

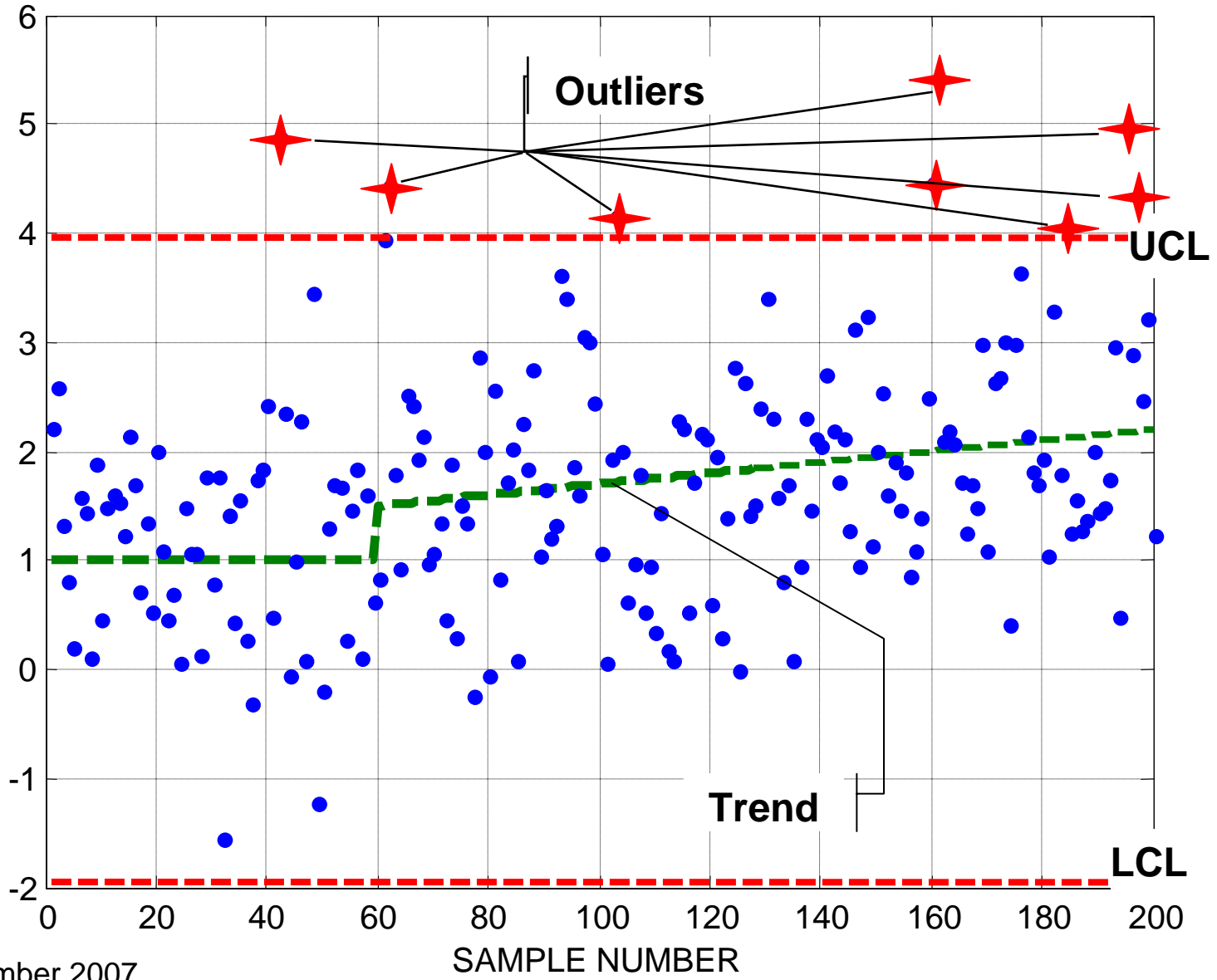
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Tools for Optimal Estimation of Hidden Trends in FDC

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DATA MONITORING



September 2007

Overview

- This talk presents:
 - Math formulation of the trending problem
 - Algorithms and tools for FDC
- Introduction
 - Where does this fit in industry practice?
 - SPC, APC, FDC...

State of the Art

SPC – Statistical Process Control

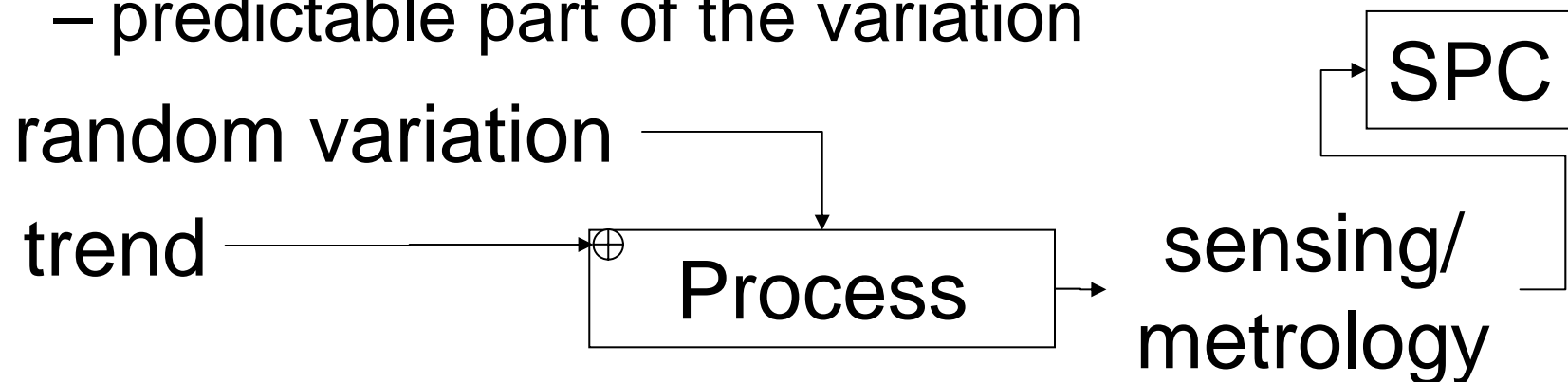
- SPC is used for 50-80 years
 - Shewart Chart
 - EWMA
 - CUSUM
- SPC operation
 - Watches for a change in the process
 - If an alarm, stop the process and troubleshoot

Multivariable SPC

- Is used for 20+ years
- Directionality of variation
 - PCA – Principal Component Analysis
- Multivariable statistics charts
 - T^2 and Q (=SPE)
- Detects a change in the process

