



NTNU – Trondheim
Norwegian University of
Science and Technology

Rotary Machine Prognostic Based on Gamma Process

Project Introduction, Current Status and Future Plan

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Ariful Islam

M.Sc candidate

Reliability, Availability, Maintainability and Safety (RAMS)

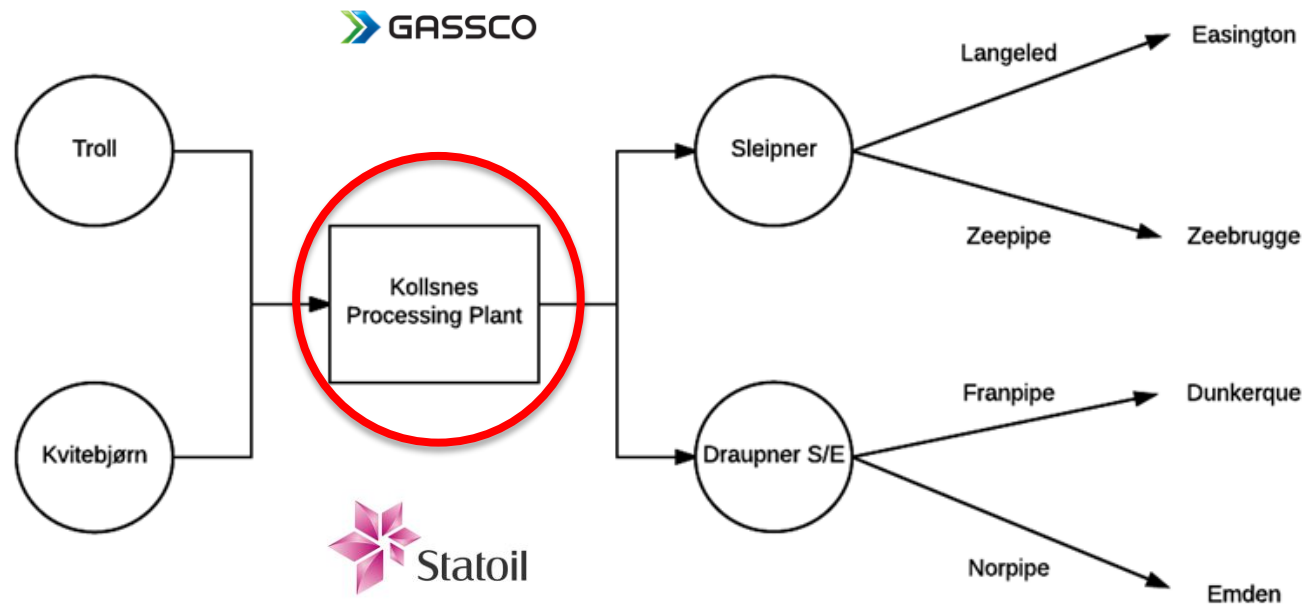
Dept. of Mechanical and Industrial Engineering, NTNU

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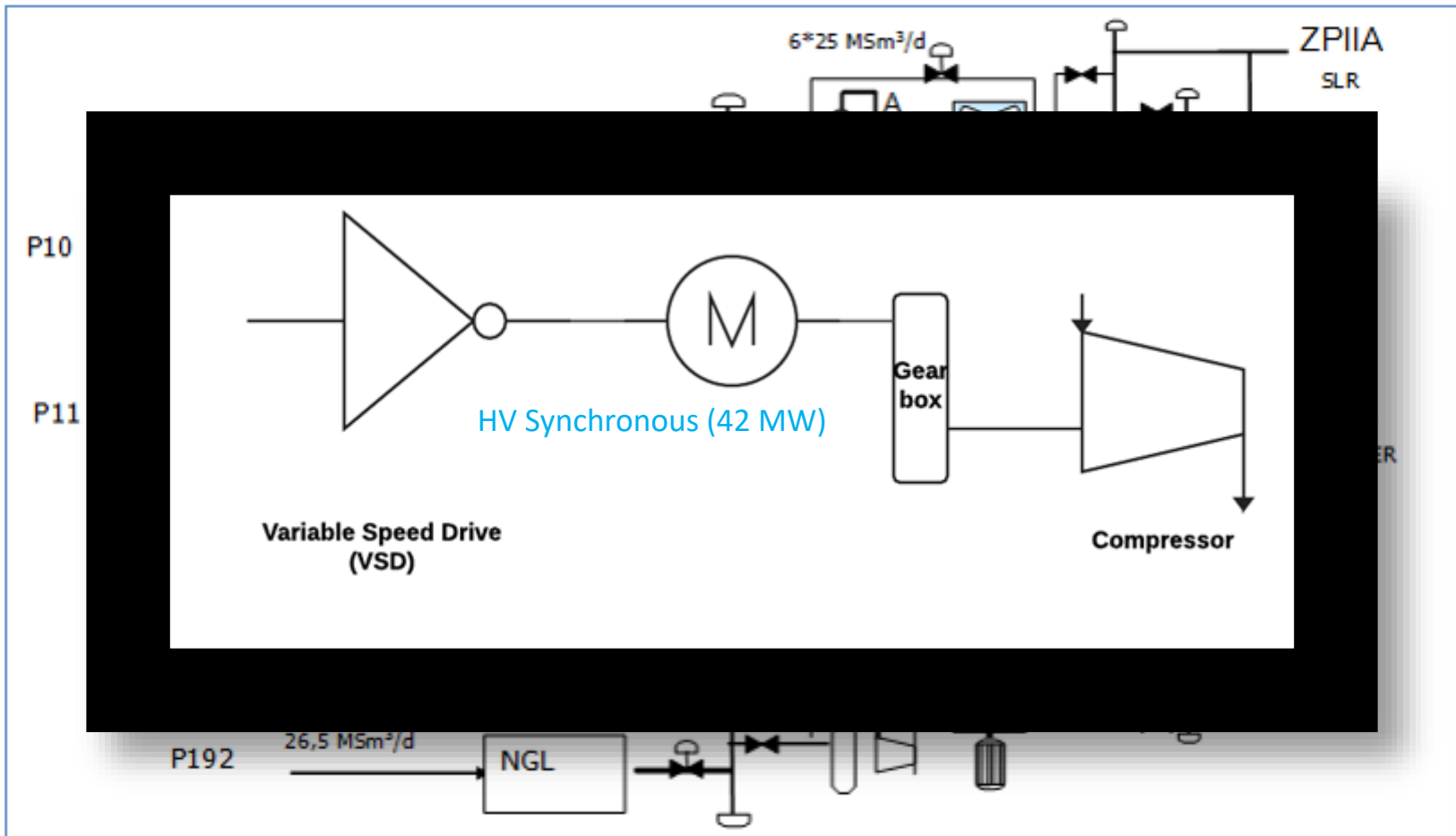


Problem Statement



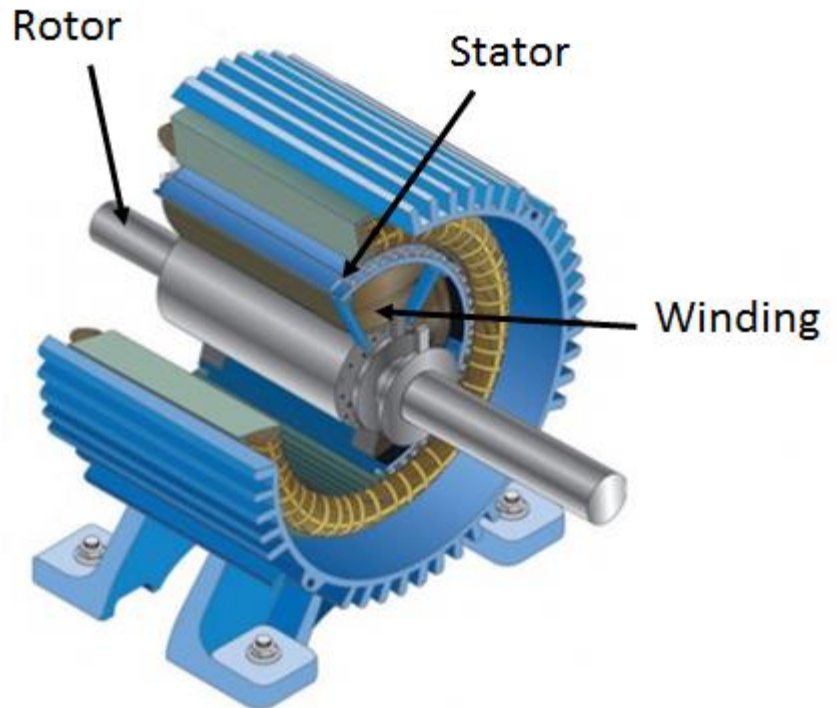
Rich gas $\xrightarrow[\text{Compression}]{\text{Dewatering}}$ gas, NGL, condensate

