismic Event) – Contribution of Concurrent CDF to Site CDF



Observations From the Seismic Event

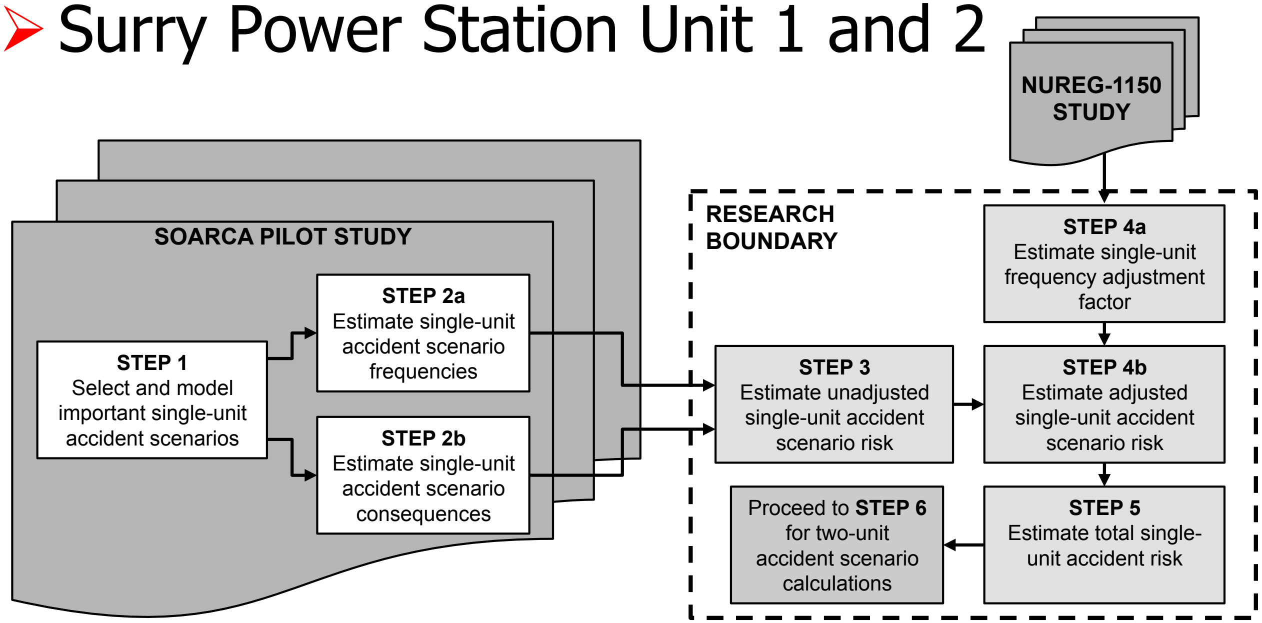
- The seismicly-induced dependencies are significant in "site" risk, and show extremely high contributions to "concurrent" risk too
- With increasing ground motions, the probability of concurrent CDs would approach "site" CDs
- The middle region of site fragility curve is the most sensitive to the potential dependencies, while it is less sensitive to both the low end and high end of site fragility curve
- The sensitivity studies of correlations show that the main sensitive region would be shifted to the lower end of site fragility curve with potentially higher dependencies
- The impact of perfect dependency assumption is too conservative for "site" risk and marginal CD risk, but not for assessing concurrent risk

MU Risk Implications on Safety Goals Quantitative Health Objectives (QHOs)

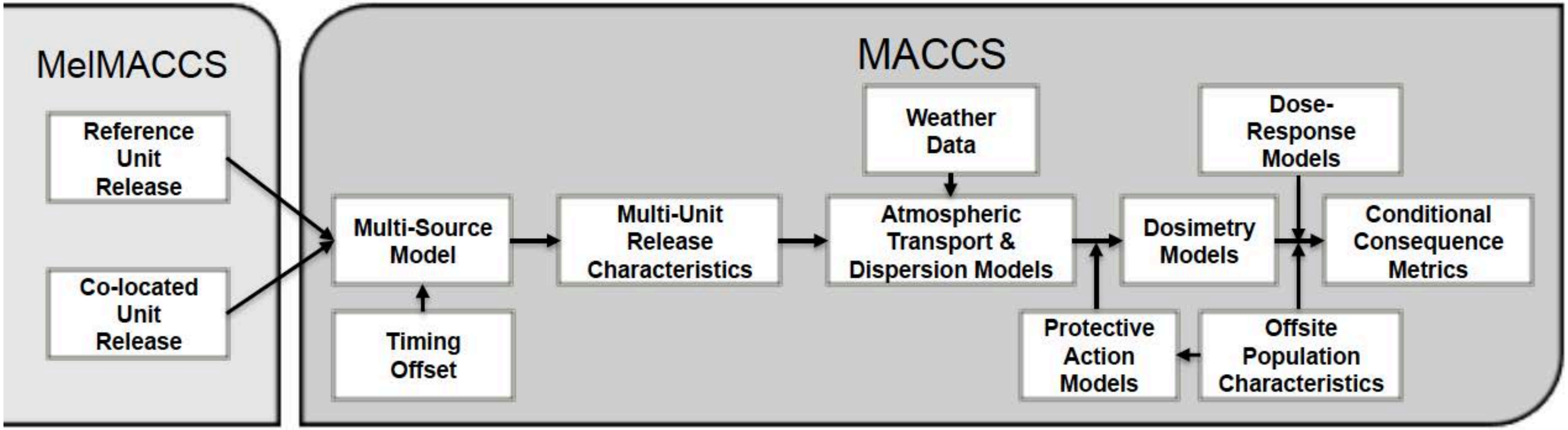
- NRC qualitative safety goals and QHOs still applicable to MU sites.
  - Prompt fatality goal remains more restrictive than the latent cancer fatality goal in multi-unit releases
- MU risk should be below the QHOs for both prompt and latent fatalities
- Surrogates for QHOs (CDF, LRF and LERF) for site risk are assessed and compared to the goals: 10^{-4}, 10^{-6}, and 10^{-5}, Respectively. But not used in this study

Multi-Unit Accident Contributions to QHOs

- To evaluate the implications of the QHOs, Level 3 consequence analyses was performed at two representative U.S. NPP sites using SORCA study.
  - Peach Bottom Atomic Power Station Unit 2 and 3
  - Surry Power Station Unit 1 and 2



Multi-Unit Accident Contributions to QHOs (Cont.)



Policy Alternatives

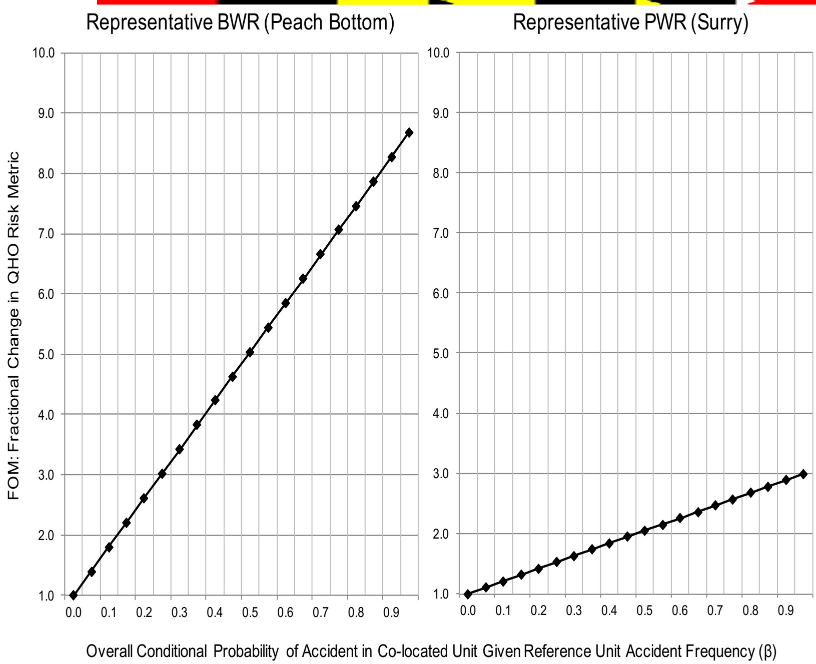
- Option 1: Status Quo
  - Only single-unit accident contributions included in estimating risk metrics for comparison to QHOs
- Option 2: Expansion in Scope of Safety Goal Policy
  - Contribution from both single-unit and multi-unit accident included in estimating risk metrics for comparison to QHOs. That is considering "Marginal" Risk
- Option 3: Expansion in Scope of Safety Goal Policy
  - Besides the ones in Option 1 and 2, single-unit exclusive accident scenarios from other units included. That is considering "site" risk

MU Risk QHO Results

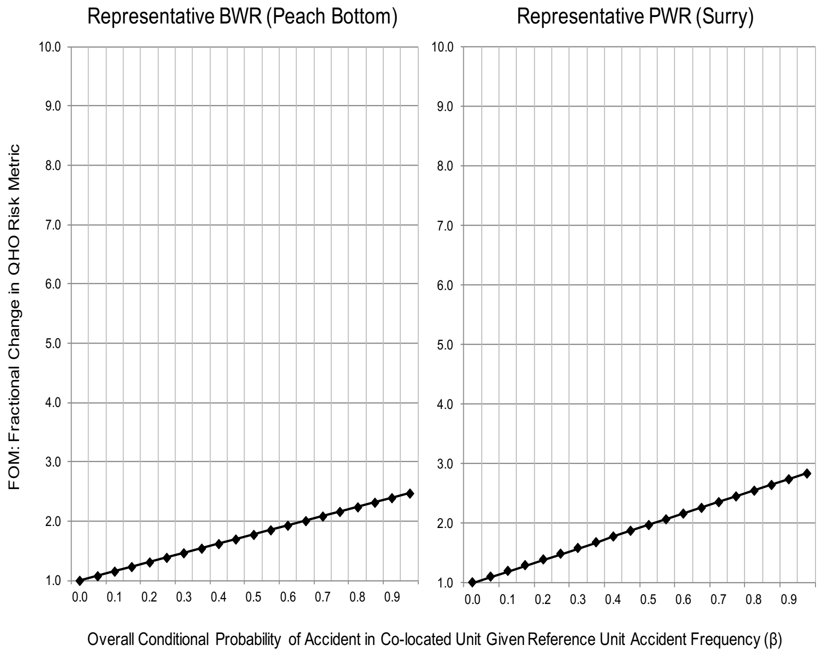
- Figures of Merit 1: Change in the mean value of QHO risk metrics, comparing Option 2 relative to Option 1
- Figures of Merit 2: Change in the mean value of QHO risk metrics, comparing Option 3 relative to Option 1
- The contribution from the two-unit accident scenarios (assuming 10% unit-to-unit dependency) results i