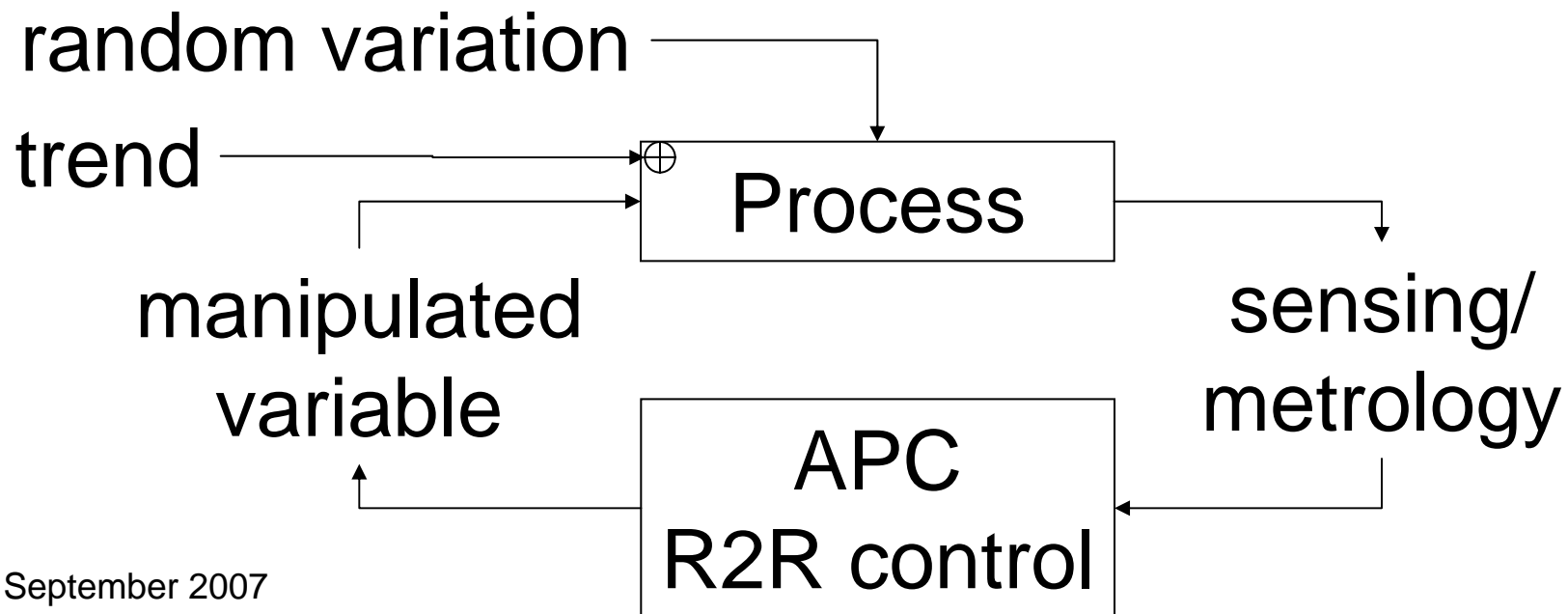
Process Variation in SPC

- Random variation
 - differs for each process run
 - unpredictable
- Trend and bias
 - same (or slowly varies) for each time sample
 - predictable part of the variation



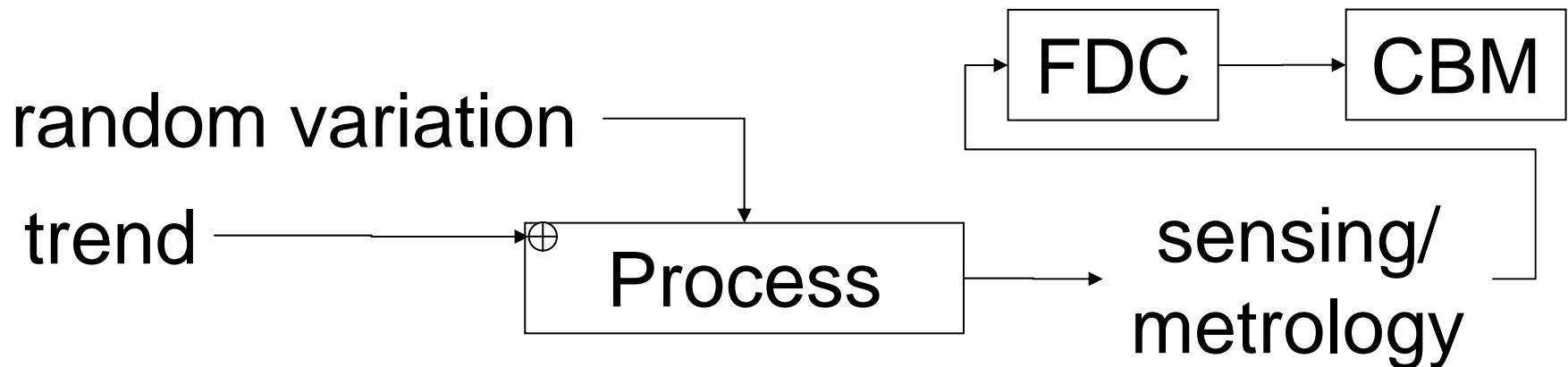
APC – Advanced Process Control

- Compensate the disturbance by feedback
- Takes care of the trend
- Continuous, automated update



FDC – Fault Detection & Classification

- FDC is the subject of this talk
- Estimates the trend and supports decisions
 - Automated troubleshooting, diagnostics
 - Condition based maintenance (CBM)



