

A data-driven adaptive model-identification based large-scale sensor management system: application to Self Powered Neutron Detectors (SPND)

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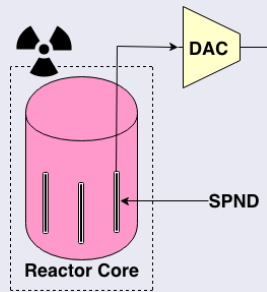
Overview

- 1 Introduction
- 2 Sensor, cluster and model database
- 3 Clustering of SPNDs
- 4 Model identification on clusters
- 5 Gross error detection and data reconciliation
- 6 Adaptive model updating
- 7 Adaptive re-clustering
- 8 Emulating server-client interaction
- 9 Results
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About SPNDs

- SPNDs are widely used to measure neutron flux inside nuclear reactor.
- Flux measurement provides direct measurement of reactor output power.
- Nuclear reactor considered for this work has 144 SPNDs.
- Positioned at different location inside the reactor core.

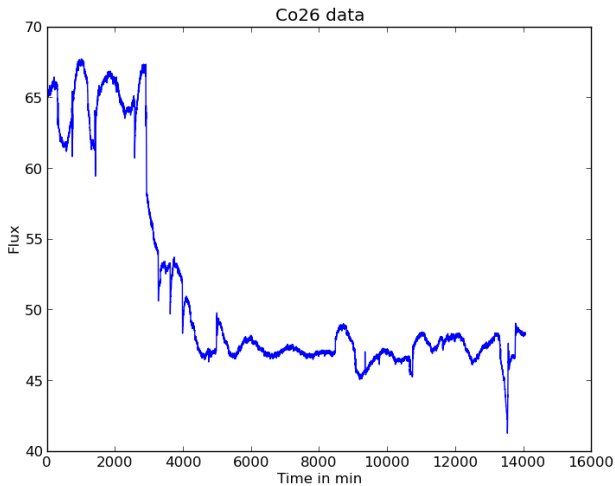
SPNDs Location



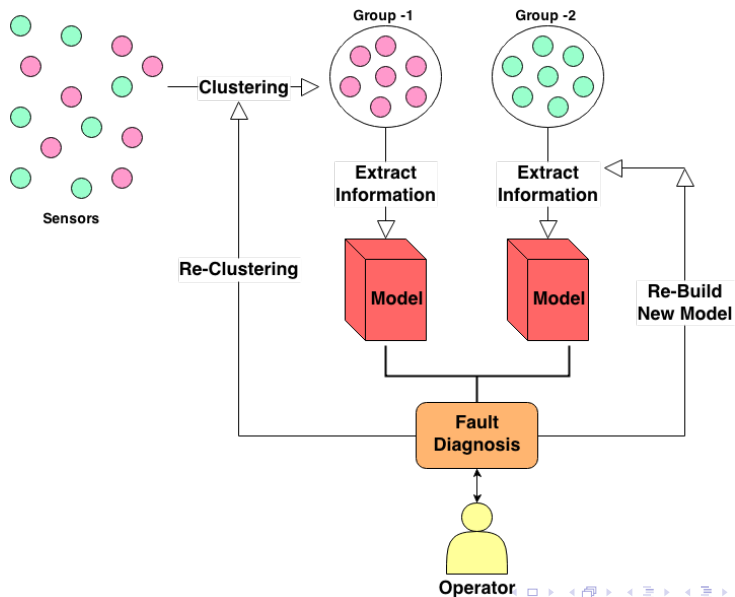
Problem:

- SPNDs can become faulty due various reasons like - aging, mechanical and electrical failure.
- Results in forced shutdown of reactor to replace faulty sensor.

SPND Output



Overall Proposed Solution



SQLite - Sensor database

- **SQLite** is used to maintain database of all 144 sensors data.
- It is the most widely deployed SQL database engine in the world.
- **sqlite3** module provides interface for using SQLite in python.

Pytables - model and cluster database

- Pytables is a python module that is build on top of **HDF5 library**.
- **Hierarchical Data Format** (HDF5) is a set of data format and libraries designed to store large amount numerical data.