Safety Goal QHO Risk Metric	FOM[a]	QHO Margin[b]	
		Option 1	Option 2
Representative BWR (Peach Bottom) Analysis			
Average Individual Early Fatality Risk (1 mi)	1.8	6.36E+05	3.60E+05
Population-Weighted Latent Cancer Fatality Risk (0-10 mi)	1.1	6.69E+02	5.83E+02
Representative PWR (Surry) Analysis			
Average Individual Early Fatality Risk (1 mi)	1.2	2.35E+04	1.96E+04
Population-Weighted Latent Cancer Fatality Risk (0-10 mi)	1.2	4.30E+02	3.63E+02
[a] The FOM represents the fractional change in risk results that occurs when the contributions from multi-unit accidents to each QHO risk metric are included. The FOM is calculated as the ratio of the mean value for each QHO risk metric when comparing Option 2 results to Option 1 results.			
[b] The QHO margin represents the relative distance between the QHO and the mean value of the corresponding risk metric. The QHO margin is calculated as the ratio of the QHO to the value of the corresponding QHO risk metric.			

QHO Sensitivity to Overall Plant Dependency



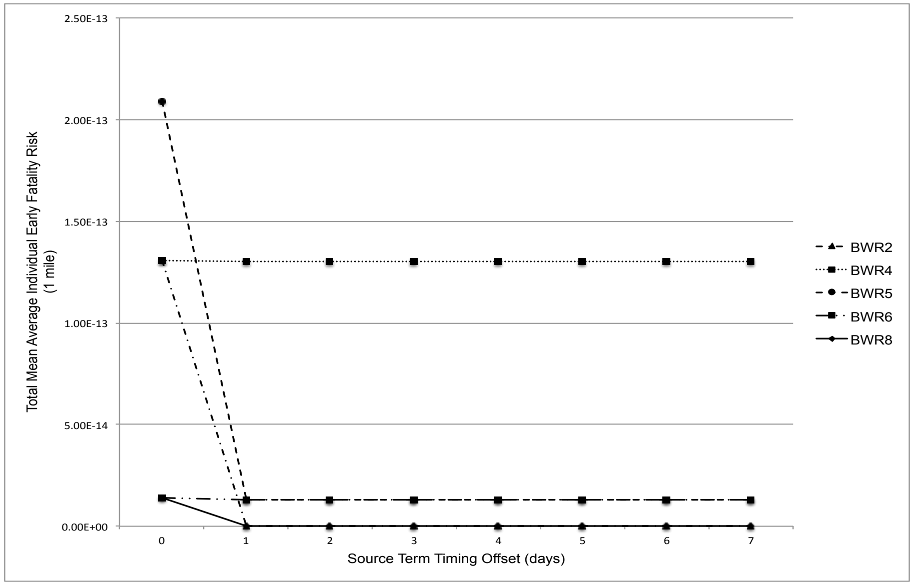
Total Mean Average Individual Early Fatality Risk (1 mi)



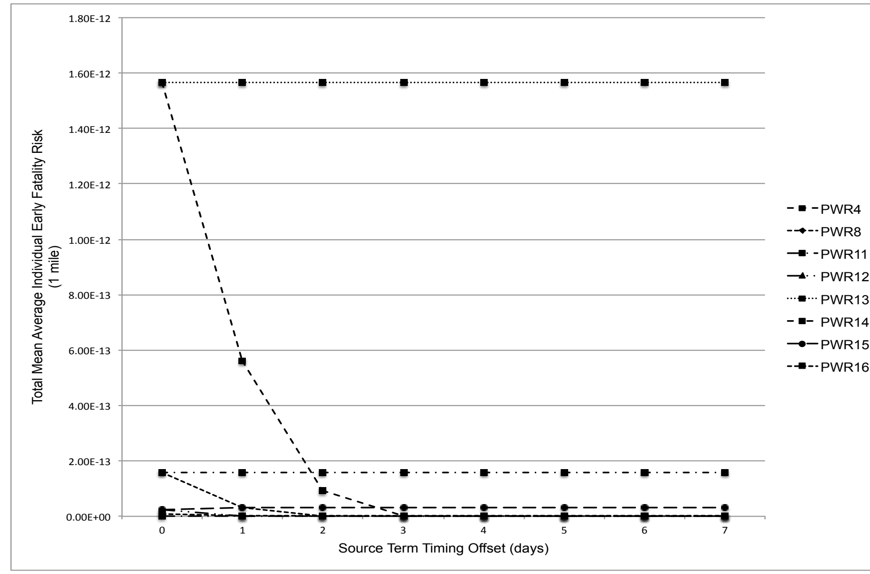
Total Mean Population-Weighted Latent Cancer Fatality Risk (0-10 mi)

Early fatality risk for the representative BWR site is more sensitive to variation in assumed inter-unit dependence than early fatality risk for the representative PWR site

QHO Sensitivity to Release Timing Offset

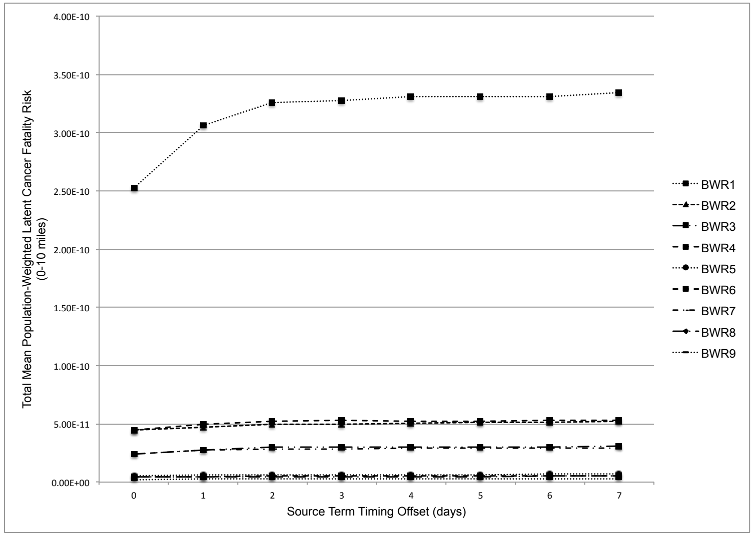


Variation in Timing Offset in Concurrent Accidents on Total Mean Individual Early Fatality Risk (1 mi)-BWR Site

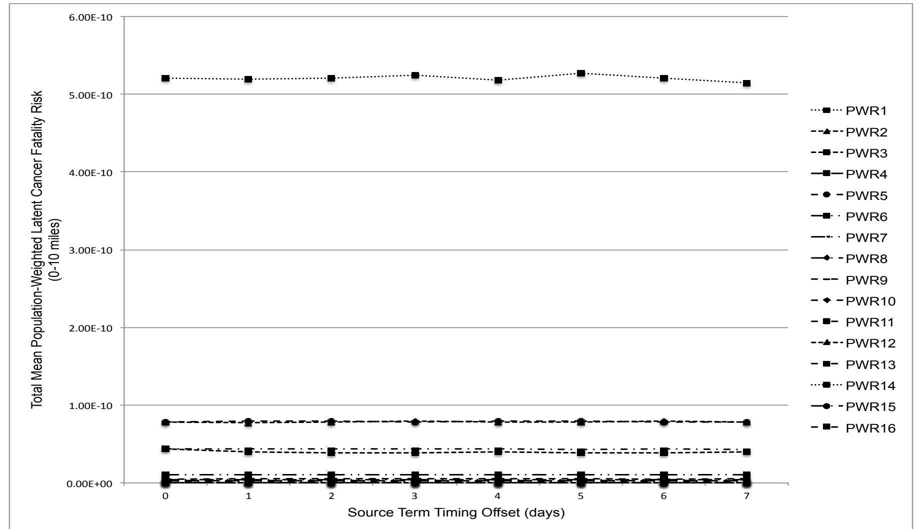


Variation in Timing Offset in Concurrent Accidents on Total Mean Individual Early Fatality Risk (1 mi)- PWR Site

QHO Sensitivity to Release Timing Offset (Cont.)



Effect of Variation in Timing Offset in Concurrent Accidents on Total Mean Population-Weighted Latent Cancer Fatality Risk (0-10 mi)-BWR Site



Effect of Variation in Timing Offset in Concurrent Accidents on Total Mean Population-Weighted Latent Cancer Fatality Risk (0-10 mi)-PWR Site

Synergistic effects of the timing offset in concurrent release scenarios and other factors such as variability in weather conditions and protective actions taken to reduce radiological dose play a role.

Results of Sensitivity Analysis

- Variation of the assumed inter-unit dependence from 0% to 100% reinforced conclusions from base case analysis.

Including the contributions from MU accidents to safety goal QHO metrics increase risk estimates, but still meet the safety goals with wide margins

- Variation of the timing offset between releases from MUs assuming 10% inter-unit dependence reinforced conclusions of base case analysis. Also,
  - Early fatality risk is more sensitive to release timing.
  - Increasing the delay between concurrent accidents may cause latent cancer fatality risk to increase for some scenarios!