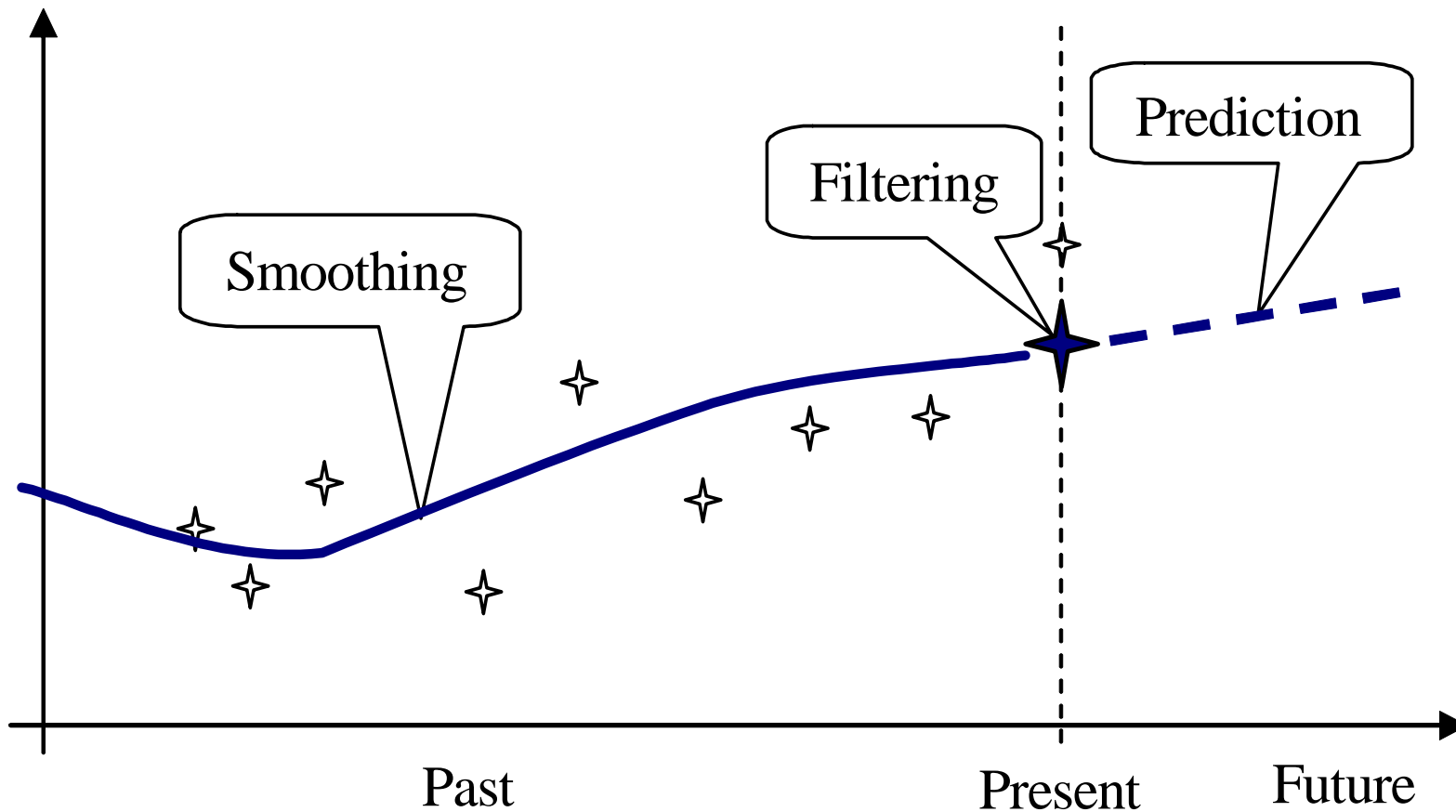
State of the Art in FDC

- Diagnostics, trending, prognostics, CBM
- Well established in process industries
 - refineries, pulp & paper
- Aerospace – Systems Health Management
 - commercial aviation, DoD, NASA
 - most advanced: jet engine monitoring
- IC manufacturing
 - emerging

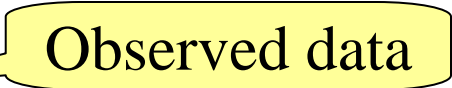
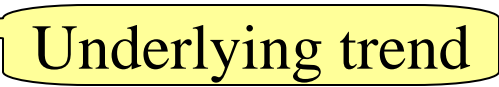
Trending

Trending Functions

- What is trending?



Trend Estimation

- Data: $\{Y\} = \{y(1), \dots, y(N)\}$ 
 $\{X\} = \{x(1), \dots, x(N)\}$ 
- Bayesian estimation

$$P(\{X\} | \{Y\}) = P(\{Y\} | \{X\}) \cdot P(\{X\}) \cdot c \rightarrow \max$$

 Observation model

 Prior

- Random walk model of the trend

$$y(t) = x(t) + e(t) \rightarrow P(\{Y\} | \{X\}) \quad e \sim N(0, Q)$$

$$x(t+1) = x(t) + v(t) \rightarrow P(\{X\}) \quad v \sim N(0, R)$$

Trending Formulation

- Batch least squares; L2 prior

$$L = \frac{1}{2} \sum Q^{-1} [y(t) - x(t)]^2 + \frac{1}{2} \sum R^{-1} [x(t) - x(t-1)]^2 \rightarrow \min$$

Observation model

Prior

- Recursive filter version = Kalman filter
- Stationary Kalman filter = EWMA
- Why this is used in practice?
 - Conceptual and computational simplicity

Advanced Trending

- Laplacian or exponential process noise
 - describe jumps in the trend well; L1 prior
- Additional constraints
 - monotonicity: irreversible deterioration
 - positivity
- Could provide a better estimate
 - is the extra complexity worth it?

Optimization-based Estimation

- Quadratic Programming (QP)

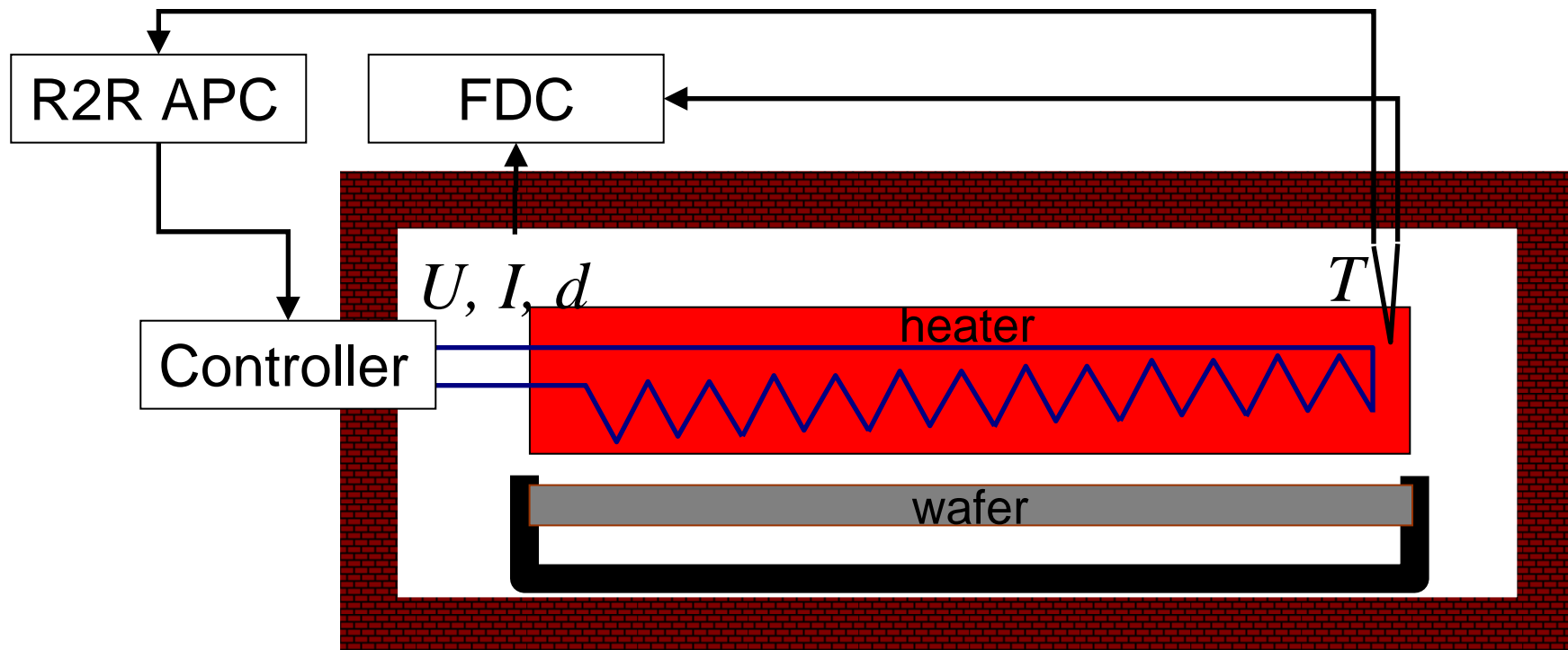
$$L = \frac{1}{2} \sum Q^{-1} [y(t) - x(t)]^2 + \sum R^{-1} |x(t) - x(t-1)| \rightarrow \min$$

