Fusing More Frequent and Accurate Structural Damage Information from One Location to Assess Damage at another Location with Less Information

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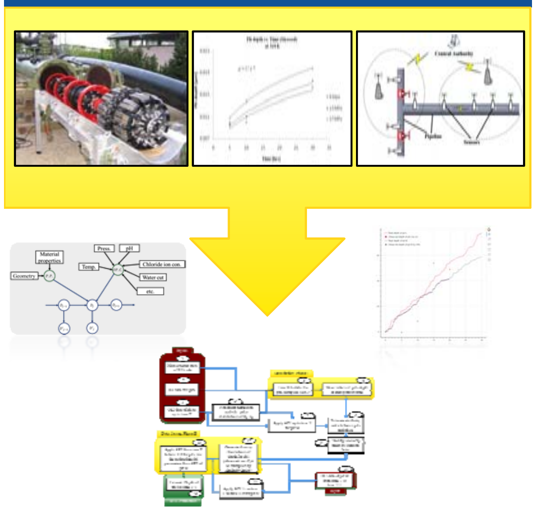
Outline

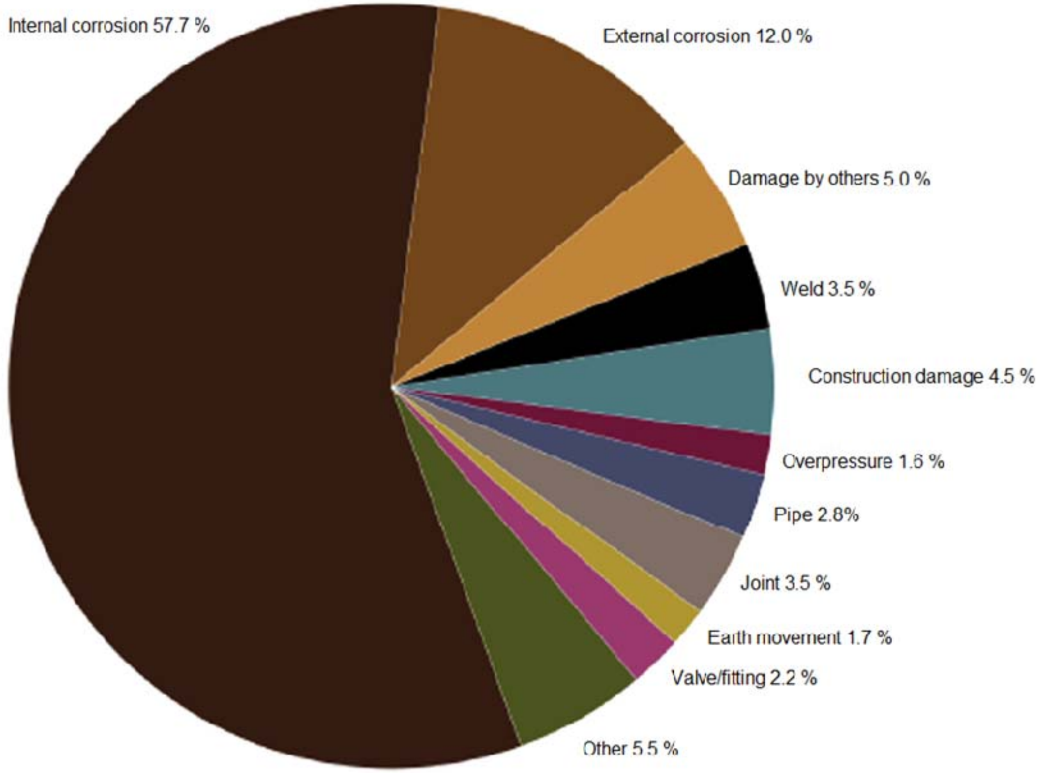
- Introduction & Motivation & Assumptions
- Literature review
- Proposed Approach
- Summary