Problem Statement



Problem Statement

- Critical Component
 - Motor (Ageing of stator winding insulation)
- Requirements
 - Summer (3 units)
 - Winter (6 units)
- Current Status
 - 5 commissioned in 1996
 - 1 new (2006)



Machinery Prognostics

- Traditional reliability approaches
 - Event data based
 - Replacement/failure times of historical units
- Prognostic approaches
 - Condition data based
- Integrated
 - Both on event and condition data
 - Depends on the availability

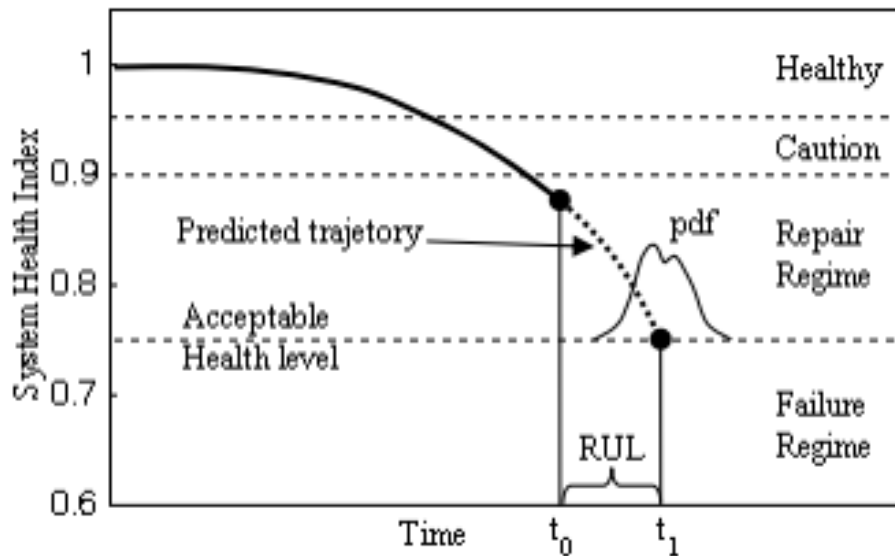
Reference: Aiwina (2009)

Prognosis

$$RUL(t) = \inf \{h: X(t+h) \in S_L | X(t) \notin S_L\}$$

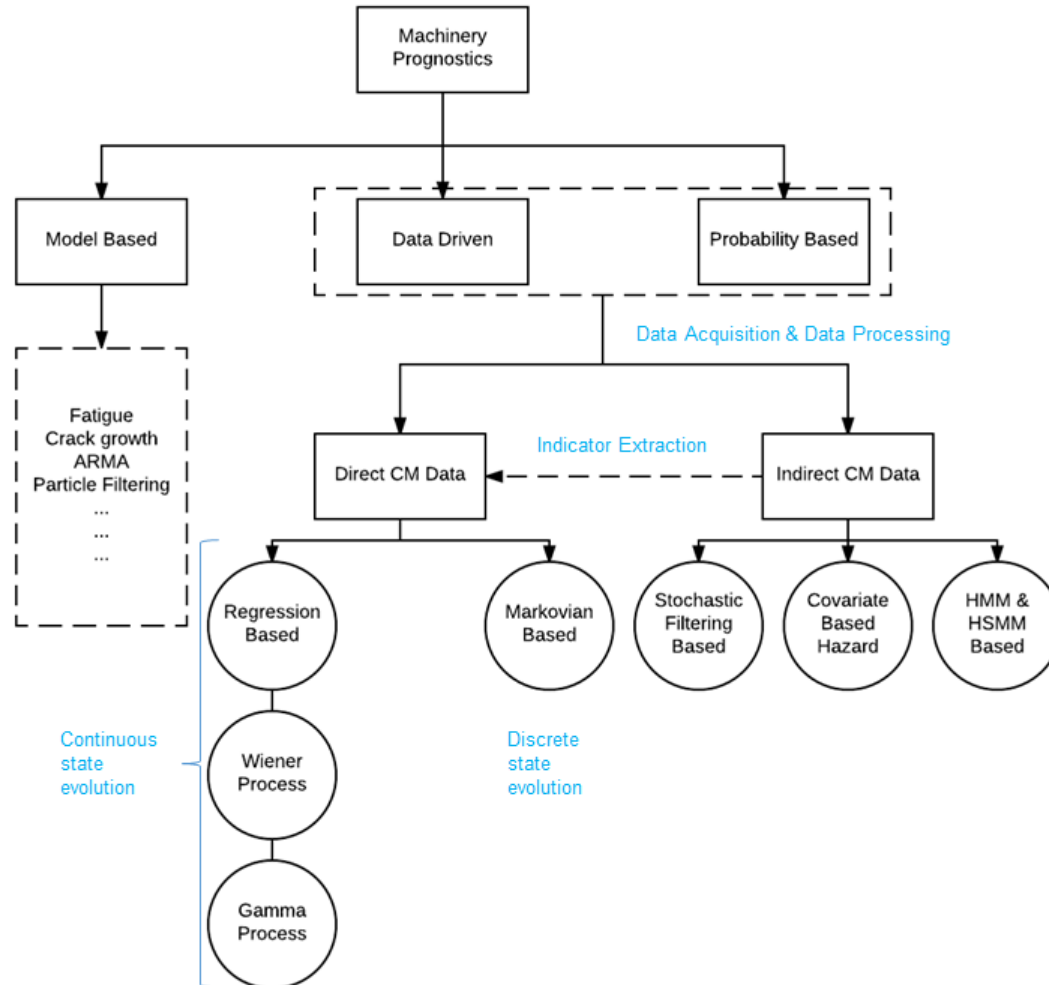
$X(t)$ = Random Variable (Condition) at time t

S_L = Set of failed states



Reference: Xiongzi (2011)

Machinery Prognostics



Under laboratory condition

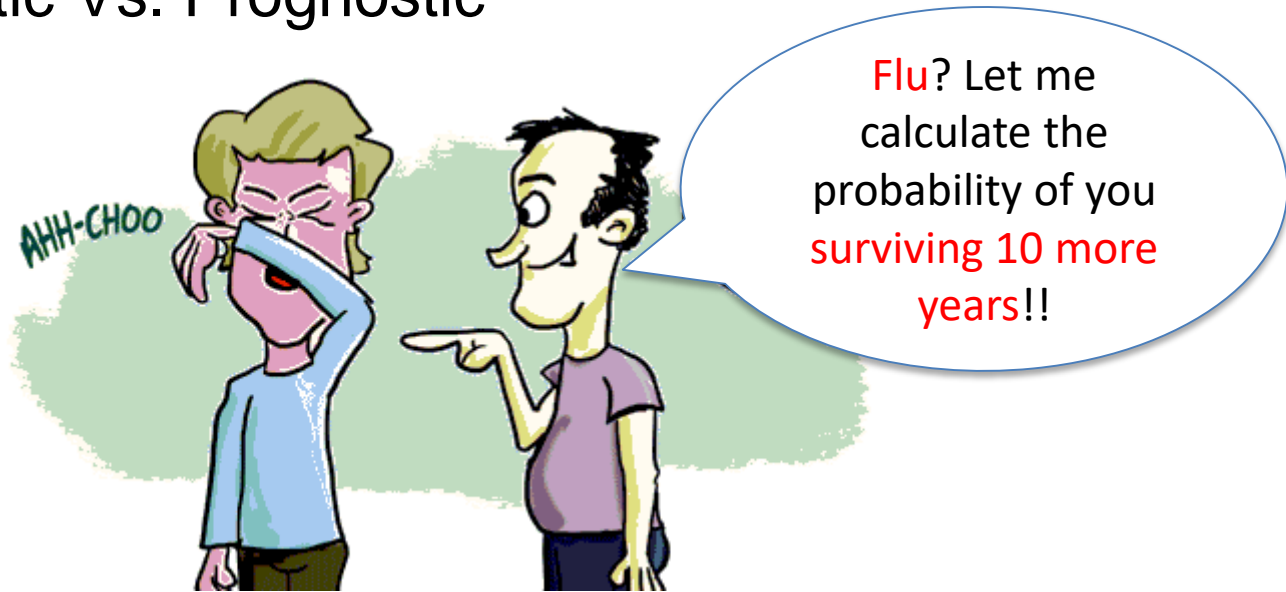
Not always practical for CM

Some tests are destructive

Reference: Based on Vachtsevanos (2006) and Si (2011)