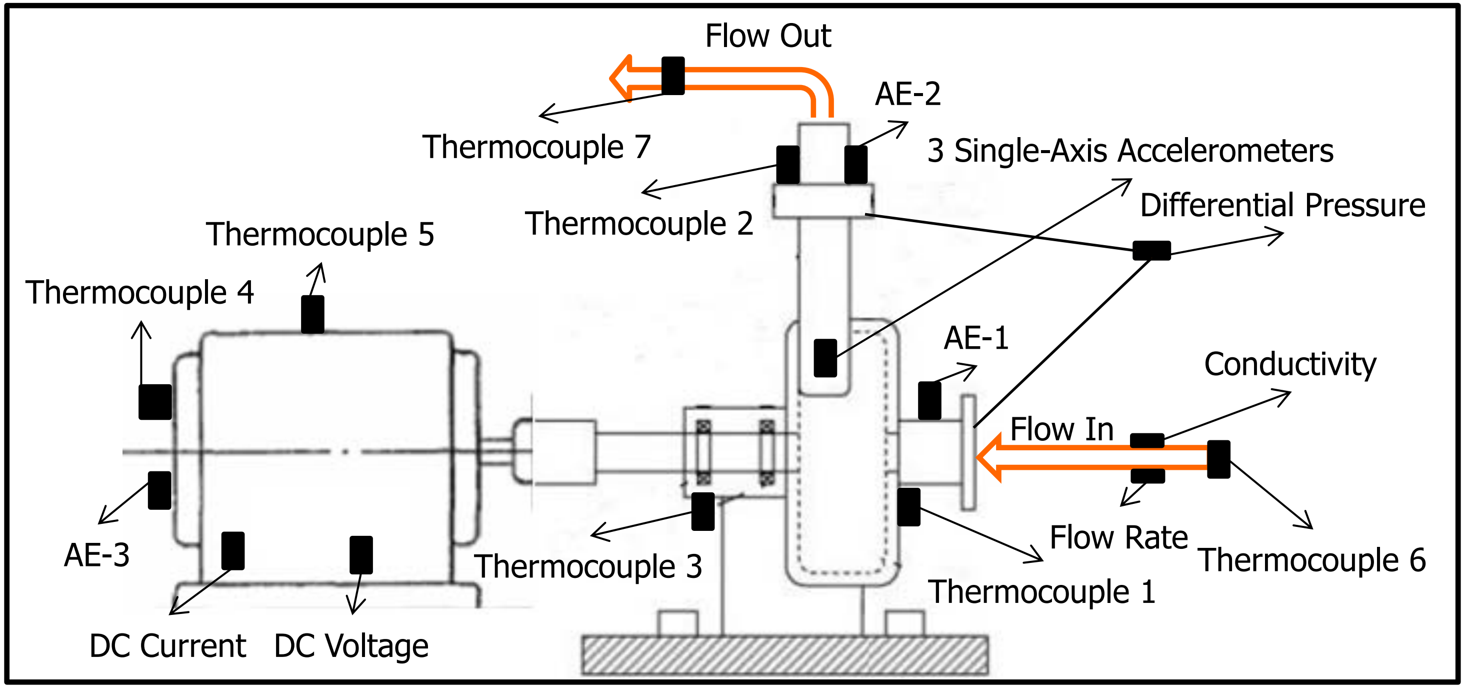
Severe accident mitigation measures that serve to delay more rapidly progressing concurrent accident scenarios in a site can lead to significant reductions in multi-unit early fatality risk.

- Experimental and Physics-Based Dependency Modeling Research
- Funding for the Experimental Effort is Provided by the Center for Risk and Reliability

Outline

- Experimental Setup & Current State
- Dynamic Bayesian Network (DBN) Modeling
- Dynamic State Monitoring
  - Multi-Sensor Measurement
  - Multi-Sensor Feature Extraction
- DBN Inference and Sensor Fusion
  - Particle Filtering
- Measure of the Strength of Dependency
  - Linear Dependency Measurement
  - Non-Linear Dependency Measurement

Experimental Setup & Current State



Working Conditions

- Testing chamber (around 60° C)
- Pump (seawater at around 60° C)

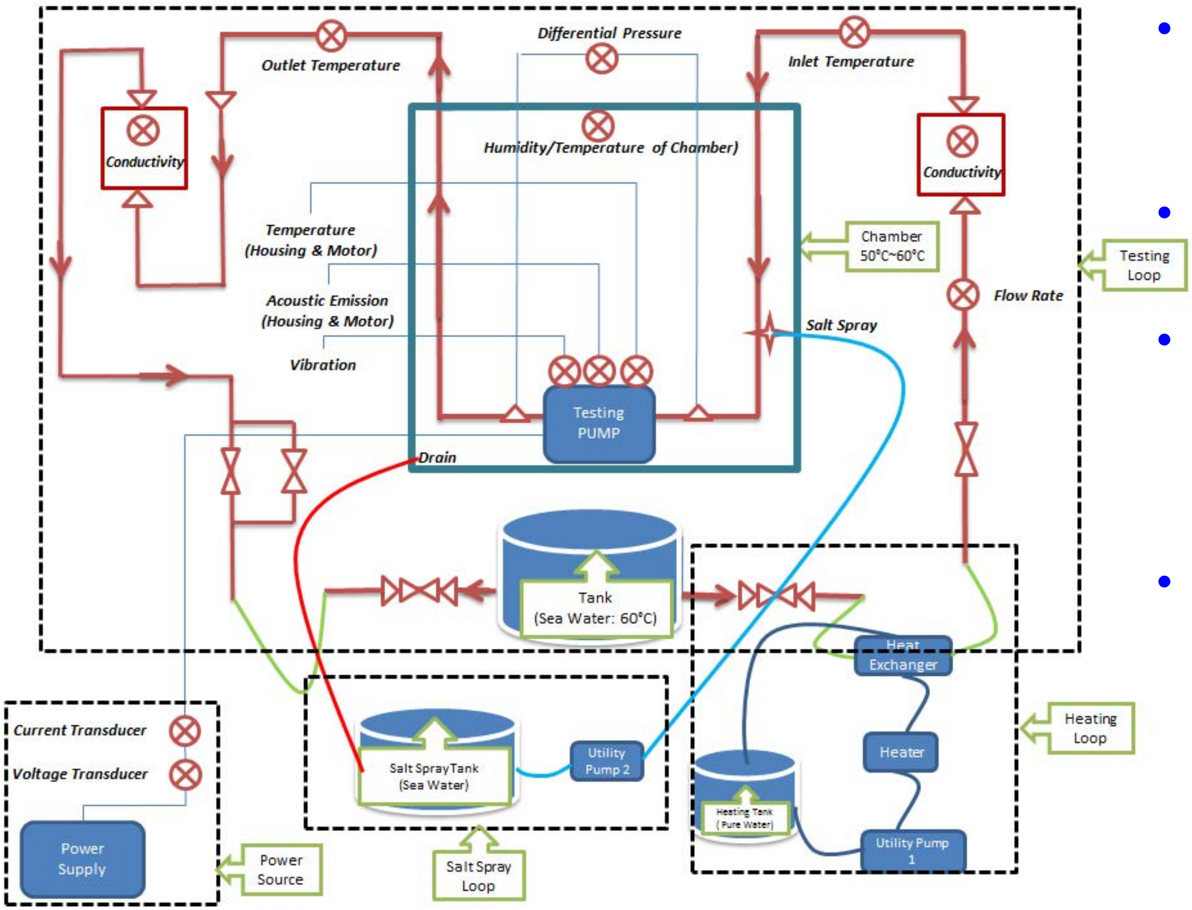
Key Performance Indicators of Pump

- Flow rate of fluid
- Differential pressure between suction and discharge
- Power absorbed (voltage & current of electric motor)
- Conductivity of fluid
- Temperature

Dynamic State Monitoring using Non-Destructive Technique

- Acoustic Emission (AE) Monitoring
- Vibration Monitoring

Experimental Setup & Current State (Cont.)



Schematics of Pump Condition Monitoring System

- Customized testing bed: testing loop, heating loop, and salt spray loop
- Advanced sensing system with 18 sensors
- Common-cause dependencies are established by the shared inter-environmental factors and intra-environmental factors
- Causal-dependencies are attributed to the system proximity and functions, which can be modeled by coupling of underlying failure mechanisms

Experiment Setup & Current State (Cont.)

Current State:

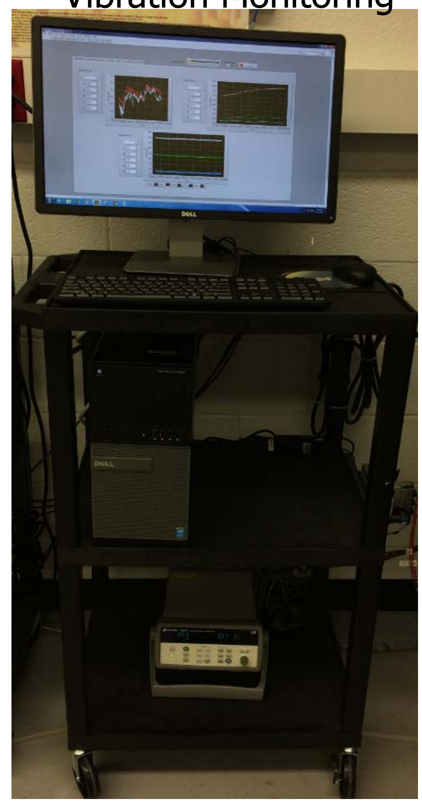
The *first pump test* has been completed (12/20/2015 ~ 03/12/2016): 83 days in total