$$x(t) \geq x(t-1)$$

- A convex constrained optimization problem
 - Can be solved efficiently and conveniently
 - Commercial solvers: 1K variables, in seconds
 - Specialized solvers: 1M variables, in minutes

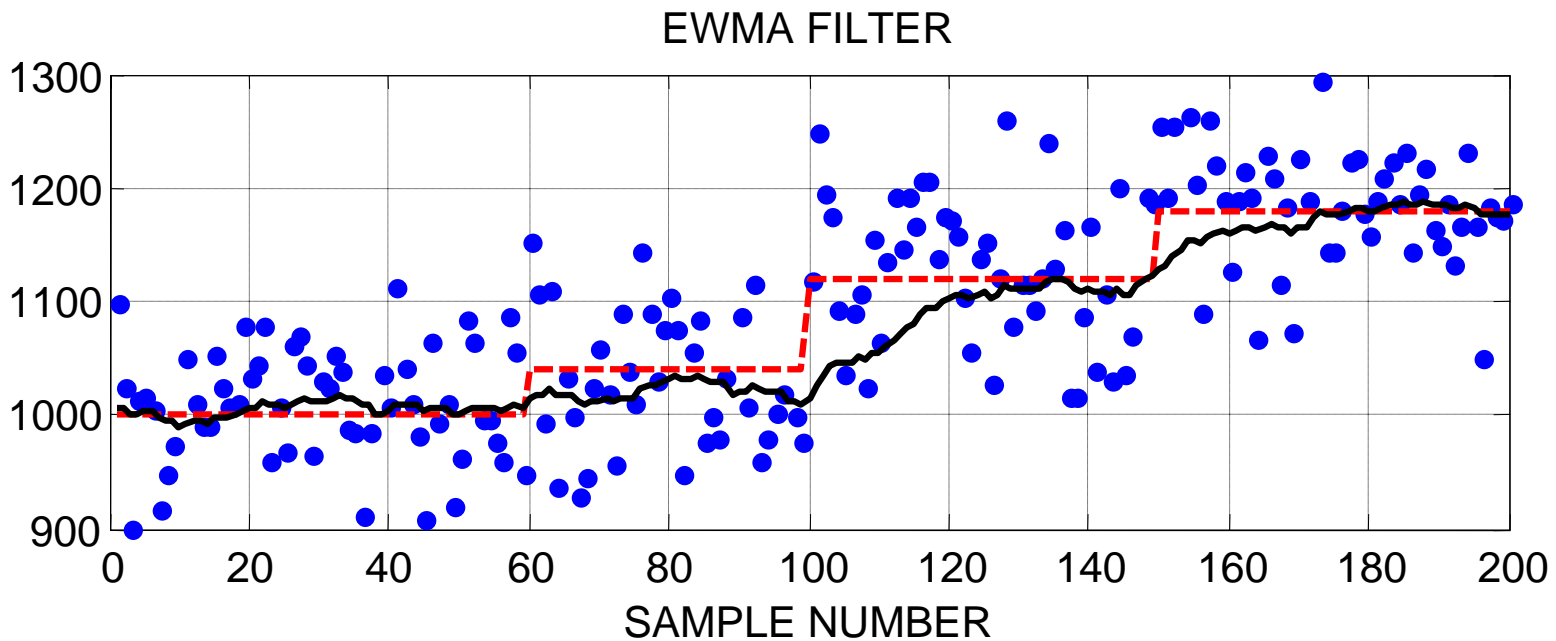
Heater Deterioration Example

- Post-exposure bake
- Increasing heater resistance

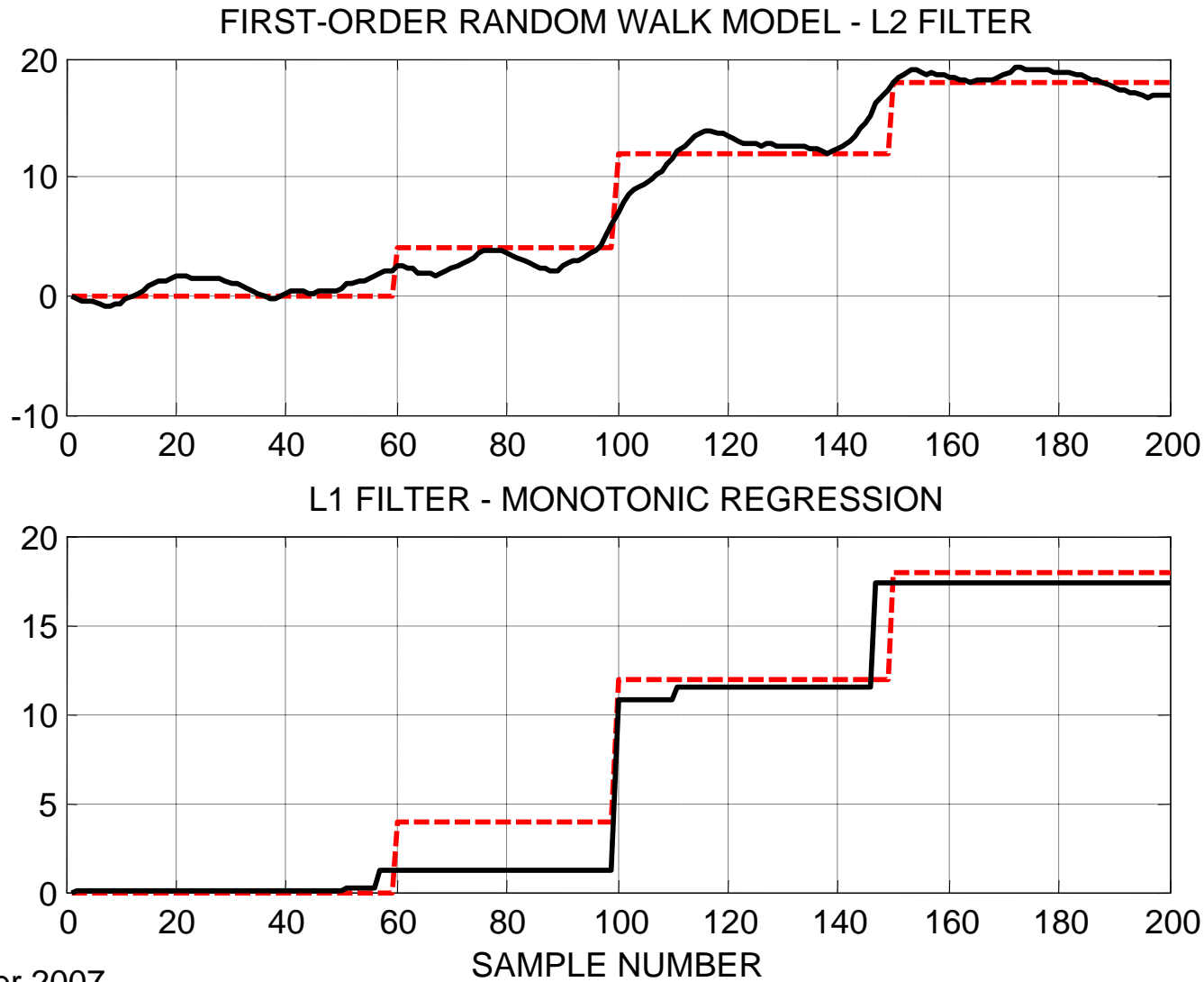


EWMA filter

- EWMA filter with $T=20$



Batch Regression: L2 and L1-Mono



Multivariable Trending