Clustering

- SPNDs with strongly correlated measurements are grouped together.
- Used **k-means** algorithm available in **Pycluster** module for python.
- High correlation is decided by - **absolute Pearson correlation distance**.

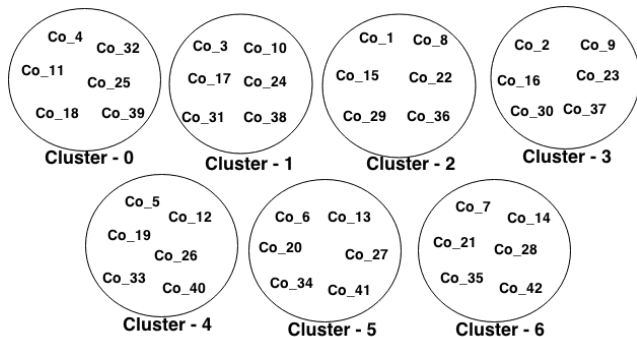
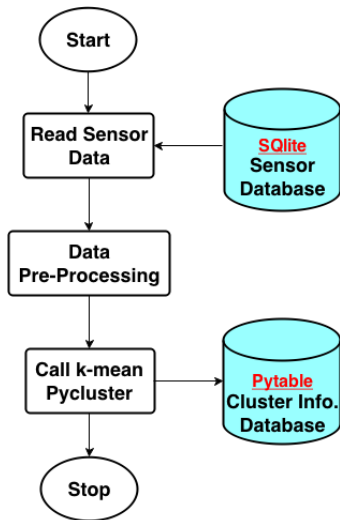
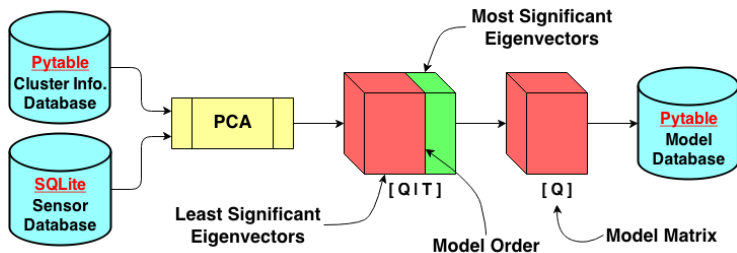


Figure : On of the cobalt SPNDs clustering solution - 7 groups each containing 6 sensors

Cluster database



Model Identification using Principal Component Analysis (PCA)