The *second pump test* is ongoing (05/24/2016 ~ Present): around 180 days so far

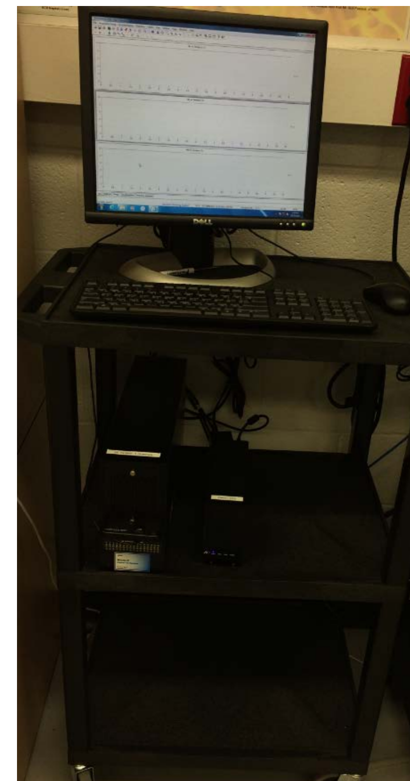
Testing Pump

Customized Testing Chamber

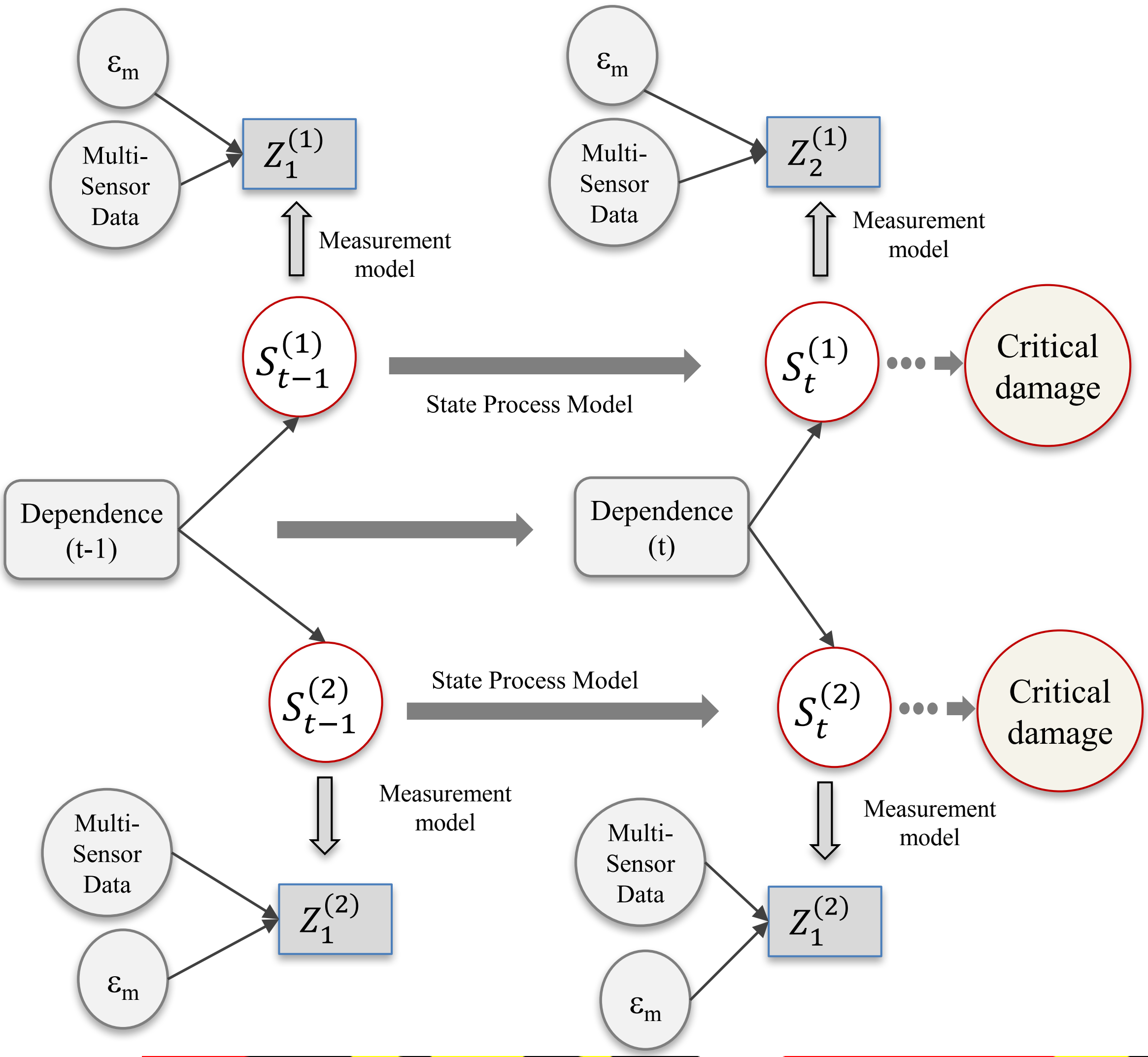
Data Acquisition & Vibration Monitoring



AE Monitoring

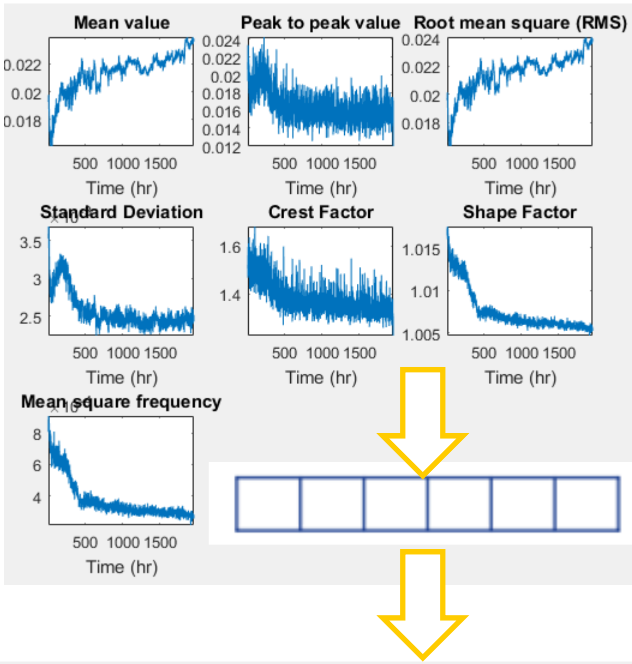


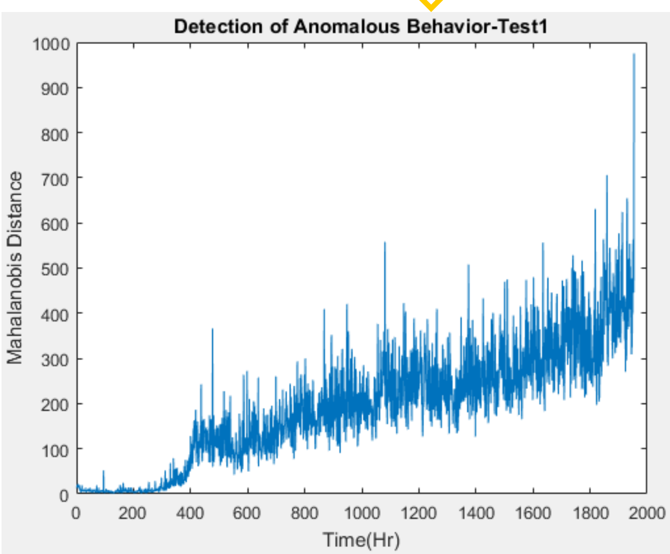
Dynamic Bayesian Network: Modeling Dependencies

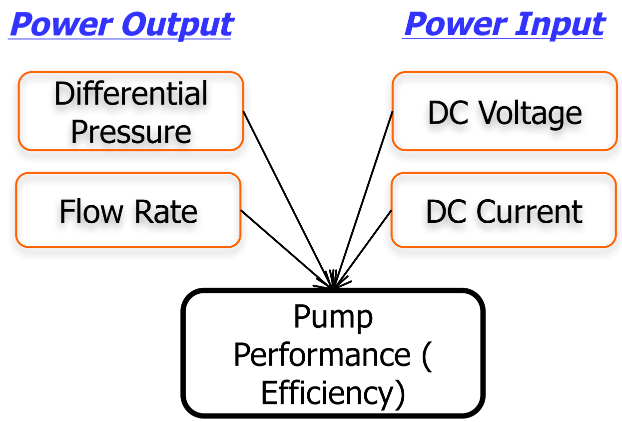


Category	Multi-Sensor Data
High-Bandwidth (1MHz)	Acoustic Emission
Median-Bandwidth (10240 Hz)	Vibration
Low- Bandwidth (0.5 Hz)	Flow Rate
	Differential Pressure
	DC Voltage
	DC Current

Low- Bandwidth Signal: Efficiency



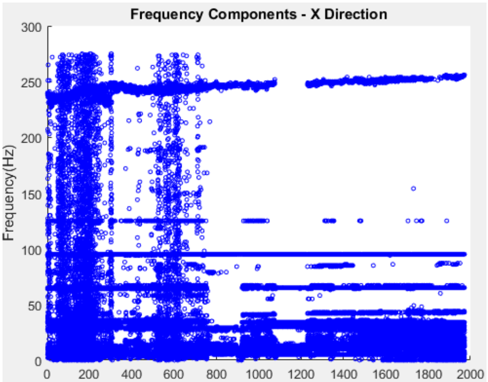


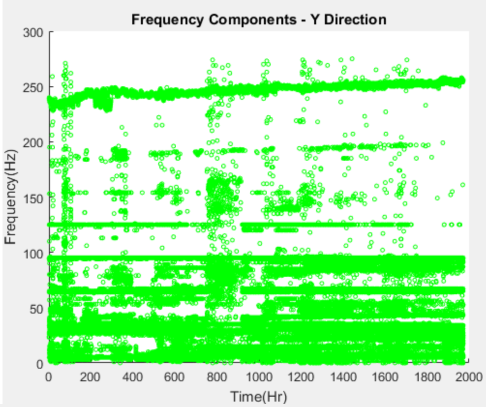


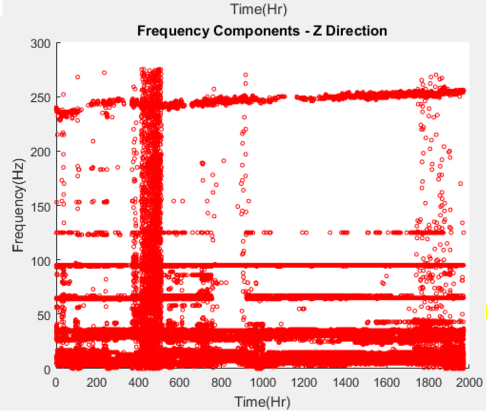
$$\eta = \frac{DP * FR}{V * I}$$

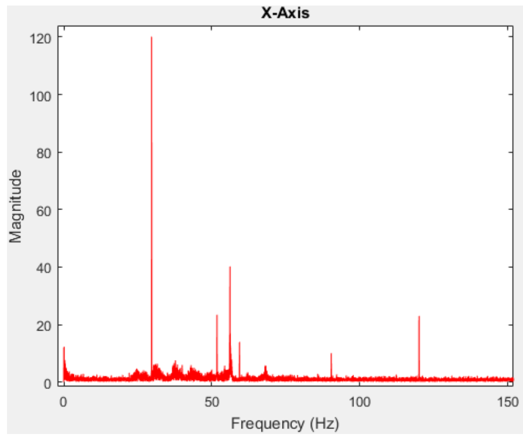
- **Measurements:**
  - *Flow rate, Differential Pressure, Current, Voltage*
- **Feature Construction**
  - The strategy is to monitor the distribution of efficiency overtime, looking for shifts in the mean values or any other features of possible defects.
  - Feature vector: extracted statistical features (Mean value , Peak to Peak value, Root Mean Square (RMS) , Standard Deviation, Crest Factor, Shape Factor, Mean Square Frequency)
- **Degradation Index Construction**
  - Mahalanobis distance based detection: compare new observations with as baseline of health condition