Condition Indicator

- Diagnostic Vs. Prognostic

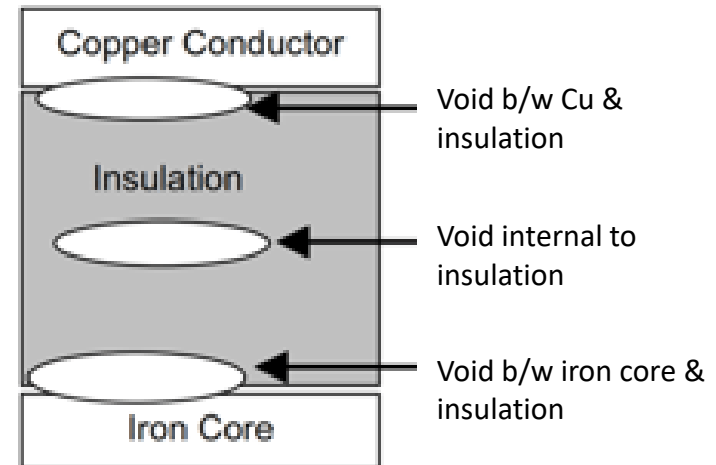


- **Diagnosis**- identify failure mode (**cause of malfunction**)
- **Prognosis**- generate rational estimation of RUL with available data (**medical history**)

Reference: Lee (2014)

Condition Indicator

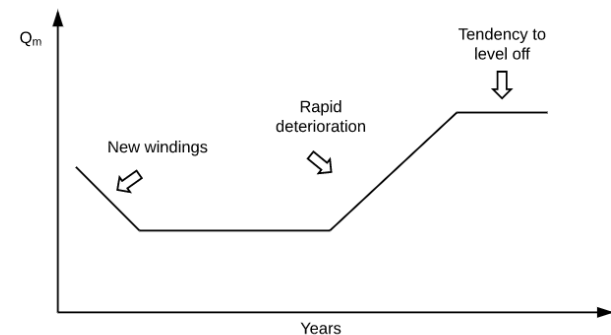
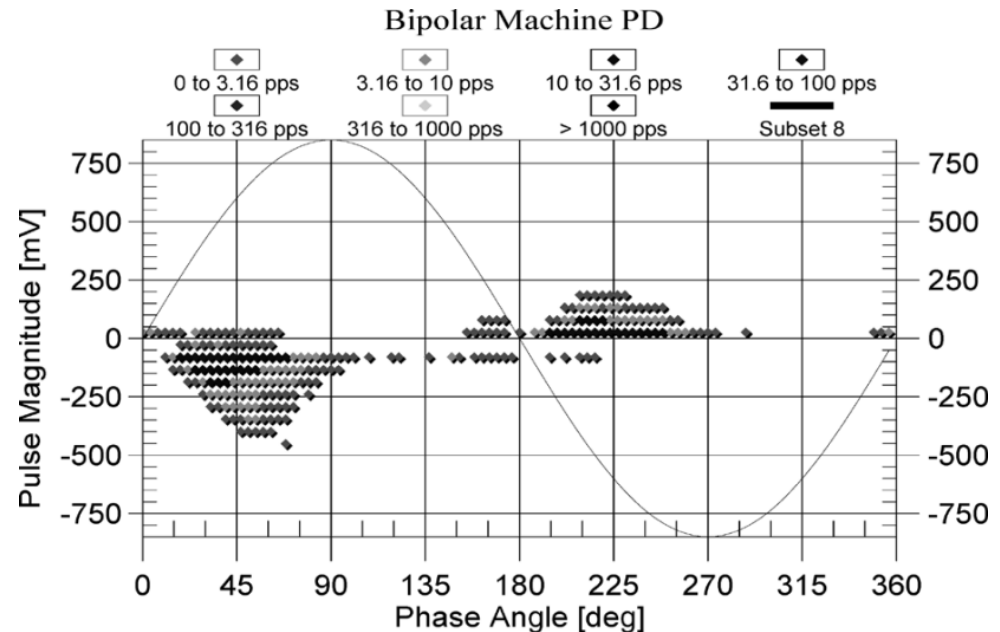
- Available Test Procedures (**Insulation Quality**)
 - Insulation Resistance
 - Polarization Index
 - Hi-Pot Test
 - Partial Discharge
 - Etc.
- Partial Discharge (PD)
 - Dielectric breakdown of electric insulation under high voltage
 - Creates small sparks in holes and bombard them



Reference: Paoletti (1999)

Online PD Monitoring

- OLPD measures-
 - Number of PD pulses
 - PD Magnitude (Q_m)
 - Phase position
- PD Magnitude
 - Highest PD pulses with minimum repetition rate of 10 pulses/sec
 - Higher value indicates more deteriorated winding (Stone, 2006)



Typical trend in PD magnitude of stator windings (Stone (2012))

Preliminary Approach

- Choice of statistical model
 - Gamma process
- Reasons-
 - Strictly monotonic increasing degradation
 - Useful for optimal inspection and maintenance decisions making
- Limitations
 - Linear expected degradation

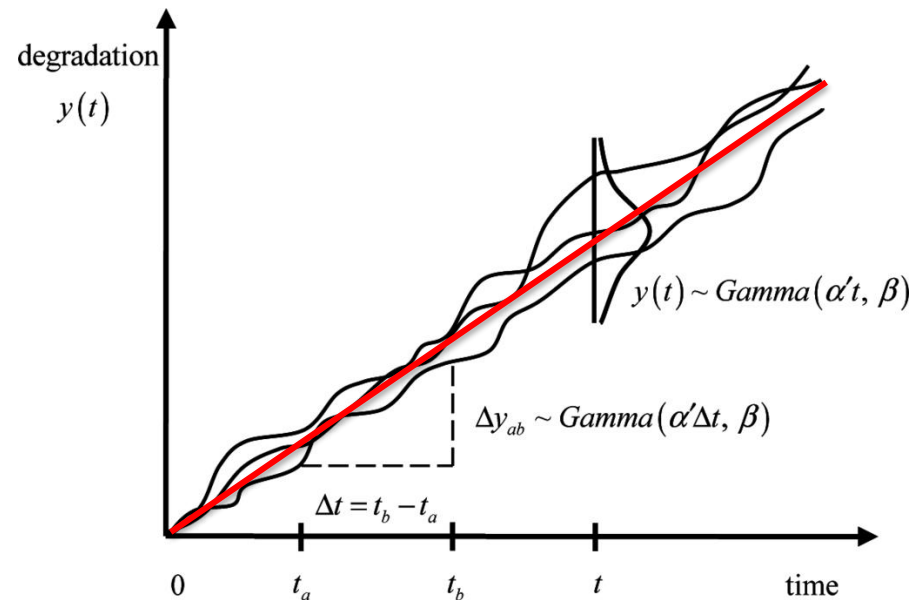


Image reference: Lim H (2015)

Gamma Process

- PDF of Gamma distribution-

$$f_{A(t),b}(x) = \frac{1}{\Gamma(A(t))} b^{A(t)} x^{A(t)-1} e^{-bx}$$

$A(t)$ = Shape function

b = Scalar parameter

$$E(X_t) = \frac{A(t)}{b}$$

$$Var(X_t) = \frac{A(t)}{b^2}$$

Non-Homogeneous Gamma Process

- Non-homogeneous Gamma Process modeling
 - How deterioration increases over time? (Assuming temporal variability)
 - Shape function, $A(t) = c \cdot t^u$ (Empirical studies)

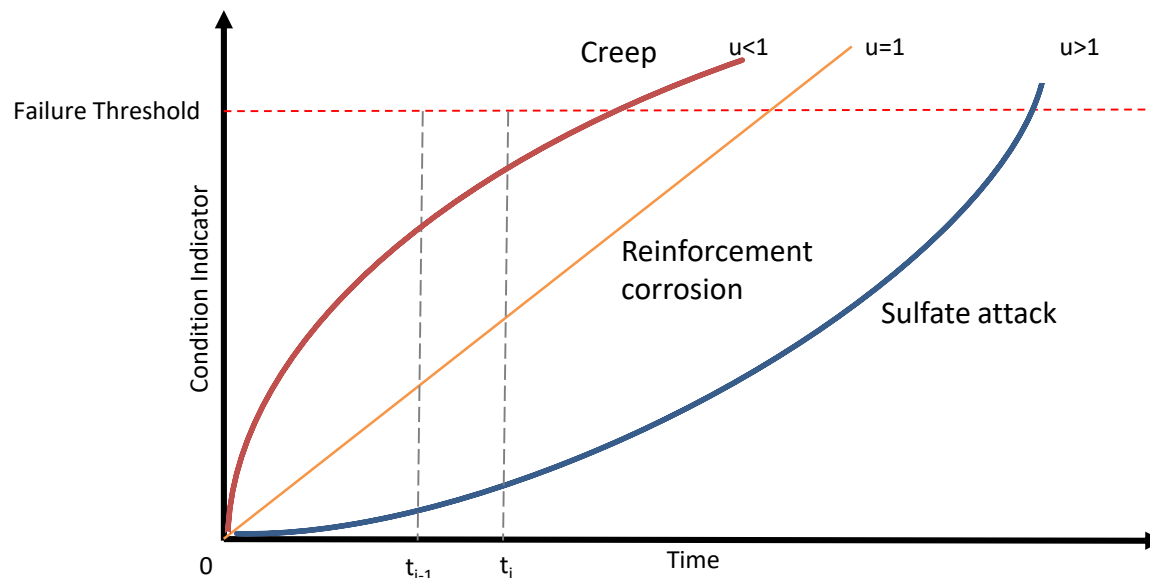


Figure: Degradation path depending on exponential parameter u
Deterioration in concrete pipes