True Measurement

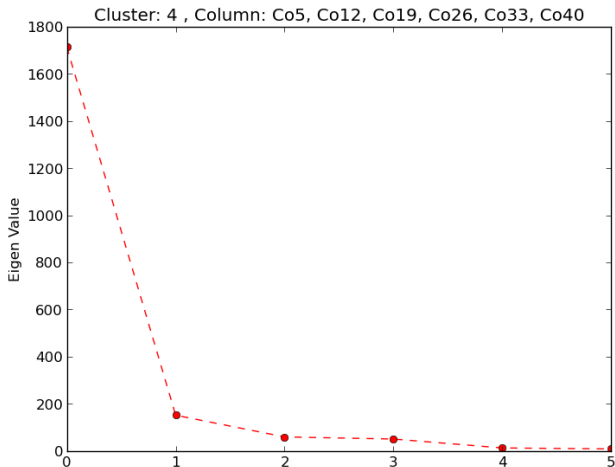
$$y(t) = x(t) + e(t)$$

Measurement Noise

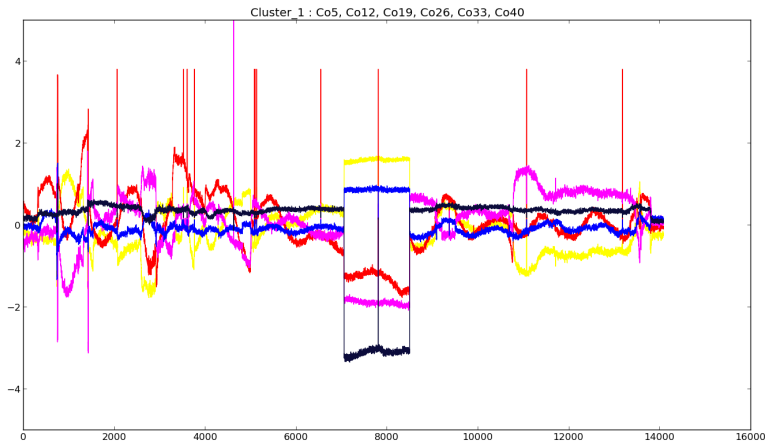
$y(t)$ \times $[Q]$ = Residual $r(t)$

The diagram shows the relationship between the measurement $y(t)$, the model matrix $[Q]$, and the residual $r(t)$. A blue block representing $y(t)$ is multiplied by a red block representing $[Q]$ to produce a residual $r(t)$.

Eigenvalue plot - Co sensors



Residuals plot - Co sensors



- For each cluster the following test statistic is considered:

$$\gamma(t) = r(t)^T V^{-1} r(t) \quad (1)$$

V is covariance matrix of residuals

- In the absence of gross error $\gamma(t)$ follows χ^2 -distribution with m degrees of freedom and α as confidence level.
- A gross error is detected if $\gamma \geq \chi_{1-\alpha, m}^2$
- Used python's statistical library `scipy.stats` for χ^2 test.
- Once gross error is detected for a cluster, the variable(s) responsible for gross errors along with estimates of gross error is identified using **Generalized Likelihood Ratio (GLR)**.

- It is process to obtain more precise estimate of true value which would satisfy the process model.
- The estimate is given by the following weighted least square optimization problem:

$$\min_{x(t)} (y(t) - x(t))^T \mathbf{W}(y(t) - x(t)) \quad (2)$$

$$\text{constraint } Ax(t) = 0$$

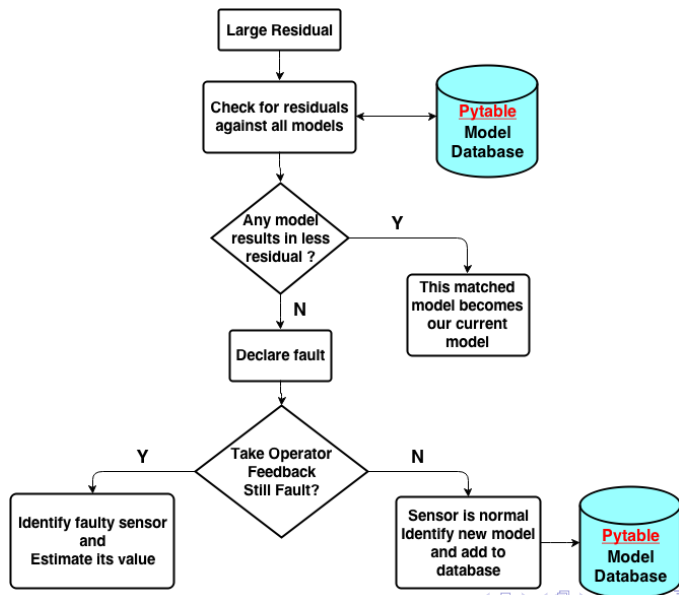
W is weighting matrix taken as inverse of noise covariance matrix.

- The solution to the above optimization problem is given by:

$$\hat{x}(t) = y(t) - W^{-1}A^T(AW^{-1}A^T)^{-1}Ay(t) \quad (3)$$

$\hat{x}(t)$ are reconciled estimate of the true values at time t .