Introduction & Motivation & Assumptions

Introduction

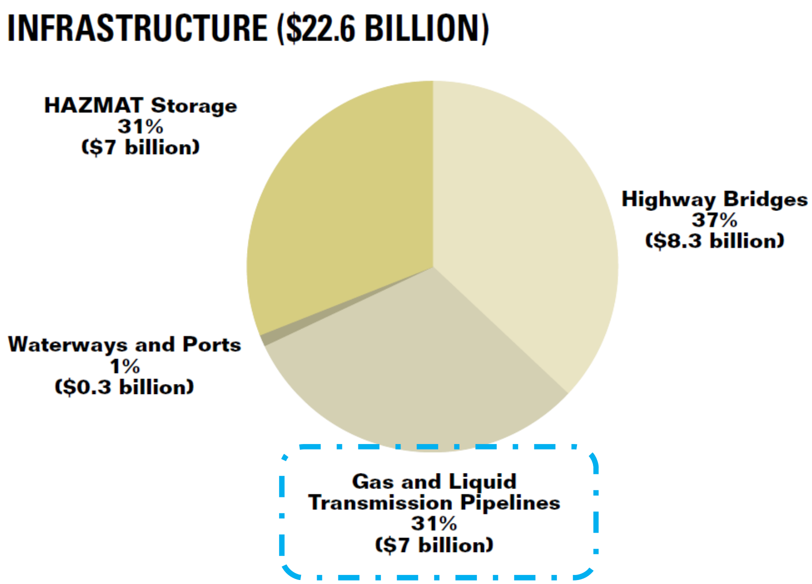
Pitting corrosion is a primary and one of the most severe failure mechanism of oil and gas pipelines because of the high rate at which pits can grow [Velázquez, Caleyo, Valor, & Hallen, 2009].



Alberta, Canada Production Pipeline Failure Data for 1980–2005. [Papavinasam, 2013]

Motivation

- To decrease the total cost due to internal pitting corrosion by finding an optimal proactive maintenance policy



Annual cost of corrosion in the infrastructure category in the USA. [Koch et al., 2002]

Motivation

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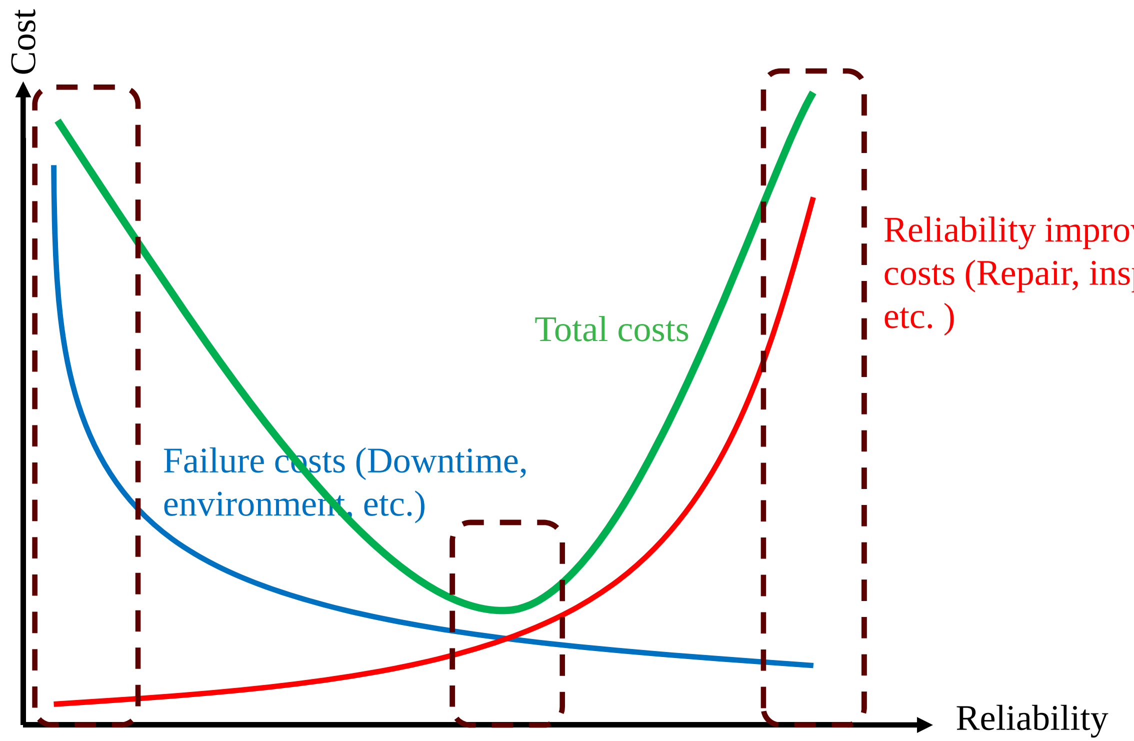