Reference: Mahmoodian (2013), Van Noortwijk, J. M. (2009)

Simulation Process

- Available Methods
 - Gamma increment sampling
 - Simulate independent increments w.r.t. tiny amount of time

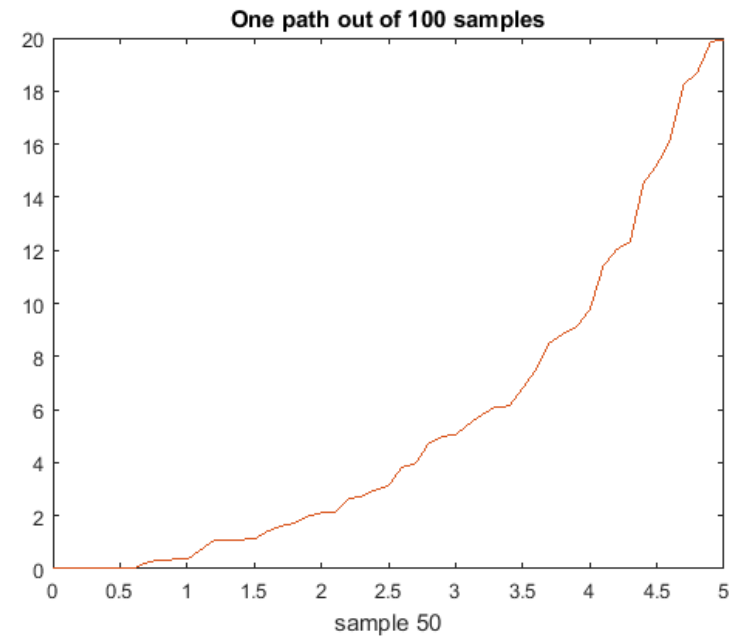
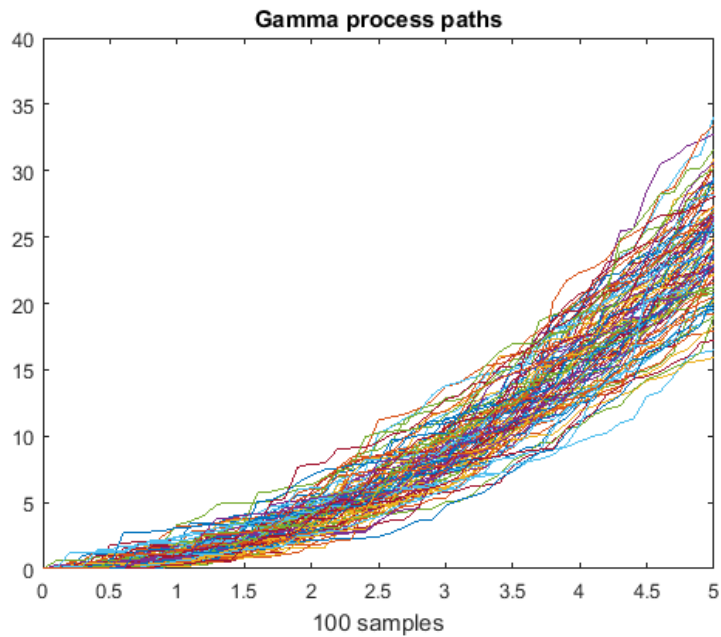
$$Ga(\delta | A(t_i) - A(t_{i-1}), b) = \frac{b^{A(t_i) - A(t_{i-1})}}{\Gamma(A(t_i) - A(t_{i-1}))} \delta^{[A(t_i) - A(t_{i-1})] - 1} e^{-b\delta}$$

A.K.A – Gamma Sequential Sampling (GSS)

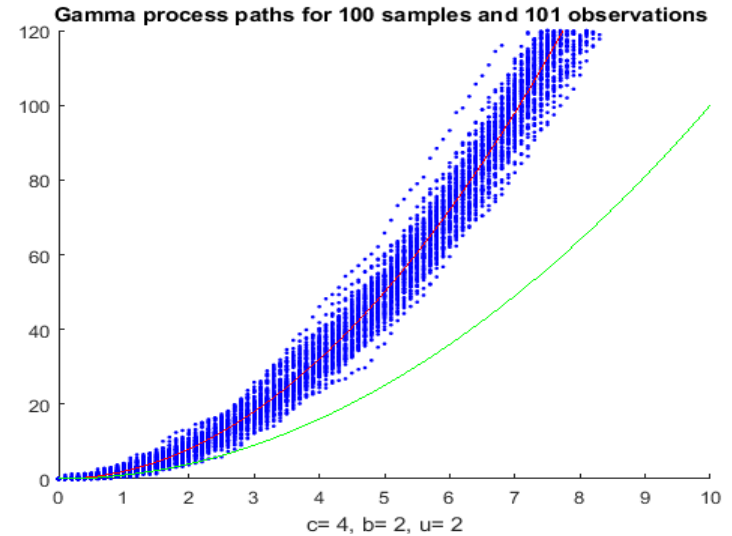
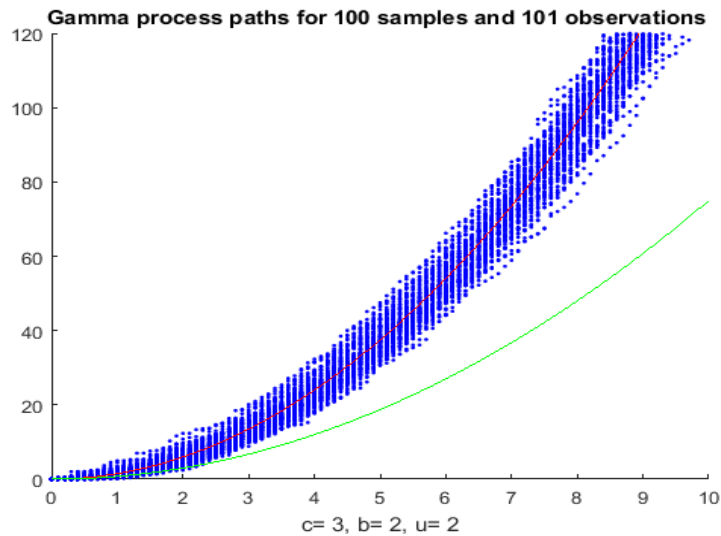
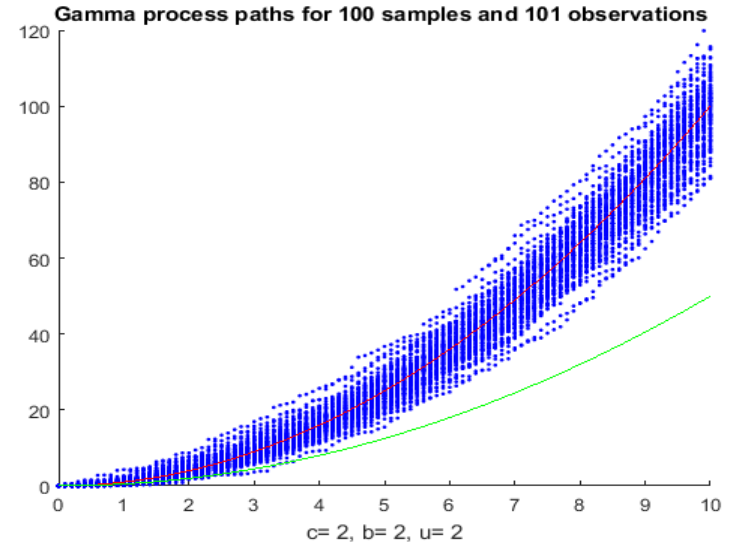
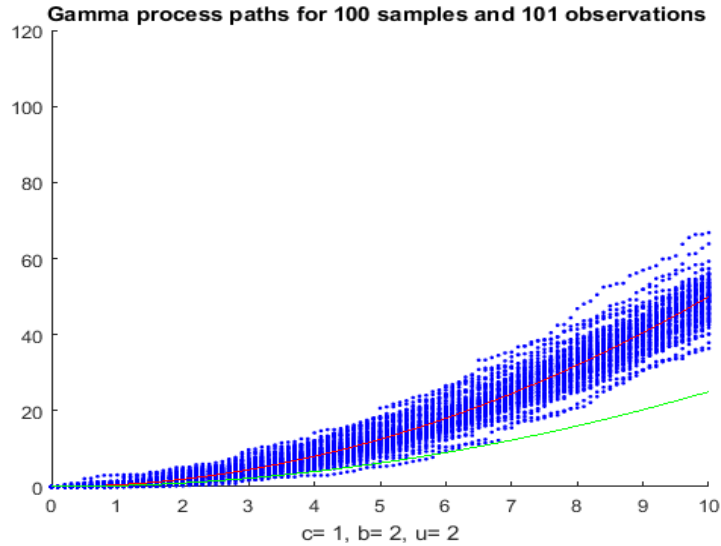
- Gamma bridge sampling
 - Draw samples from CDF of deterioration