Multivariate Observation Model

$$Y(t) = S(t)f(t) + e(t)$$

- Multiple fault parameters
- Fault signatures $S(t)$ could come from empirical data or engineering analysis
- Goal: estimate hidden fault parameters $f(t)$
 - With prior models optimal estimation is a QP

Prior Models: Process

- Separate fault component models
- Random walk

$$f_k(t+1) = f_k(t) + \xi_k(t)$$

- Second-order random walk

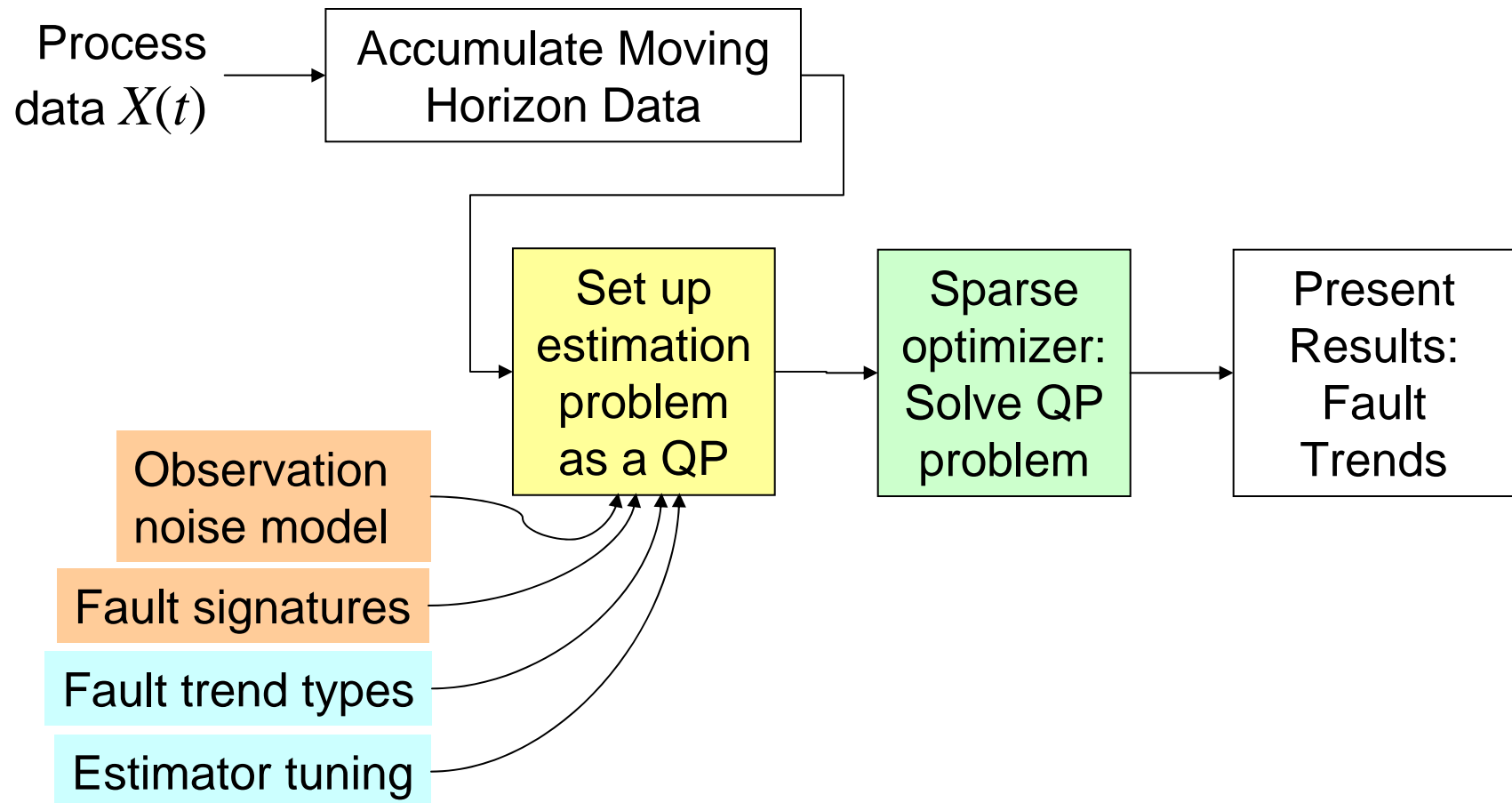
$$f_k(t+1) = f_k(t) + r_k(t) + \xi_k(t)$$

