# Performance Variability and Causality in Complex Systems

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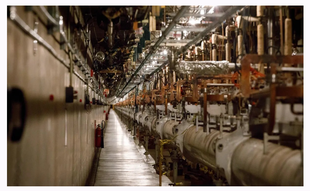
## Background

**Performance degradation in complex systems**

Monitoring Cyberphysical Systems (CPSs)



Particle Accelerators: High-energy beam, Lots of sensors, time-series logs (signals)

Diverse Subsystems

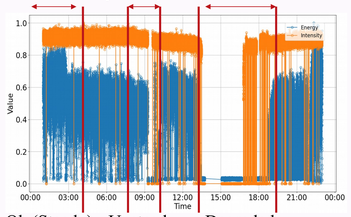
- **High-energy beam** → Essential in particle accelerators for various scientific experiments
- **Anomalous conditions** → Multi-component interactions [1], Subsystem malfunctioning → Performance instabilities

- Can we detect performance degradation?
- Can we identify anomalous subsystems leading to instabilities?

## Motivation and Objectives

- **What is missing?**
  - Lack of automated tools
    - Detect degradation
    - Identify potential defective subsystems
  - Subsystem [2] correlation with system performance
  - Efficient diagnosis + recovery
- **Domain Experts → Manually examine instabilities**
- **Wasted machine time**
  - High diagnosis efforts
  - Operational costs

System (Beam) Performance

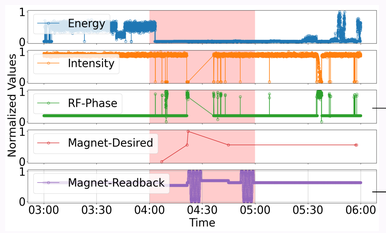



Ok (Steady) Unsteady Degraded

- **Detect Performance Degradation** → Beyond failures (i.e., complete system downtimes)
  - Golden Signals → System performance indicative signals (e.g., Intensity, Energy)
  - Increased variability of golden signals → Relative to reference time of normal behaviour
- **Anomaly Localization**: Reduce the search space [3]
  - Contains the anomaly-indicative signals (need not necessarily be the exact root cause)
  - Guide operators towards efficient problem diagnosis

## Challenges

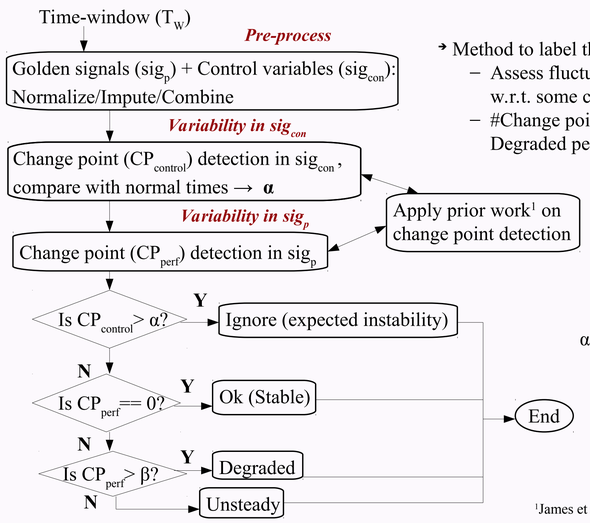
- **Tuning Side-effects**: Specific CPS configuration → For different experiments
  - Manual parameter tuning (control variables) → Signal deviations
  - Deliberate+anomalous signal fluctuations → Anomaly detection difficult
- **Localization Accuracy**: Shortlisting → Minimal domain knowledge
  - Short yet precise set of signals (low false positives)
  - Irregular, sparse, low resolution signals (less information time-series)




Correlation is not causation

- **Lack of Time-delay**: Signals across different spatial regions
  - Insignificant propagation delay → Hard to establish *happens-before* relationship [4]
  - Highly dynamical system → Many simultaneous events

## Solution (Detection of Degradation)




- Method to label the quality of performance
  - Assess fluctuations in golden signals w.r.t. some control variables
  - #Change points > Threshold → Degraded performance

α, β → Derived thresholds

[1]James et al. IEEE BigData 2016

## Solution (Causal Analysis)

**Considered Signal List**

Identify subsystem problems leading to performance degradation (beam instabilities)