Reference: Van Noortwijk, J. M. (2009), A. N. Avramidis (2003)

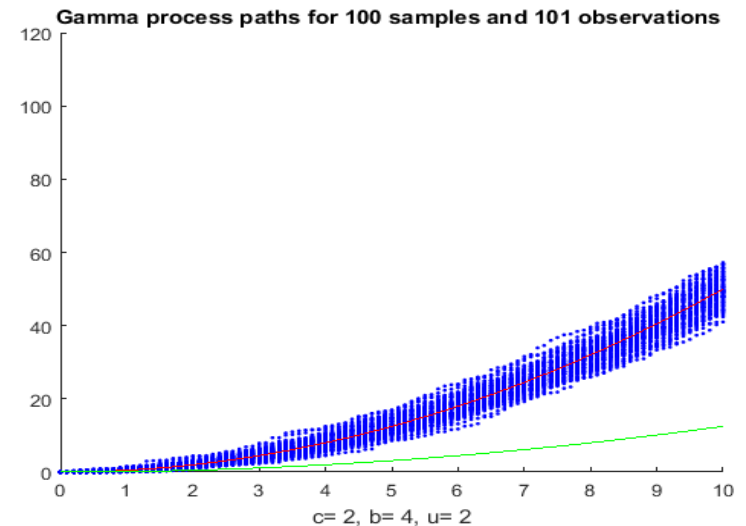
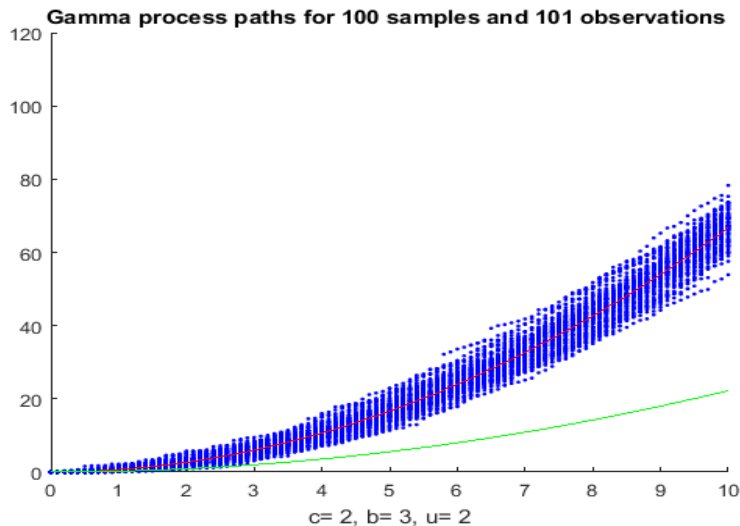
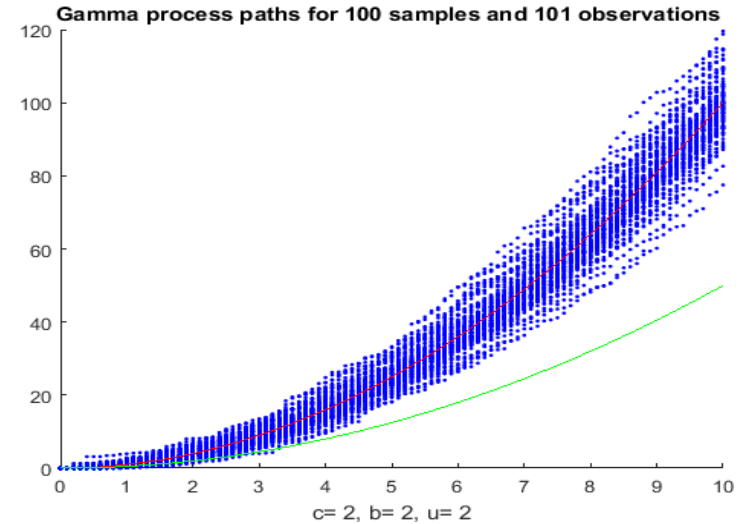
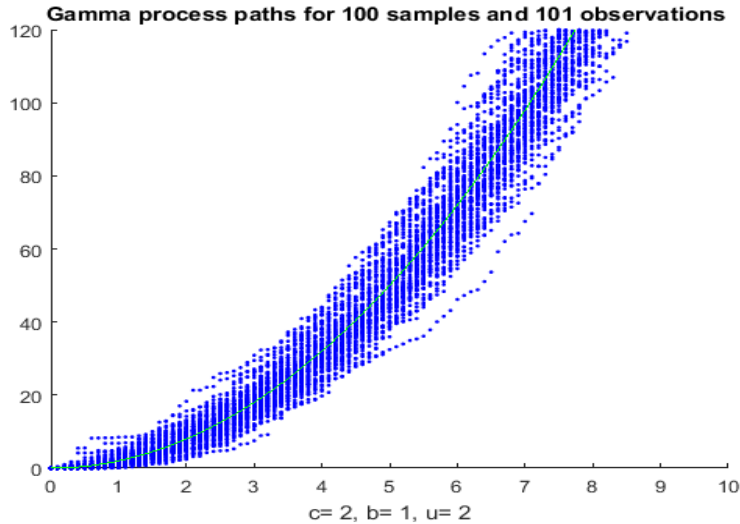
Simulated NHGP Paths



Changes in Shape



Changes in Scaler Parameter



Parameter Estimation

- Maximum Likelihood Estimation

$$\begin{aligned}\mathcal{L}(\delta_i|c, b) &= \prod_{i=1}^n f_{X(t_i)-X(t_{i-1})}(\delta_i) \\ &= \prod_{i=1}^n \frac{b^{c(t_i^u-t_{i-1}^u)}}{\Gamma[c(t_i^u-t_{i-1}^u)]} \delta_i^{c[t_i^u-t_{i-1}^u]-1} e^{-b\delta_i}\end{aligned}$$

$$\begin{aligned}\psi(x) &= \frac{d}{dx} \ln \Gamma(x) \\ &= \frac{\Gamma'(x)}{\Gamma(x)}\end{aligned}$$

$$\hat{b} = \frac{m\hat{c}t_n^u}{\sum_{j=1}^m x_{n,j}}$$

$$\sum_{i=1}^n [t_i^u - t_{i-1}^u] \psi(\hat{c}[t_i^u - t_{i-1}^u]) - \frac{\sum_{j=1}^m \sum_{i=1}^n [t_i^u - t_{i-1}^u] \ln(\delta_{i,j})}{m} = t_n^u \ln\left(\frac{m\hat{c}t_n^u}{\sum_{j=1}^m x_{n,j}}\right)$$

\hat{c} Must be computed iteratively (Newton-Raphson Method)

Test Result (Example)