$$r_k(t+1) = r_k(t) + \eta_k(t)$$

Prior Models: Fault Types

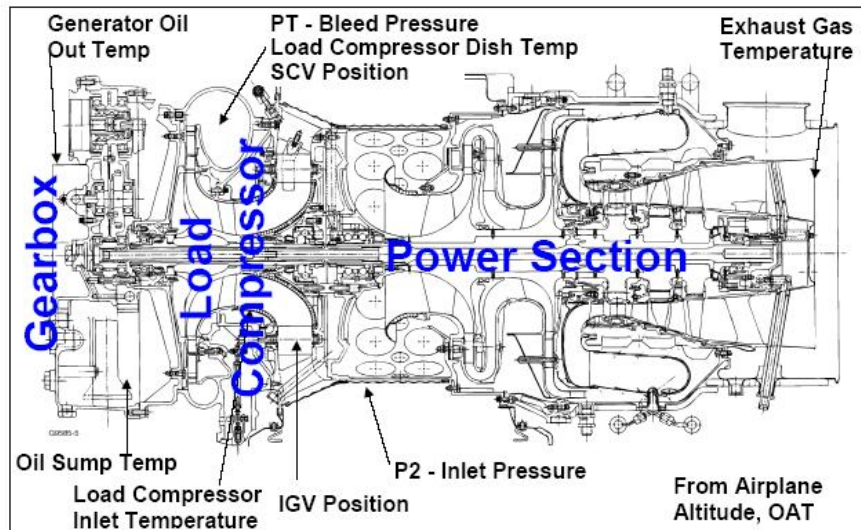
- Gaussian process noise model
 - Linear estimation (least mean squares)
- Laplacian process noise
 - Jumps (step changes) in the trend
- Exponential process noise
 - Irreversible deterioration
- Additional constraints
 - Positivity, upper bound

Estimation for FDC



Technology Applications

- Aircraft turbines
 - Deployed for a fleet



From IEEE CCA'02,'04

- NASA

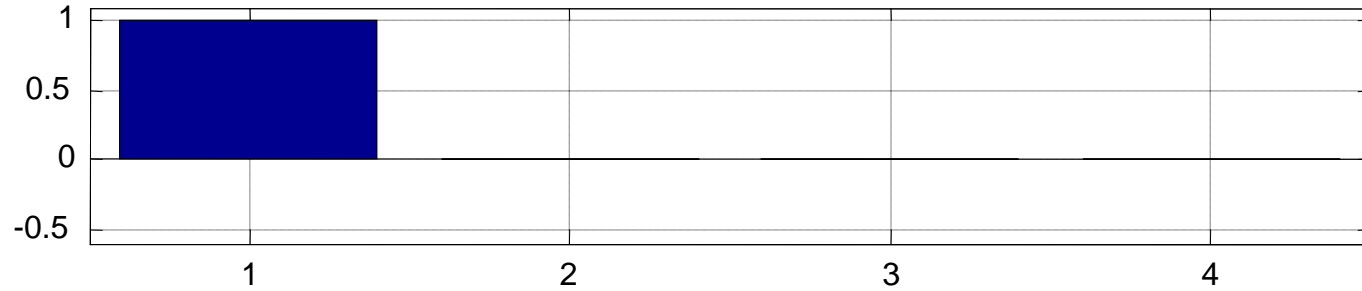


Etch Process Example

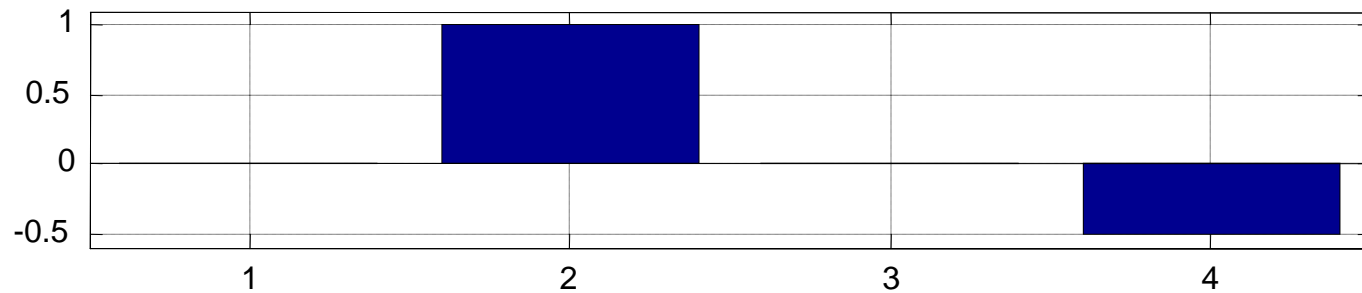
- Observed variables
 - RF Reflected Upper
 - Lower electrode cooling water temperature
 - Pressure control valve
 - Endpoint detector
- Faults
 - High reflected RF power
 - Drift in the lower electrode temperature
 - Chamber leak