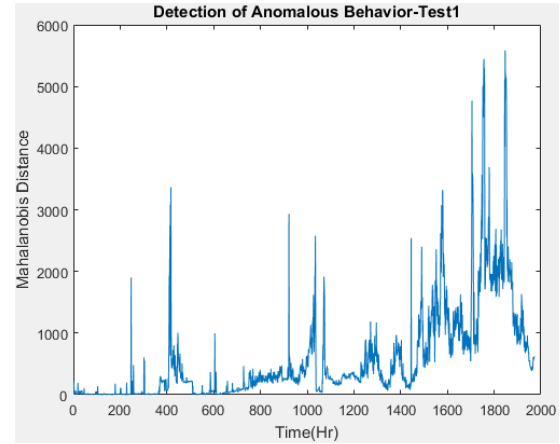
Median-Bandwidth: Vibration Signal





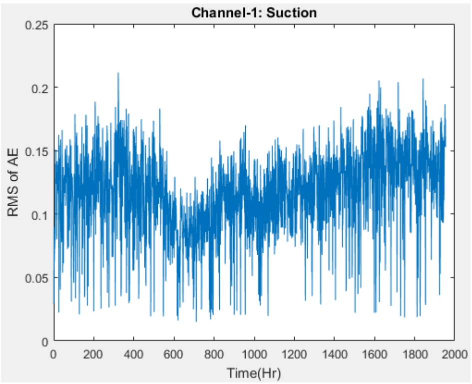


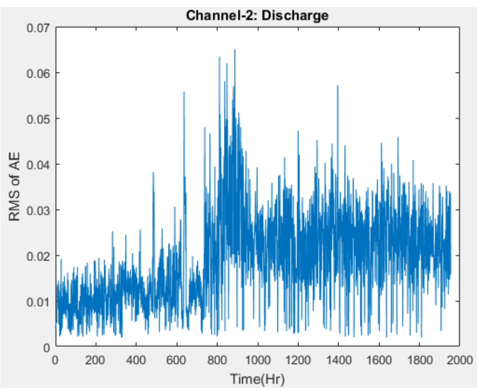


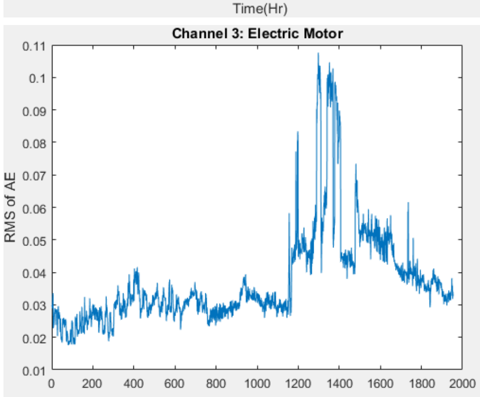


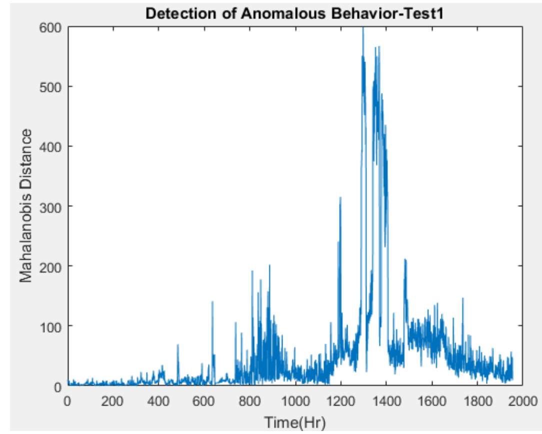
- Measurements: *Vibration* (from three single-axial accelerometers)
- Feature Construction
  - Segment the data with a certain time window (i.e., each minute)
  - Transform each segment into frequency spectrum with Fast Fourier transform
  - Identify the frequency band of interest according to domain knowledge and/or experimental data (i.e., six bands identified)
  - Calculate the RMS or Energy of each frequency band around each interested frequency
  - Construct the feature vector with the calculated RMS of each band with respective to the three directions respectively
- Degradation Index Construction
  - Mahalanobis distance based detection: compare new observations with as baseline of health condition

High-Bandwidth: Acoustic Emission Signal





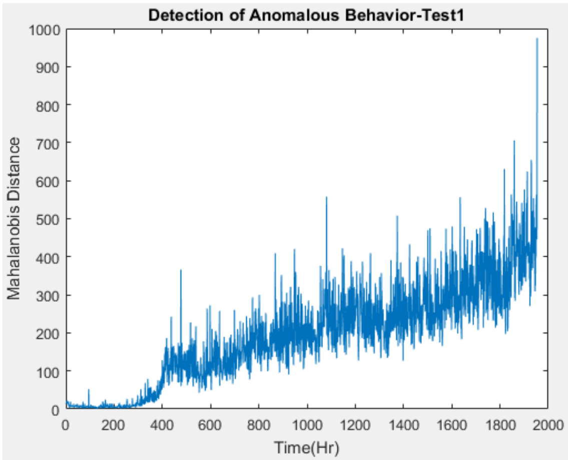


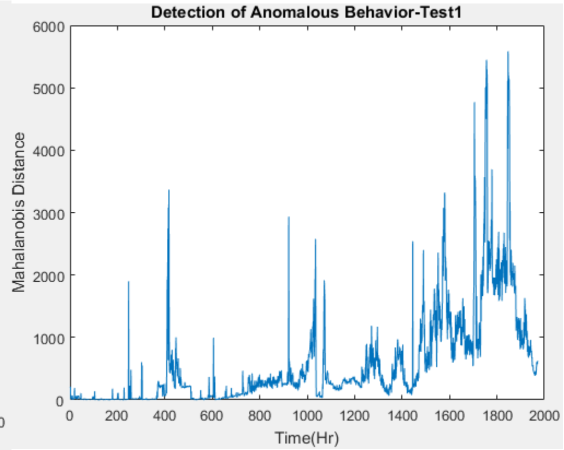


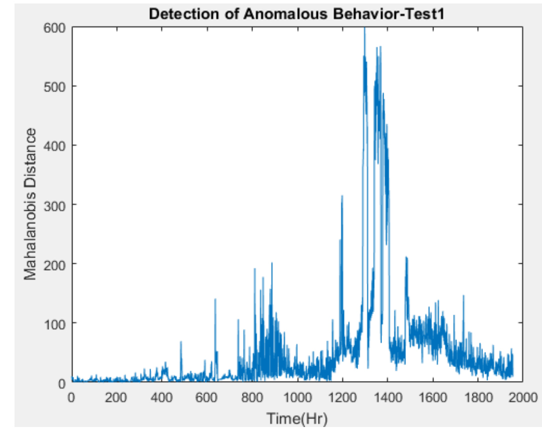
- Measurements:
  - Acoustic Emission (from three AE sensors attached to pump inlet, outlet, and electric motor)
- Feature Construction
  - Extract the Energy, Absolut Energy and RMS features from the AE signals
  - All these three features are highly correlated
  - Construct the feature vector using the extracted RMS of each AE sensor
- Degradation Index Construction
  - Mahalanobis distance based detection: compare new observations with as baseline of health condition

Compare the Two Pumps

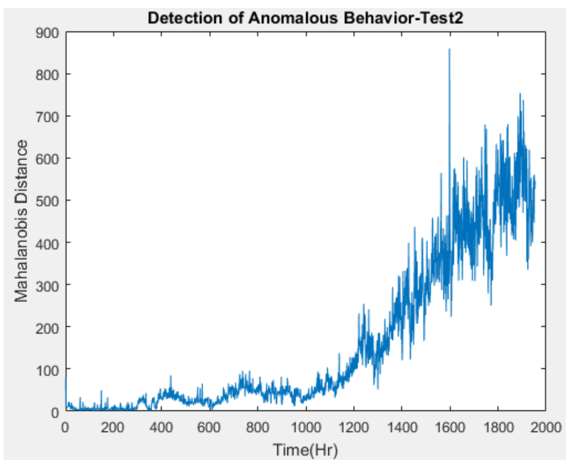
Pump1

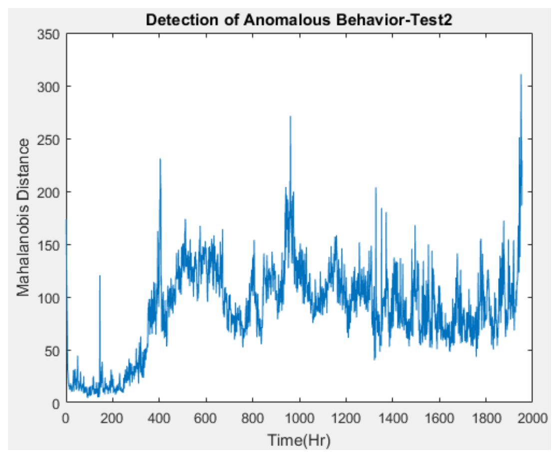


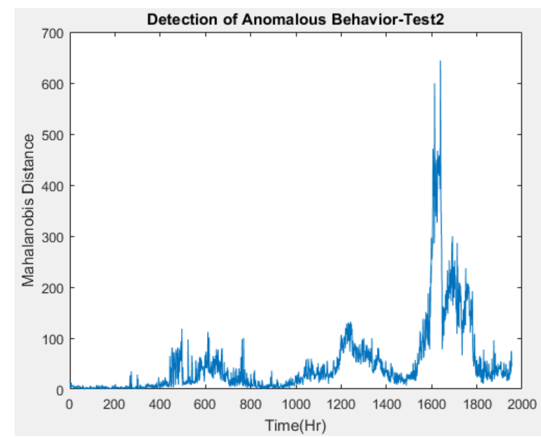




Pump2







Efficiency

Vibration

Acoustic Emission

Empirical Mode Decomposition (EMD) Based Signal De-noising and De-trending

- EMD can be applied to improve the prediction precision, since the data is not smooth.