Shape function, $A(t) = c \cdot t^u$

Scaler parameter = b

Number of components, $M = 100$

Total time, $T = 10$ unit

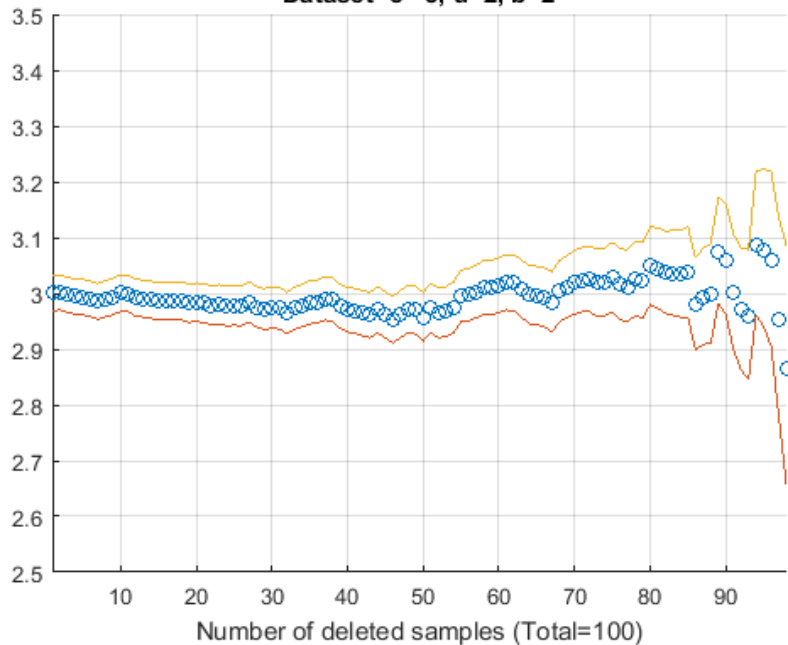
Time increment = 0.1

Parameter value of generated data, $b = c = u = 2$

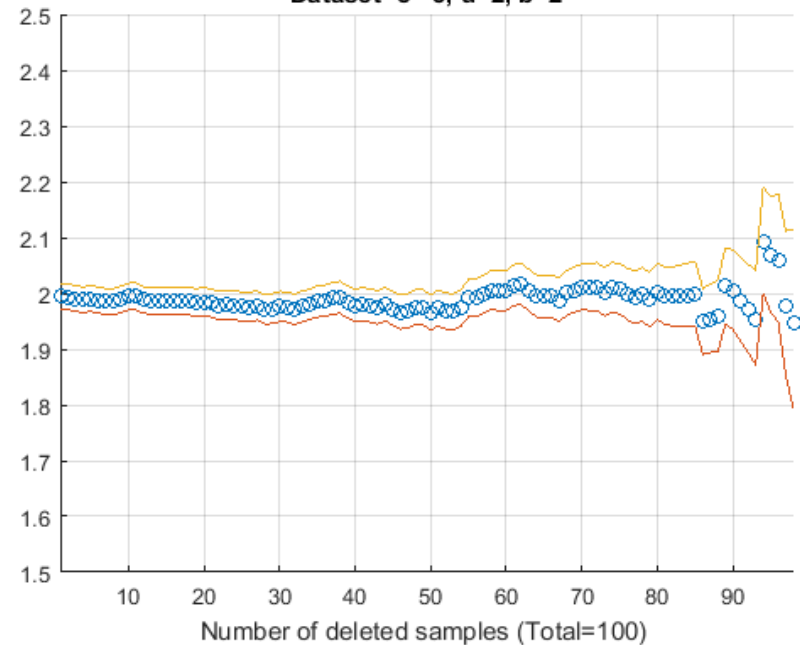
| Parameter | Estimate | Confidence Level | Lower Bound | Upper Bound |
|-----------|----------|------------------|-------------|-------------|
| c | 2.0919 | 95% | 2.0146 | 2.1722 |
| b | 2.0441 | | 1.9584 | 2.1336 |