Etch Fault Signatures

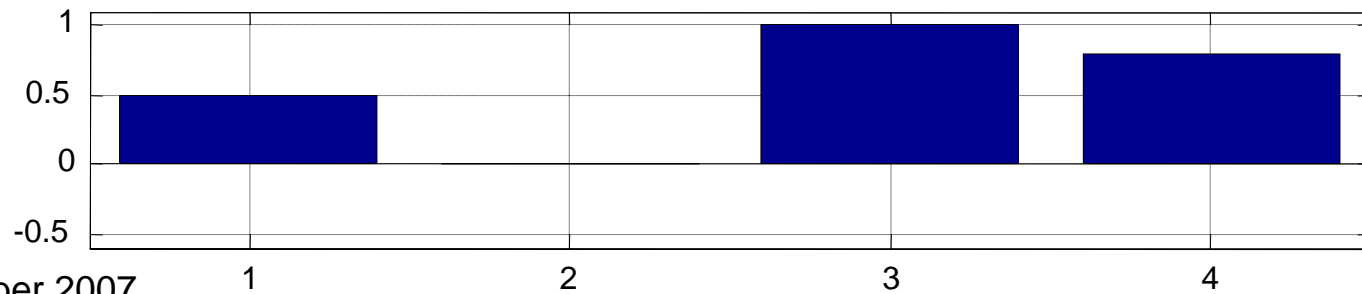
HIGH REFLECTED RF POWER SIGNATURE



LOWER ELECTRODE TEMPERATURE SIGNATURE

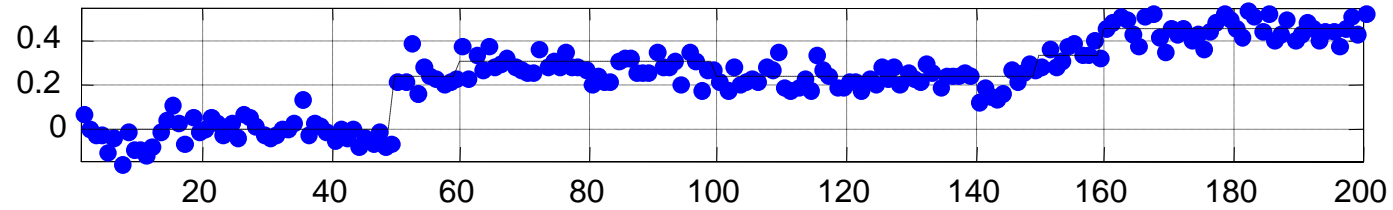


CHAMBER LEAK SIGNATURE

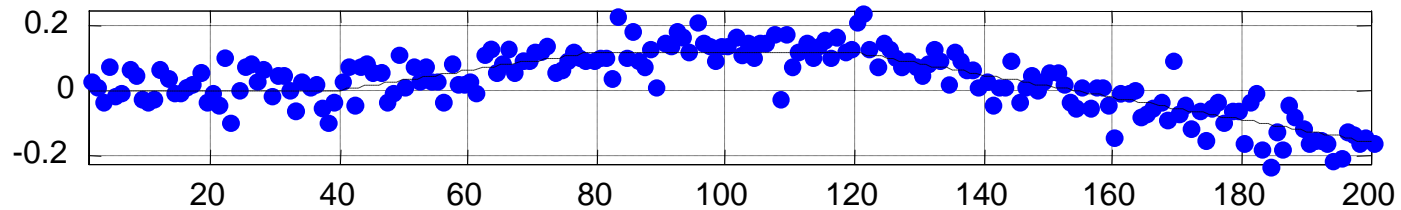


Etch Simulation Data

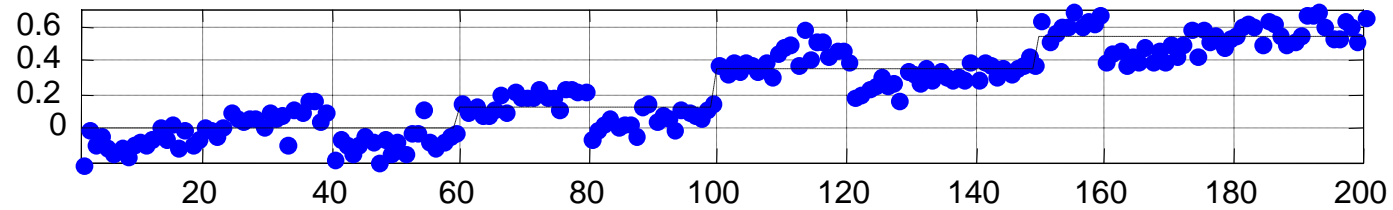
REFLECTED RF POWER



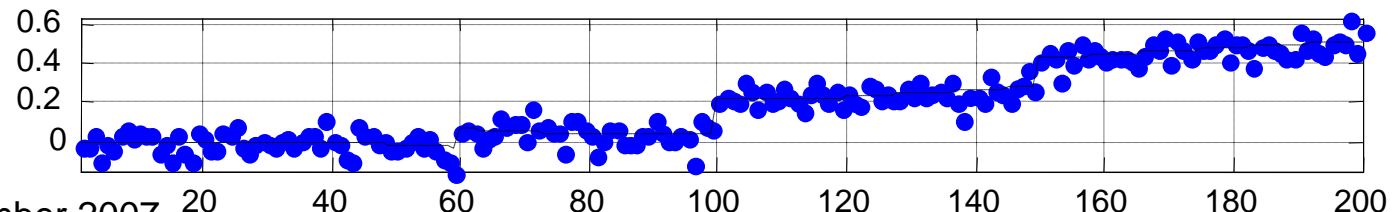
LOWER ELECTRODE TEMPERATURE



PRESSURE CONTROL VALVE



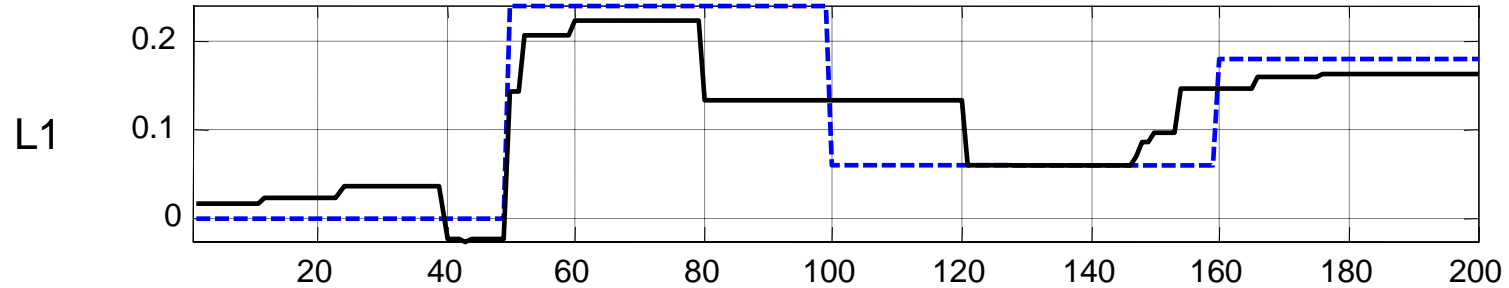
ENDPOINT DETECTOR



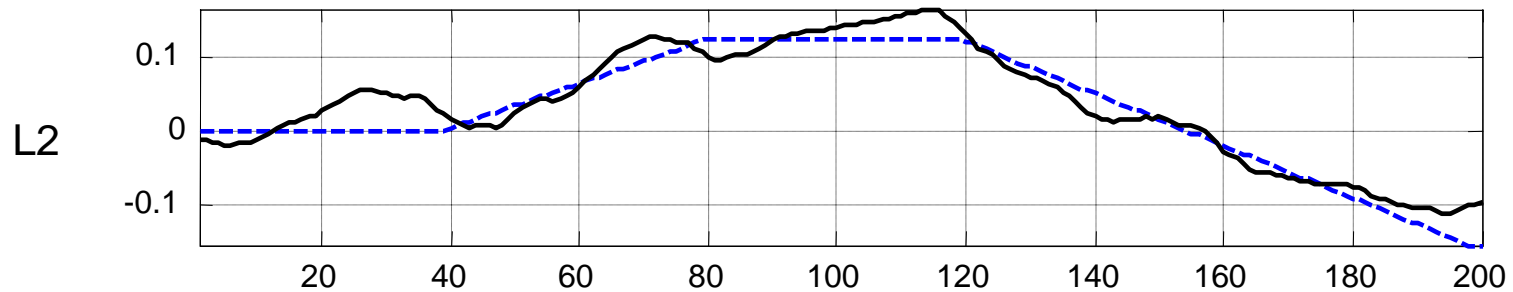
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Fault Estimates