Adaptive model updating

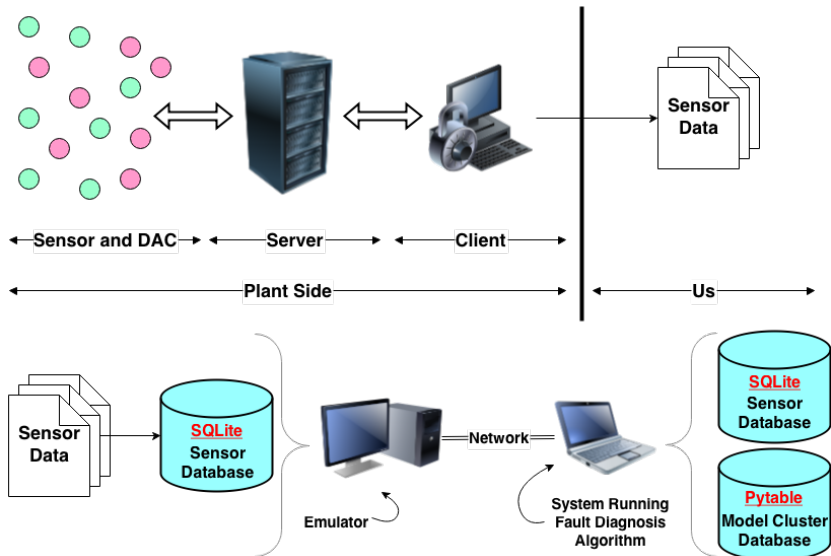


- Re-clustering decision is at higher level than updating model.
- Cluster configuration may change depending on normal operating condition of plant.

Rules used for re-clustering sensors:

- 1 If faults are detected in multiple clusters simultaneously.
- 2 Once again take operator feedback before re-clustering.

Emulating server-client interaction



Results - Profiling - Cluster building

- **cProfile** module of python is used for profiling.
- **Cluster building:**
 - Data points = 7000

SPND	No. of clusters	npass	nfound
Cobalt	7	100	13
Vanadium	12	100	1

Table : Clustering Parameters

npass = No. of times clustering algorithm is run.
nfound = No. of times optimal solution is found.

SPND	Time(sec) - build_cluster()	Time(sec) - kcluster()
Cobalt	4.192	3.292
Vanadium	25.278	23.277

Table : Timing analysis - Cluster building

Results - Profiling - Model building and Gross error detection

- **Model Building:**

- Data points = 7000

SPND	Time(sec) - Serial Code	Time(sec) - Parallel Code
Cobalt	0.428	0.015
Vanadium	1.314	0.058

Table : Timing analysis - Model building

- **Gross Error Detection:**

- Data Points = 14061

SPND	Time(sec) - error_detect()	Time(sec) - per cluster
Cobalt	20.055	2.867

Table : Timing analysis - Gross error detection

Conclusion and Future work

Real-Time

The key challenge would be to implement the proposed techniques in real-time.

Real-Time Communication

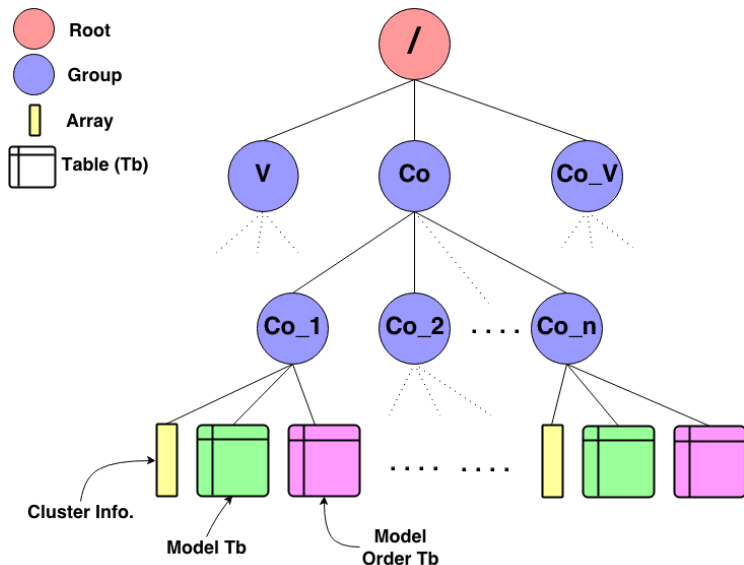
Actual interaction with the client system and remotely situated server requires knowledge of network protocol and thus establishment of real time communication.

Fully-supervised

The decisions for re-clustering and re-building of models are required to be ratified by the operating personal.

Thank you!

Pytable - cluster and model database



- S. Narasimhan and R.S.H Mah. *Generalized Likelihood Ratios for gross error identification in dynamic process*. AIChE Journal, 34:1321-1331, 1998.
- S. Narasimhan and C. Jordache. *Data reconciliation and gross error detection: intelligent use of process data*. Gulf Pub. Co., 2000.