Estimation Accuracy- Sample size

Accuracy of c estiamtes
Dataset- c= 3, u=2, b=2

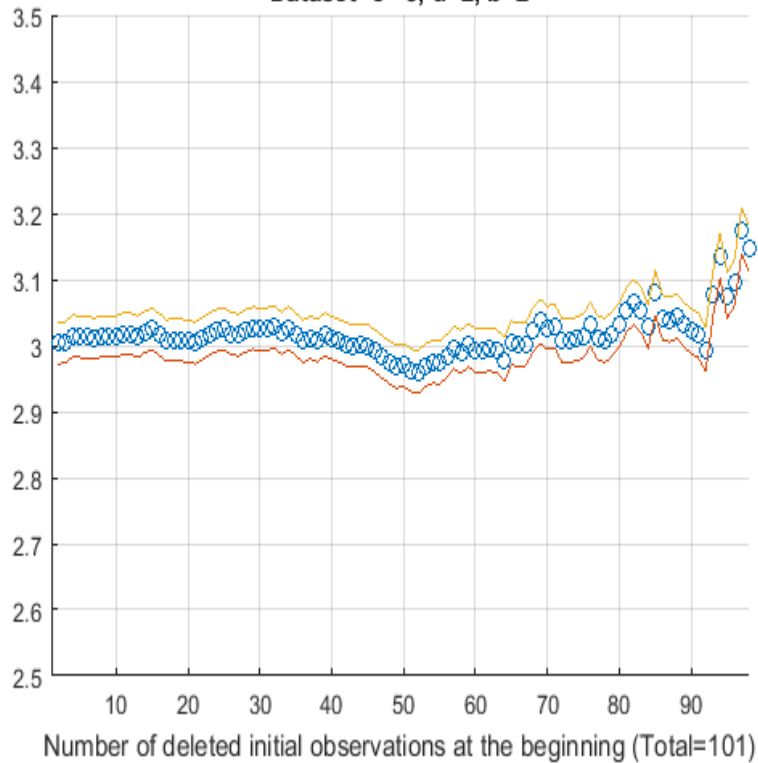


Accuracy of b estiamtes
Dataset- c= 3, u=2, b=2

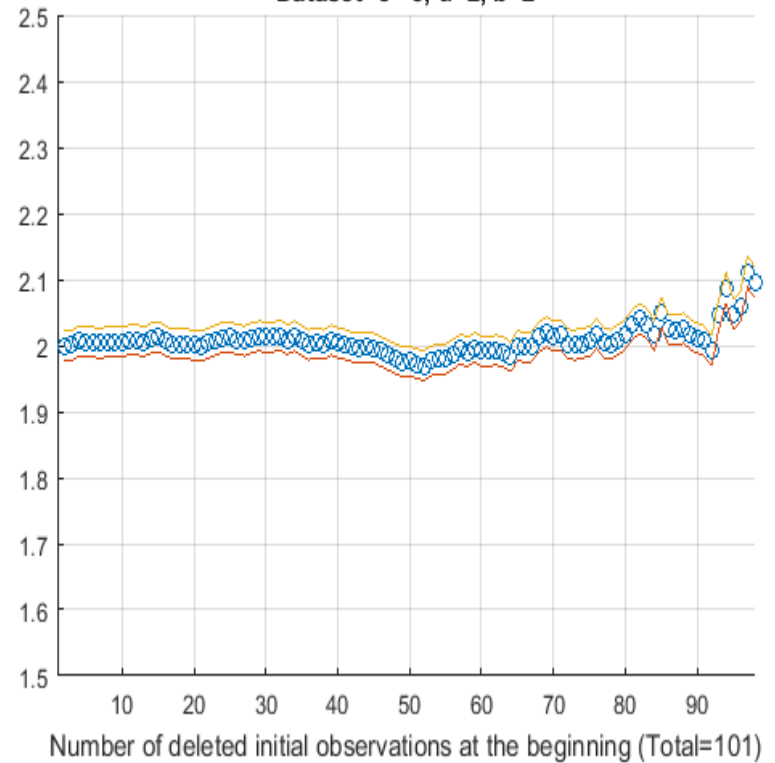


Estimation Accuracy- Initial Observation

Accuracy of c estiamtes
Dataset- c= 3, u=2, b=2

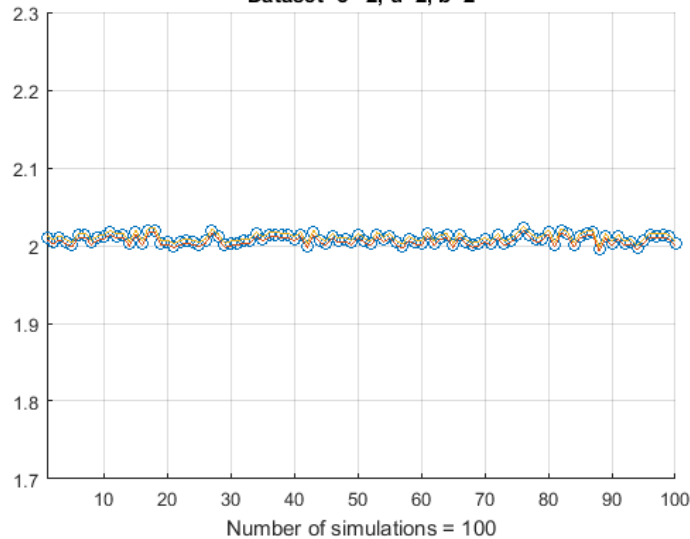


Accuracy of b estiamtes
Dataset- c= 3, u=2, b=2

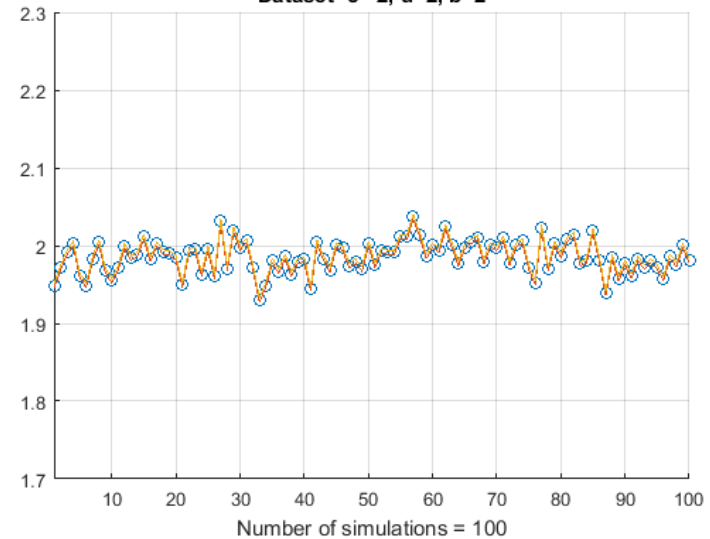


Opportunistic Observation

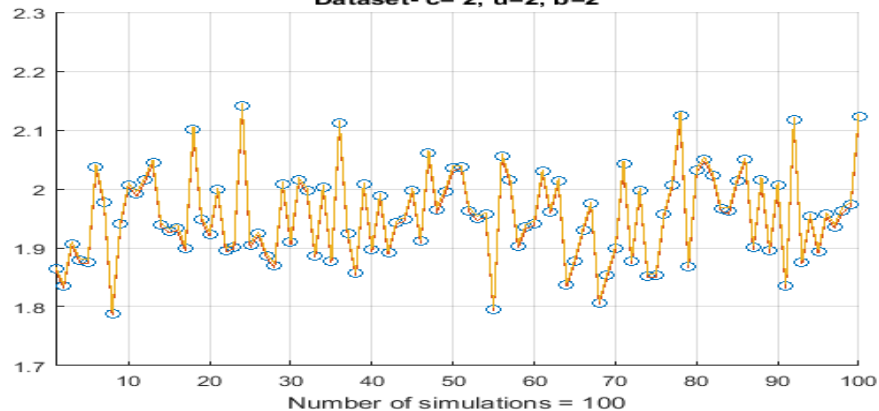
Accuracy of c estimates removing 5 observations (original estimate = 2.0108)
Dataset- $c=2$, $u=2$, $b=2$



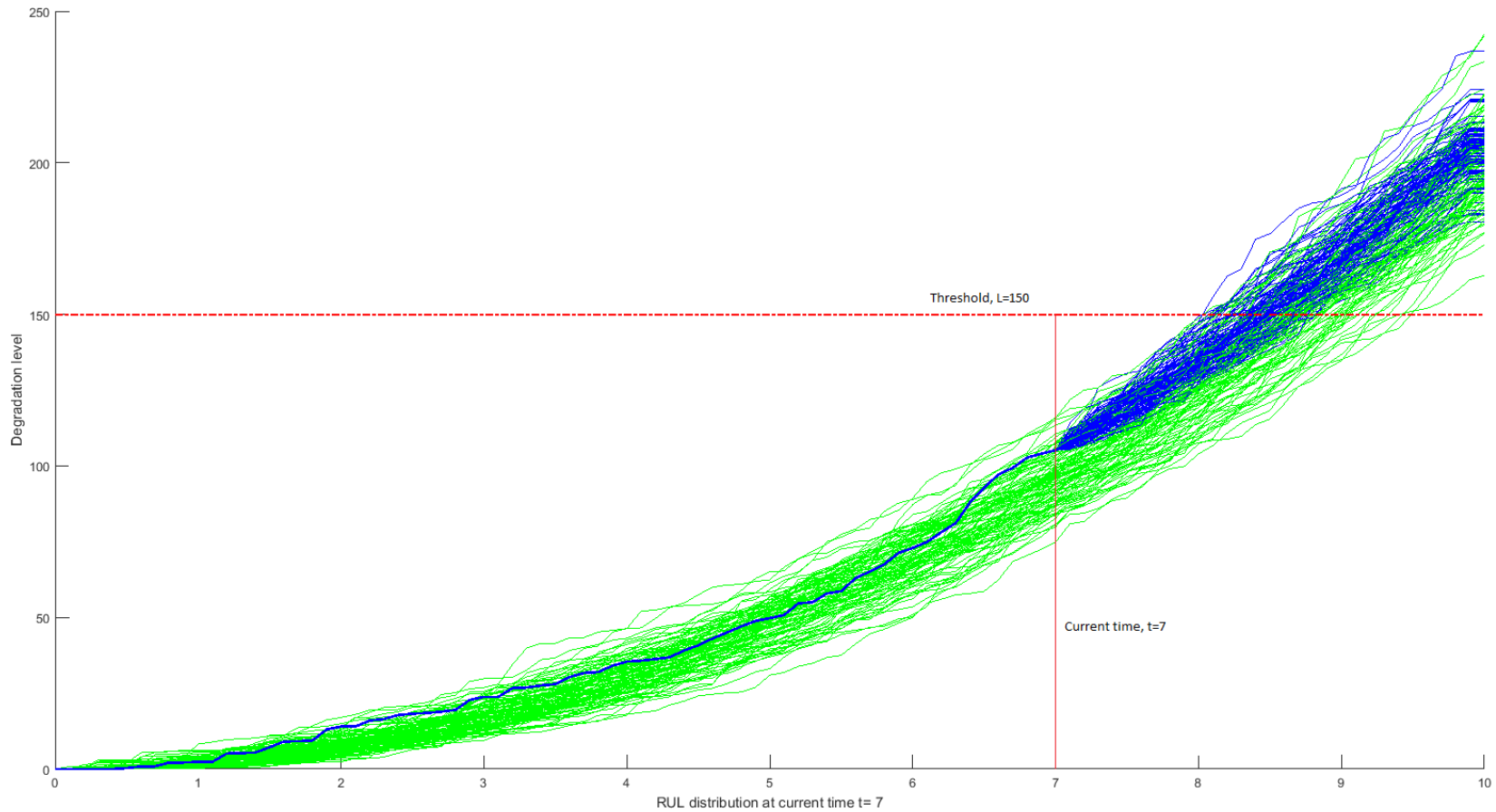
Accuracy of c estimates removing 50 observations (original estimate = 2.0108)
Dataset- $c=2$, $u=2$, $b=2$



Accuracy of c estimates removing 95 observations (original estimate = 2.0108)
Dataset- $c=2$, $u=2$, $b=2$



RUL (Illustration)