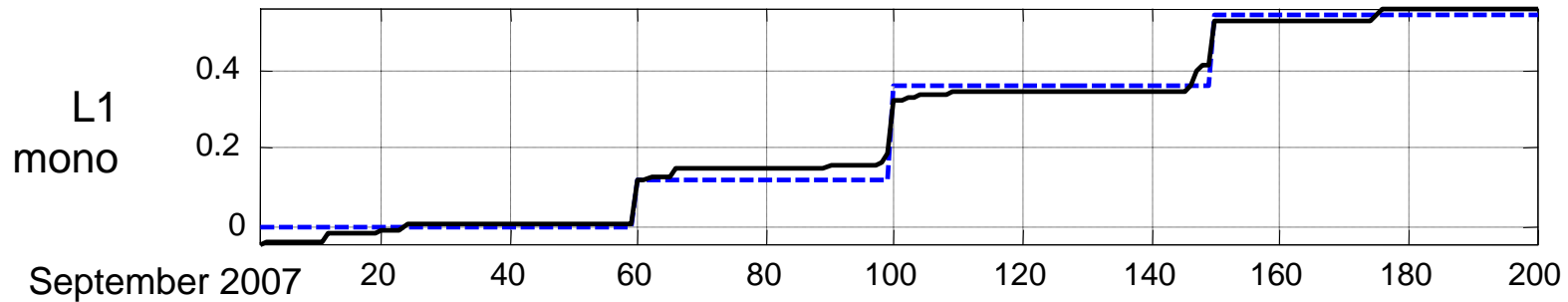
HIGH REFLECTED RF POWER ESTIMATE



LOWER ELECTRODE TEMPERATURE ESTIMATE



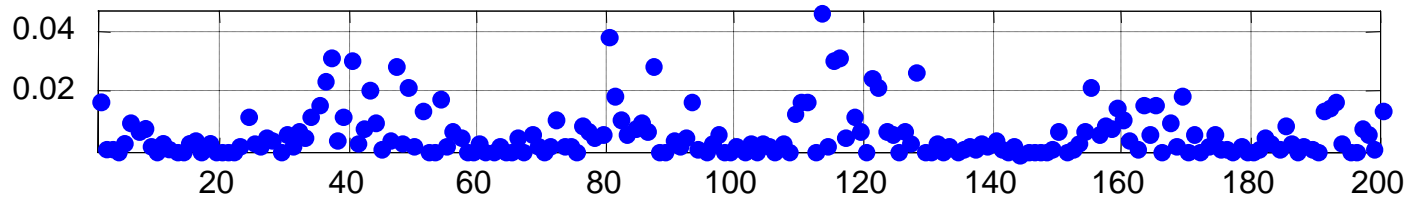
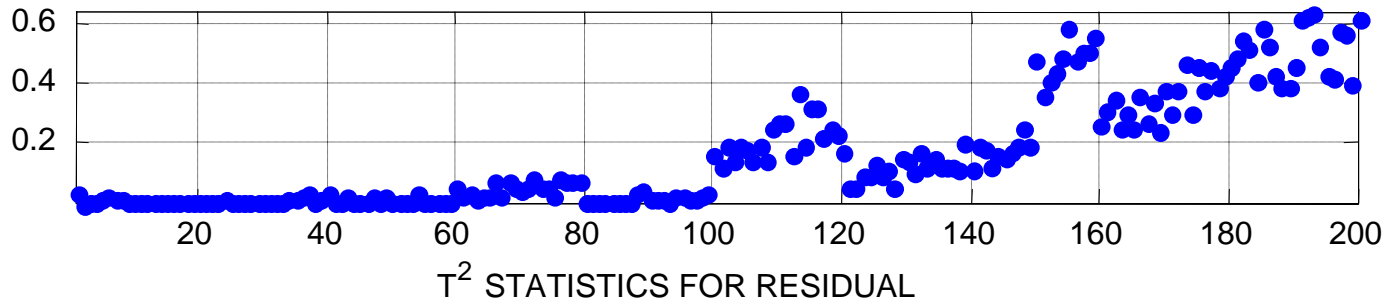
CHAMBER LEAK ESTIMATE



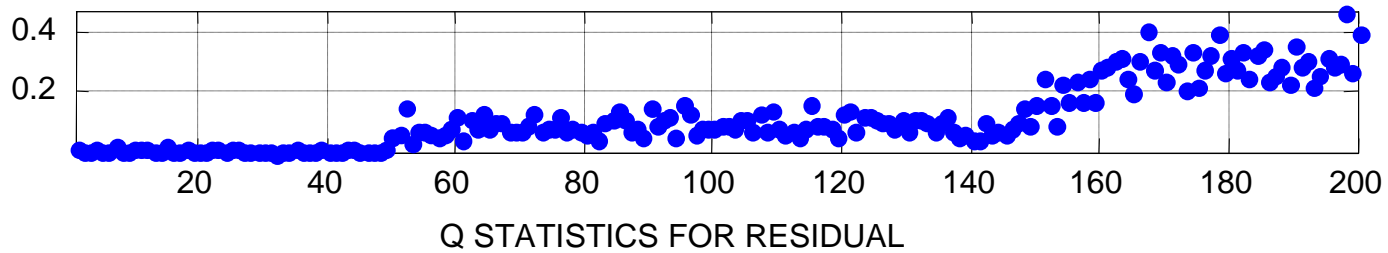
Etch T² and Q Statistics

HOTELLING T² STATISTICS

T²



Q



Conclusions

- Presented new and efficient algorithms
 - Optimal estimation of hidden trends
 - An extension of least-squares estimation
 - Based on solving QPs (standard software)
- Model-based algorithms
 - Fault signature models
 - Fault trend models (random walk, monotonic,...)
- Practical significance
 - Diagnostics, prognostics, CBM