Bivariate Correlation: Subsystem signal correlation (i.e., Correlation Coefficient CC) with system performance

Noise Filter: Filter inherently variable signals w.r.t other time-windows (variance V)

Examine permutation entropy ($E_p$) to assess signal complexity

Dynamic linear model: Examine finer univariate time-series patterns ($D_M$)

Assign Score: $(W_1*CC+W_2*V+W_3*E_p+W_4*D_M)/\sum W_j$, $1 \le j \le 4$, Rank Signals; W=Weights

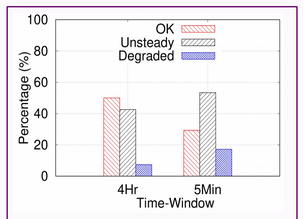
System Guided Re-ordering, if applicable → Ranked List Top N (~50) Signals

**Ranked Signal List**

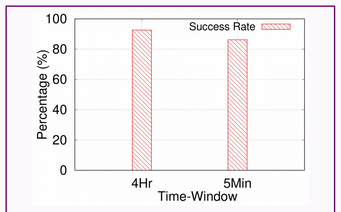
| Rank | Signal | Score |
|---|---|---|
| 1 | WATR:A1:1:PRES | 73.2 |
| 2 | WATR:A1:1:TEMP | 55.6 |
| 3 | RF:A1:K2:CURRENT | 49.3 |
| 4 | SMOK:A2:1:KG26 | 41.7 |

Anomalous Time-Window ($T_w$)

## Results



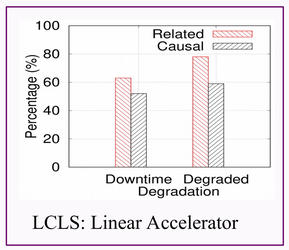

Performance Labels



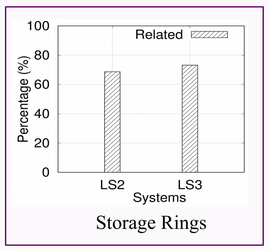

Detection Errors: <15%

- Labels: OK: 29.3% to 50% of samples, Unsteady: 42.6% to 53.4%, Degraded: <17.2%
- Success Rate: 86.2% to 92.6% of the times → Correctly labeled system performance
- *Variance* alone → Less reliable indicator for degradation

## Results




LCLS: Linear Accelerator




Storage Rings

Evaluation: 3 Systems (#Signals)
- LCLS (LS1: ~4000-8000)
- NSLSII (LS2: 70)
- APS (LS3: 1331)

- LS1: 52% to 59% of the shortlisted signals are causal, ≤78% related (to the cause) signals
- LS2 and LS3: 68.7% to 73.2% of signals relate to faulty conditions; (limited experimentation)

**Rank Improvement**

| Signal | CC | $N_F$ | $E_p$ | All |
|---|---|---|---|---|
| WATR-A1 | 50 | 27 | 18 | 2 |
| ROOM-A2 | 48 | 39 | 21 | 9 |
| RF-A2 | 38 | 24 | 16 | 2 |

- Subsequent steps in causal analysis → Aid in ranking anomaly-related signals higher
- False positives exist: Additional studies with domain insights needed for improved confidence

## Conclusions and Future Work

- Detection of performance degradation and localization of anomalous conditions
  - Evaluated on a class of complex Cyberphysical systems
    - Beam-based experimental facilities
  - 86.2% to 92.6% of the times → Quality of performance correctly classified
  - Ranks related signals → Top ~1.2% of the considered parameter space
- Feasible to rank causal signals high enough → Facilitate problem diagnosis for operators

- **Future Work**
  - Generalization across diverse anomalous conditions
  - Automated hyperparameter optimization
  - Handling small-scale changes, discrete-valued signals

**References:**

[1] A. J. Oliner and A. Aiken, Online detection of multi-component interactions in production systems, in DSN, 2011.

[2] Q. Han, P. Nguyen et al., Toward an integrated approach to localizing failures in community water networks, in IEEE ICDCS, 2017.

[3] C. Wu, N. Zhao, L. Wang, X. Yang et al., Identifying root-cause metrics for incident diagnosis in online service systems, in IEEE ISSRE, 2021.

[4] M. Momtazpour, J. Zhang et al., Analyzing Invariants in Cyber-physical systems using latent factor regression, in ACM SIGKDD, 2015.

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