RUL Estimation

First Hitting Time, T_L

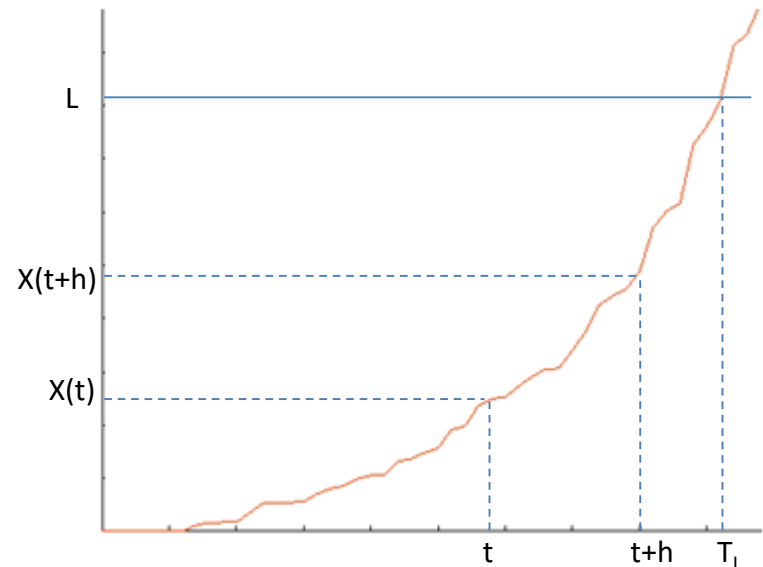
$$T_L = \inf(t > 0: X(t) \geq L)$$

CDF of FHT,

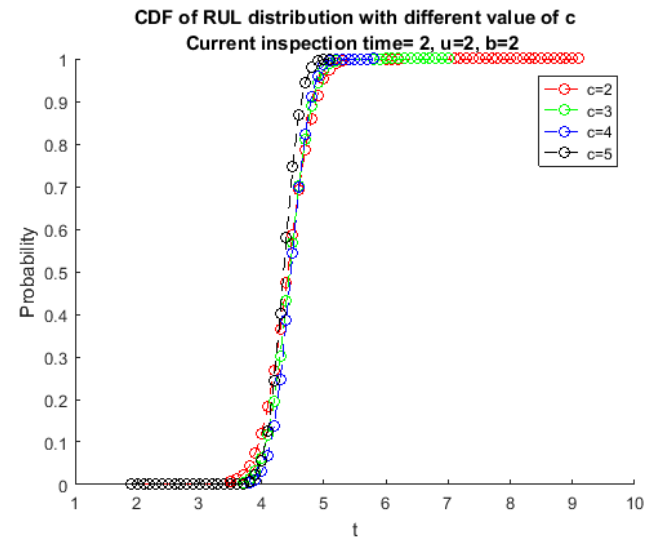
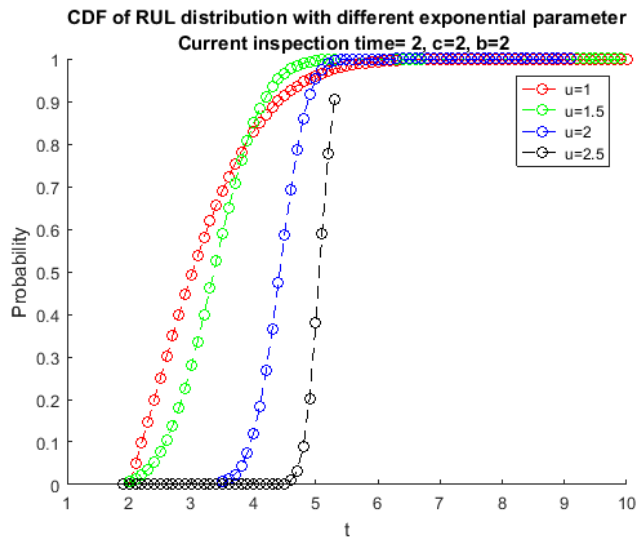
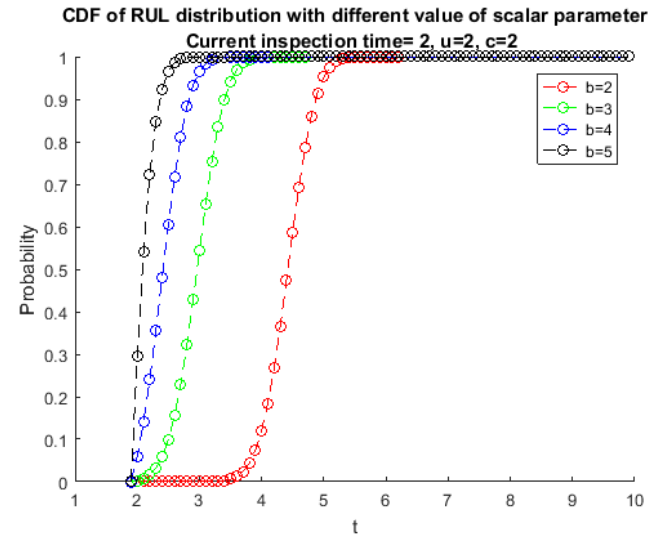
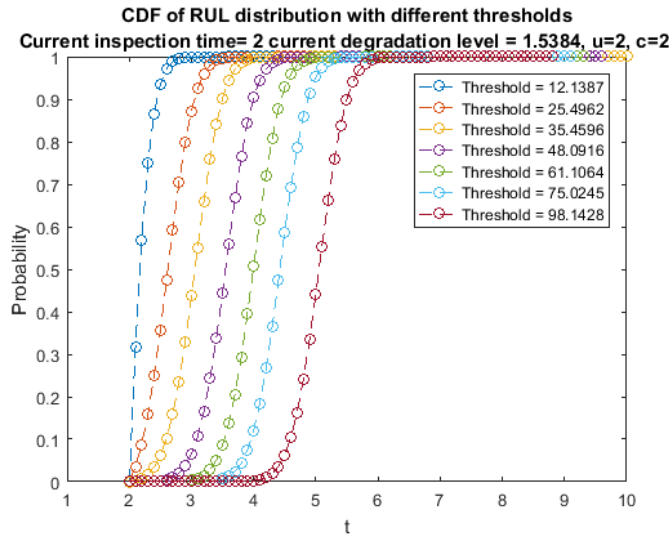
$$\begin{aligned} F(t) &= \Pr(T_L < t) = \Pr(X(t) \geq L) \\ &= \int_{x=L}^{\infty} f_{X(t)}(x) dx = \frac{\Gamma(A(t), Lb)}{\Gamma(A(t))} \end{aligned}$$

At time t when $X(t)=x(t)$, $RUL < h$

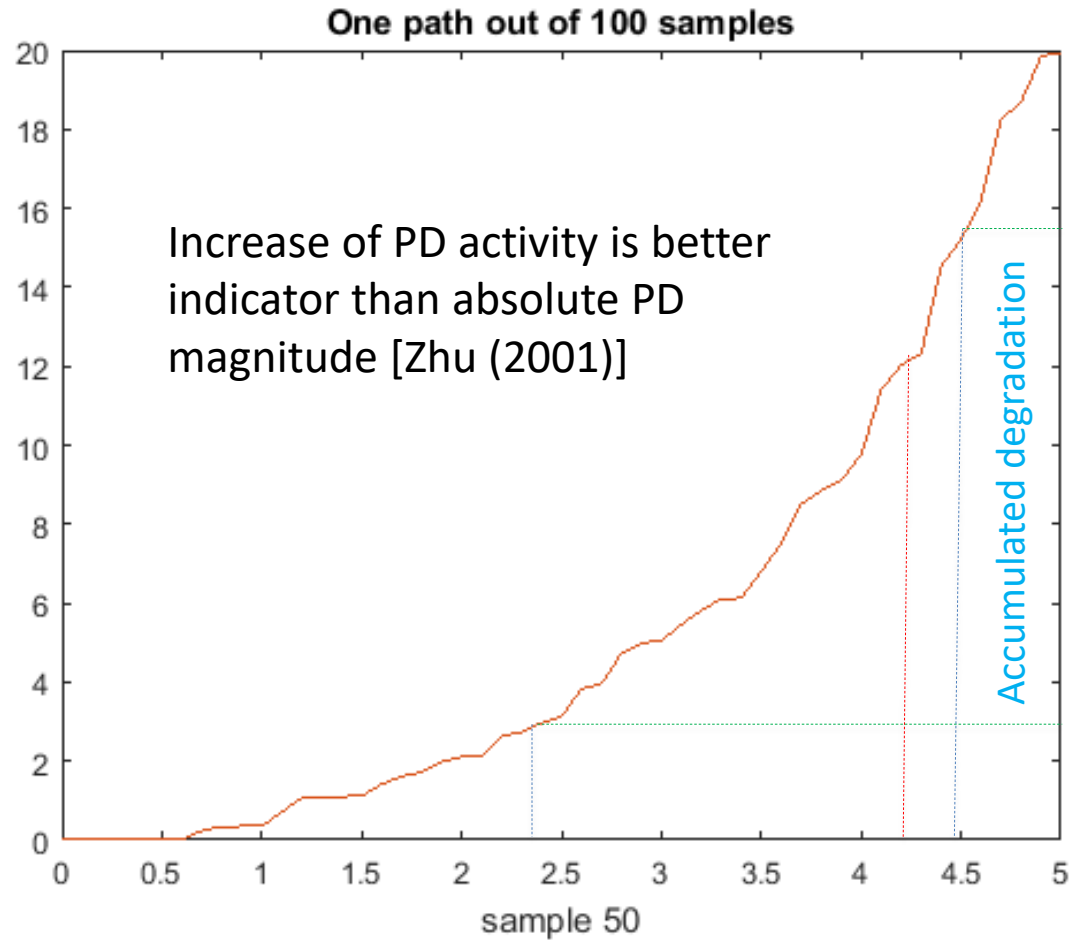
$$\begin{aligned} P(RUL \leq h) &= 1 - P(RUL > h) \\ &= 1 - P[X(t+h) < L | X(t) = x(t)] \\ &= 1 - \frac{P[X(t+h) - x(t) < L - x(t)]}{P(X(t) < L)} \end{aligned}$$



RUL Results



An Insight



Further Workplan

- Compare RUL estimations
 - Inspection intervals
 - Interpretations
- Discuss improvement
 - Adaptive model (update parameter)
 - Stochastic threshold
- Discuss System level RUL
 - Implementations
 - Challenges
- Data collection
 - Requirements
 - Conditions
 - PD? Misinterpretation?

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