- The key idea of EMD is that any complex signals consists of some different, simple, non-sine function component signals. The decomposition of one-dimensional signal x(t) can be displayed as:

$$x(t) = \sum_{i=1}^{n} imf_i(t) + r_n(t)$$

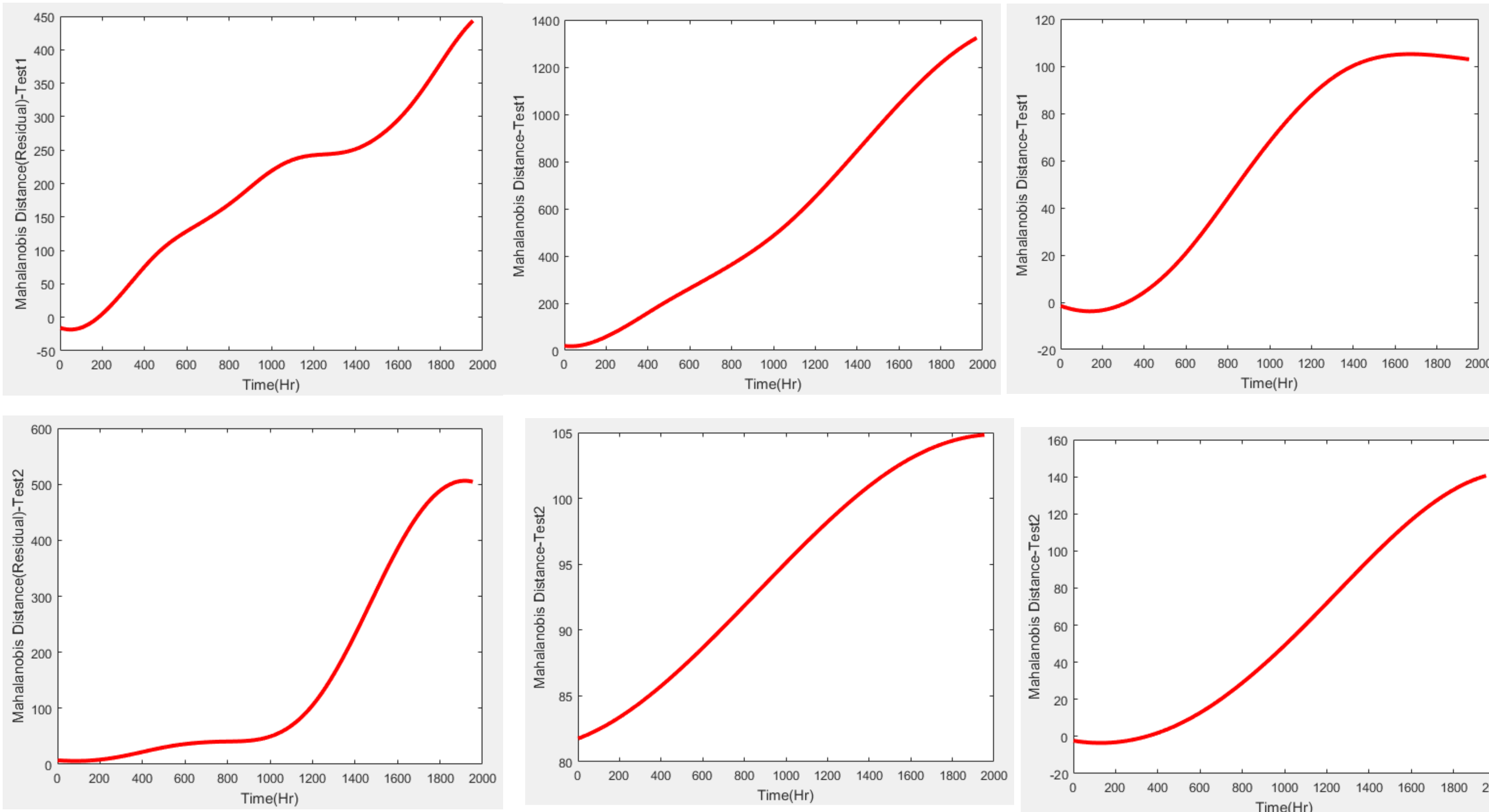
which $imf_i(t)$ is the intrinsic mode functions, $r_n(t)$ is the residual element.

- The residual element includes the lowest frequency component which indicates the trend of the signal.

Compare the Trend of Two Pumps

Pump1

Pump2



Efficiency

Vibration

Acoustic Emission

Health Definition and Insights

- The degradation process is complex involving multiple underlying faults
- The run-in and healthy period are selected as 240 hours
- Objective: investigate the strength of dependencies along the degradation evolution
- Preliminary Analysis: 240~ 1240 hours

Particle Filtering as an Inference and Data Fusion Tool for DBN

- Capable of handling *nonlinear dynamics* and of dealing with *non-Gaussian noises* at no further computational or design expenses
- It is a Sequential Monte Carlo-based computational tool particularly useful for Bayesian-framed prognostics
- Implements Bayesian recursive estimation process to infer variables of a dynamic system based on noisy and uncertain observations
- Sensor data integration/fusion and inference in DBN

Recursive Bayesian Estimation for PF inside DBN

- The unknown of interest is the state of the system (x_k)
  - Stochastic state process model:
    $$x_k = f(x_{k-1}, \omega_k) \rightarrow P(x_k|x_{k-1})$$
  - Probabilistic measurement model:
    $$y_k = h(x_k, v_k) \rightarrow P(y_k|x_k)$$
  - The goal is to find:
    $$P(x_k|y_{1:k})$$

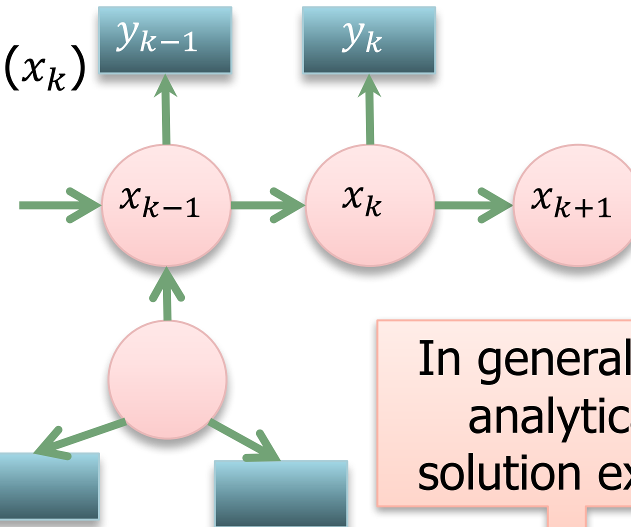
Based on Bayesian framework:

$$P(x_k|y_{1:k}) = \frac{P(y_k|x_k)P(x_k|y_{1:k-1})}{P(y_k|y_{k-1})}$$

Where the prior and normalizing factor are:

$$P(x_k|y_{1:k-1}) = \int P(x_k|x_{k-1})P(x_{k-1}|y_{1:k-1})dx_{k-1}$$

$$P(y_k|y_{k-1}) = \int P(y_k|x_k)P(x_k|y_{1:k-1})dx_k$$

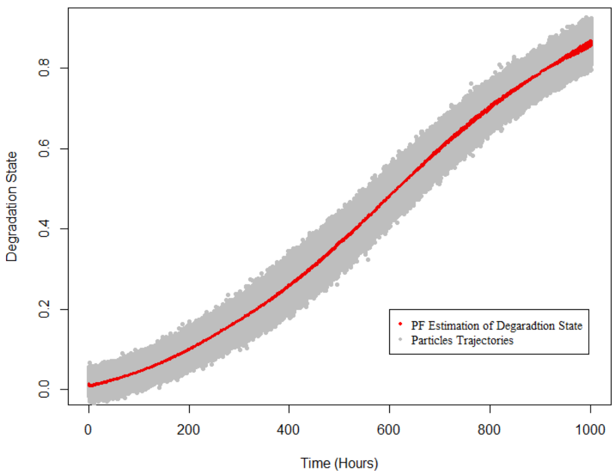


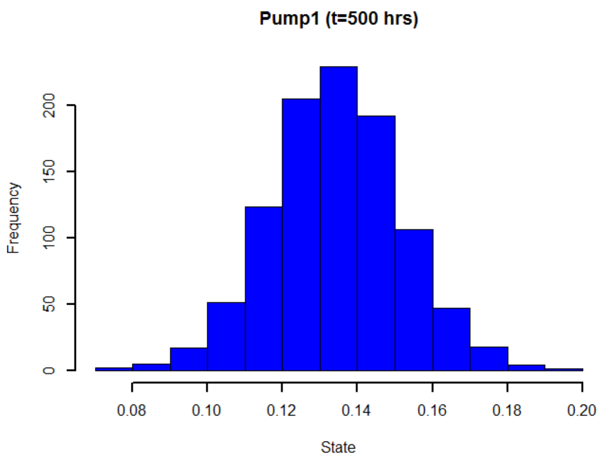
In general, no analytical solution exists

Key idea of PF is to represent the required posterior density function $P(x_k|y_{1:k})$ by a set of random samples $\{x^{(i)}\}$ with associated weights $\{w^{(i)}\}$

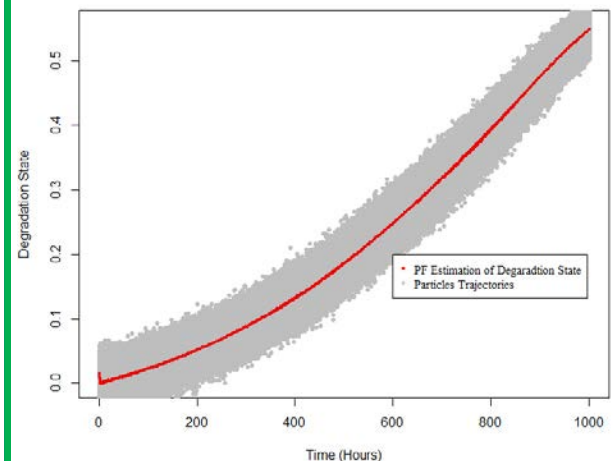
Degradation Dynamics

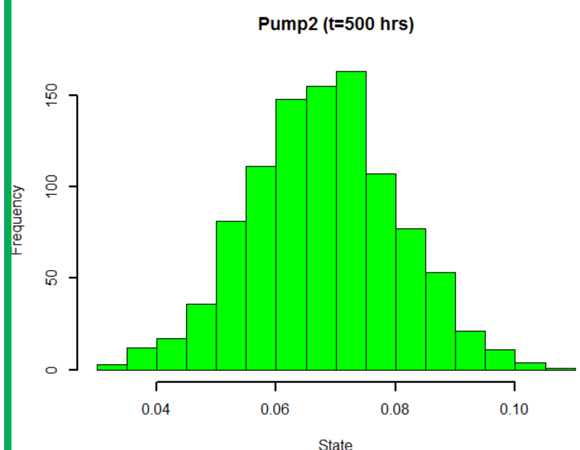
Pump1

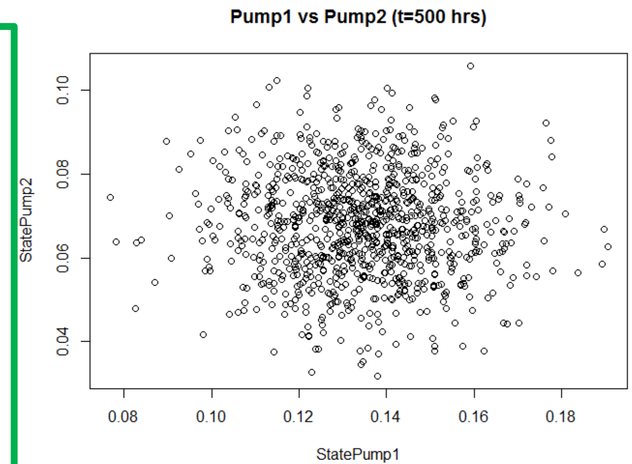


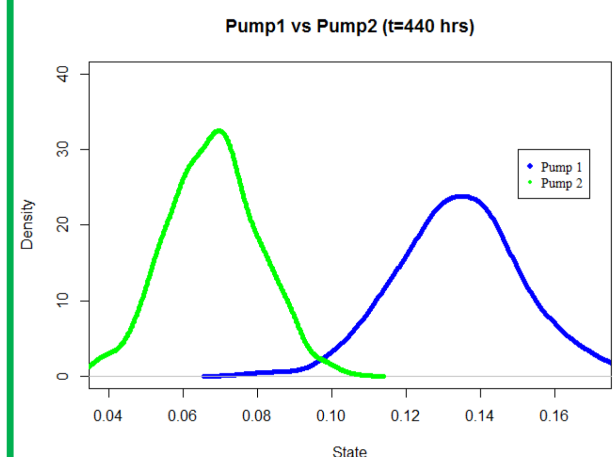


Pump2







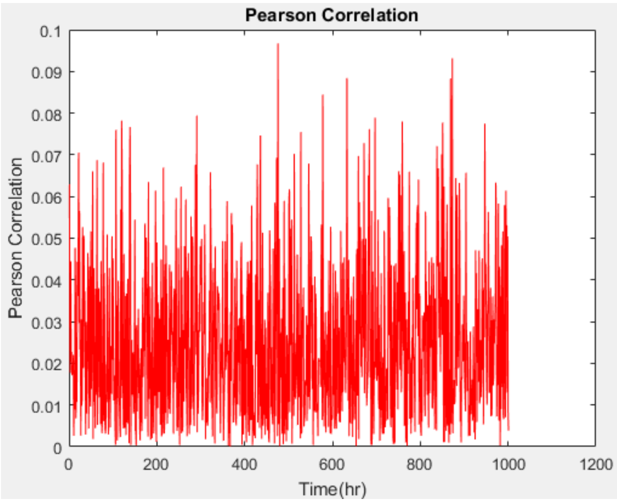


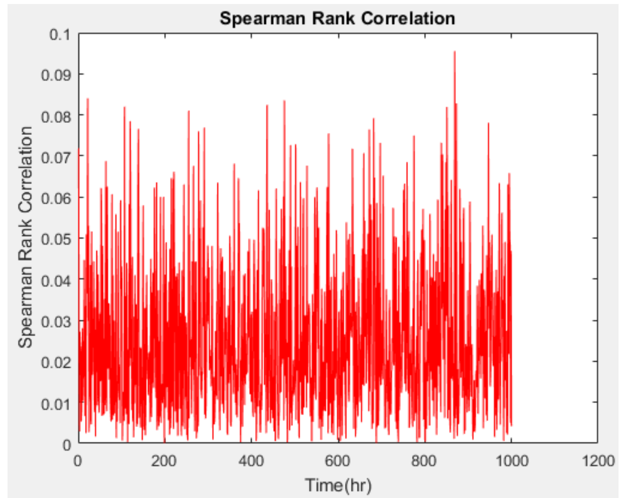
Measure of the Strength of Dependency

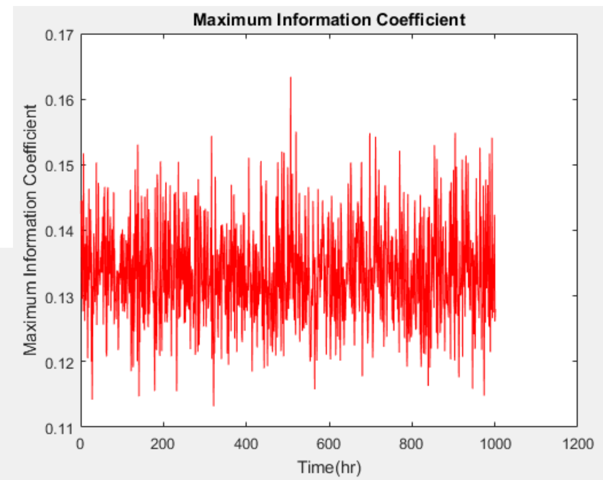
- Linear Dependence Measurement
  - Pearson Correlation

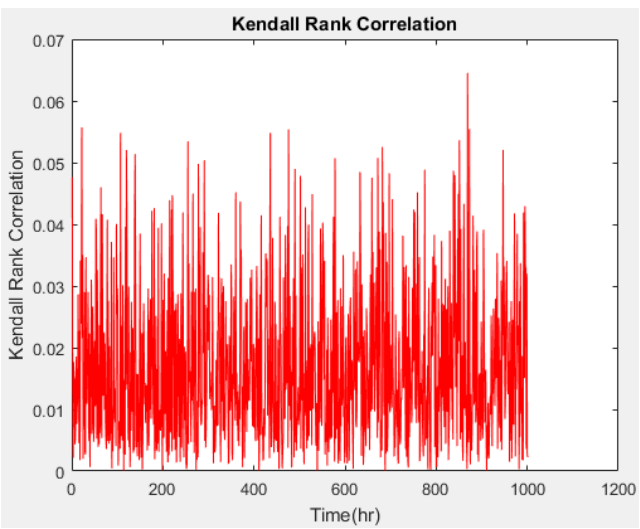
- Non-Linear Dependence Measurement
  - Rank Based: Spearman’s Rank Correlation, Kendall Rank Correlation
  - Distance Based: Distance Correlation
  - Mutual Information Based: Maximum Information Coefficient (MIC)

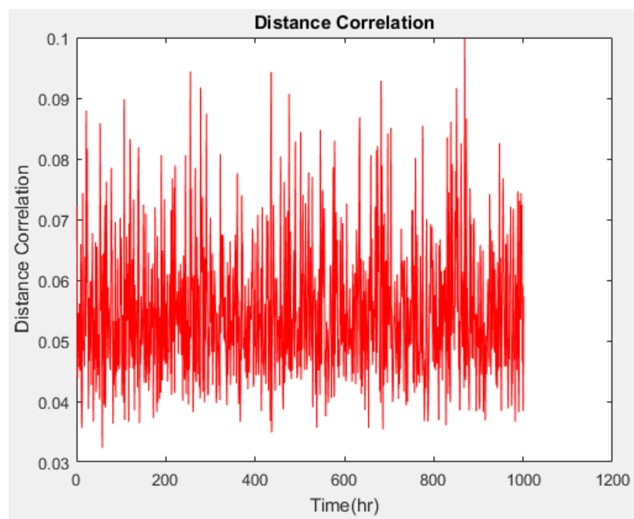
Strength of Dependencies



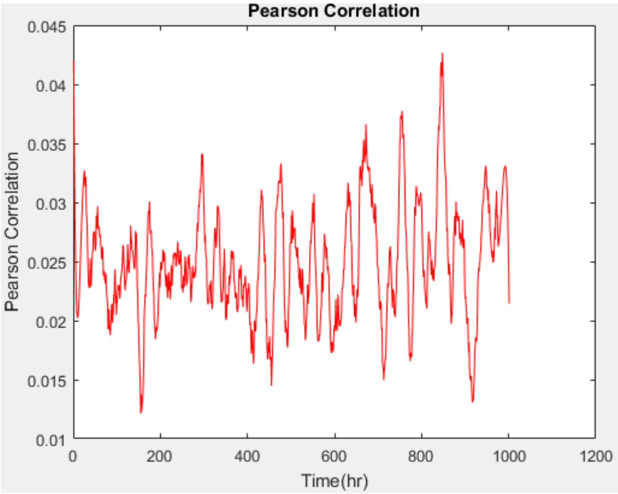


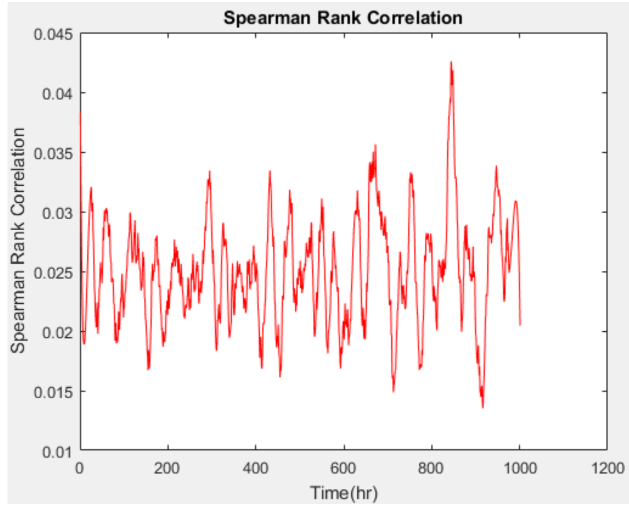


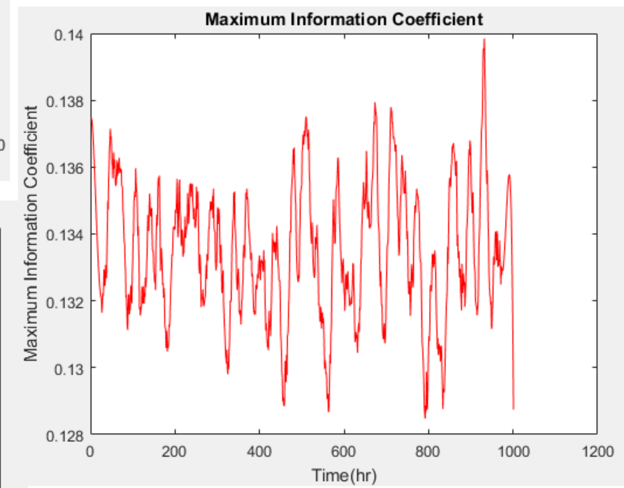


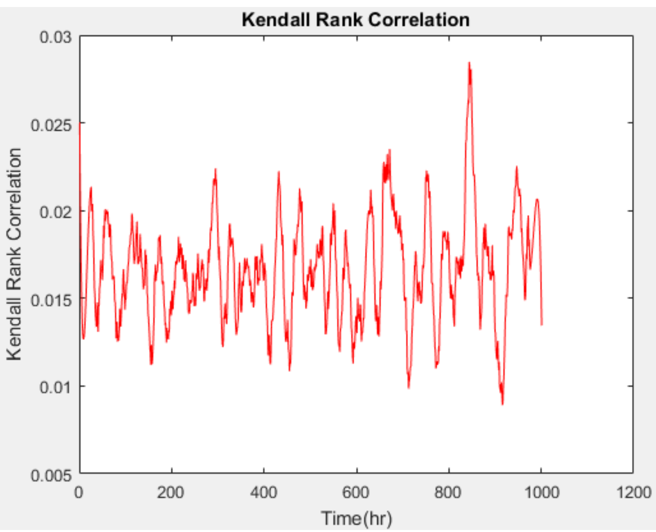


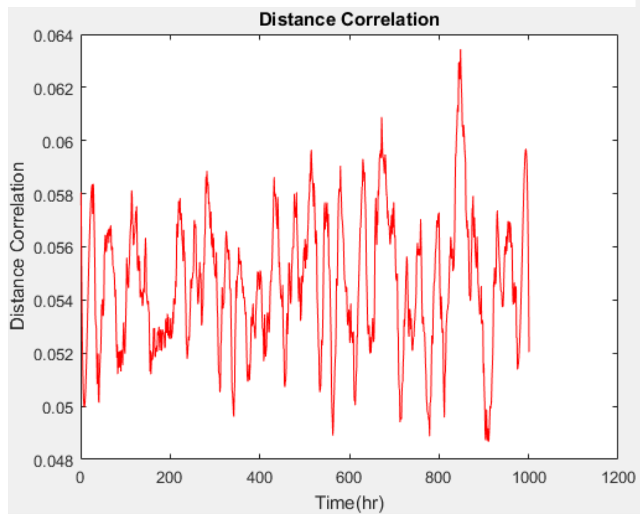
Smoothed Strength of Dependencies



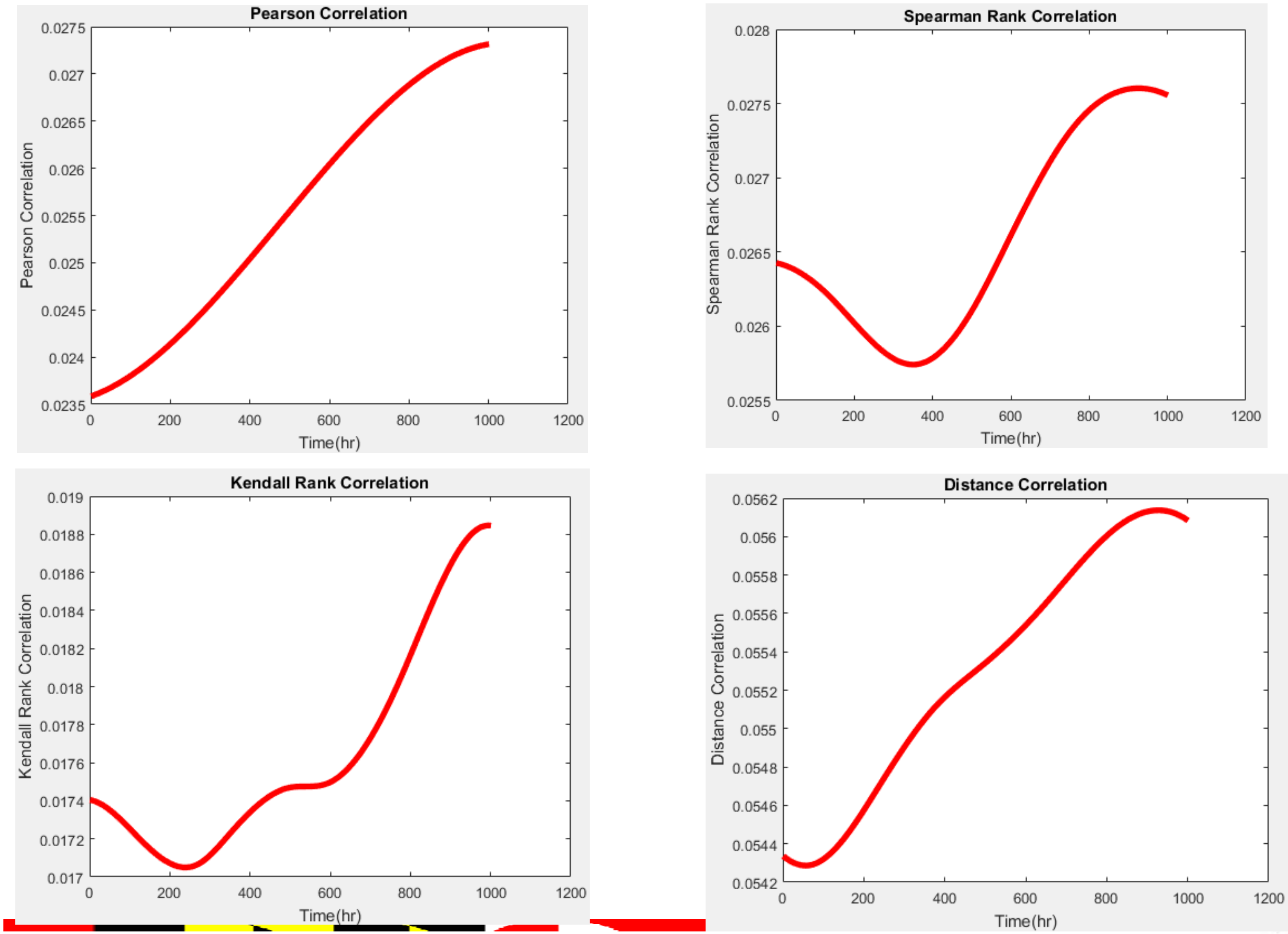








Trend of Strength of Dependencies



Publications As Part of This Grant

1. Multi-Unit Accident Contributions To Quantitative Health Objectives: A Safety Goal Policy Analysis, D. W. Hudson, M. Modarres, N. Technology (In Print).
2. Advance s in Multi-Unit Nuclear Power Plant Probabilistic Risk Assessment, M. Modarres, T. Zhou, M. Massoud, Reliability Engineering and System Safety, J. Vol. 27, Jan. 2017, http://dx.doi.org/10.1016/j.ress.2016.08.005.
3. A Hybrid Probabilistic Physics of Failure Pattern Recognition based Approach for Assessment of Multi-Unit Causal Dependencies, T. Zhou, E. Droguett, M. Modarres, ICONE24, June 26-30, 2016, Charlotte, North Carolina.
4. A Hybrid Probabilistic Physics of Failure Pattern Recognition based Approach for Assessment of Multi-Unit Causal Dependencies, T. Zhou, E. L. Droguett, M. Modarres, Topical PSAM Meeting. Nov. 23- 25, 2015 - Rio de Janeiro, Brazil.
5. Multi-Unit Nuclear Plant Risks and Implications of the Quantitative Health Objectives, M. Modarres, International Topical Meeting on Probabilistic Safety Assessment (PSA2015), April 26-30, 2015, Sun Valley, ID.
6. A Multi-Unit Probabilistic Risk Assessment Approach with Application to Seismic Events, T. Zhou, M. Modarres, E. L. Droguett, PSA-2017, Pittsburg, PA (Submitted)

Conclusions

- Multi-unit accidents are important contributors to site risks
- Parametric MUPRA is useful: LER a starting point
- Causal dependence modeling needs further research
- Unit-to-unit causal events are significant in external events
- Site-level surrogates to latent cancer and prompt fatality QHOs need better definition in the MUPRA context
- Contribution from MU scenarios reduce margin to QHOs
- Seismic event hazard dependency research a possible path to developing dependencies in unit response and fragilities
- Research on economic and societal disruption risks quantitatively monetized a critical addition to the QHOs

Conclusions (Cont.)

- Framework for degradation assessment based on multi-sensor data fusion
  - Based on Dynamic Bayesian Network
  - Particle Filtering used for inference in DBN
- It allows for quantification of strength of dependence in multi-unit systems
  - Linear and non-linear dependence metrics
- Dependencies trends are worrisome as units age

- Grant Funding For this Research the US NRC is Highly Appreciated