Low reliability leads to high failure cost

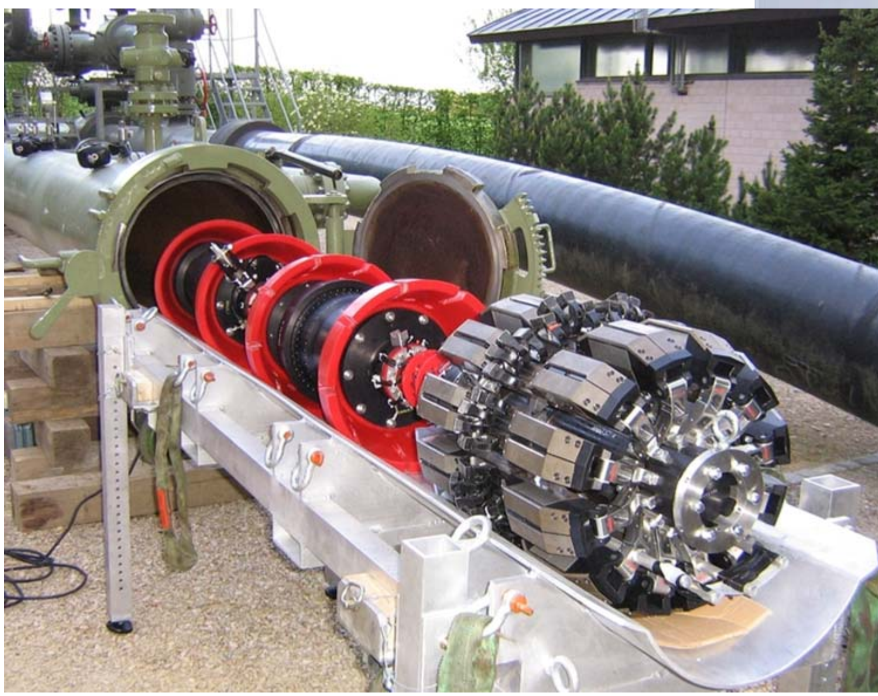
Optimal reliability level to minimize the total cost

High reliability leads to high maintenance cost

In order to calculate the reliability level of the pipeline, a proper degradation model is required.

Assumptions

- ILI or pigging data (infrequent, discrete and low quality information) for most segments of the pipeline are available.

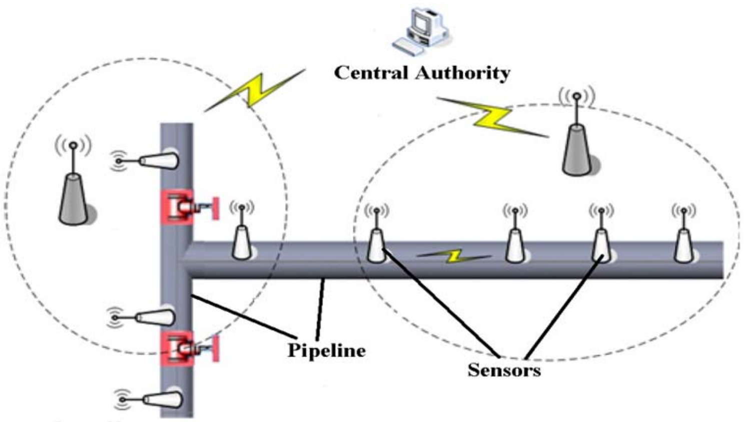


iecetech.org

https://constructionreviewonline.com/2014/12/ethiopia-receives-us1-4bn-petro-pipeline-project-proposal/

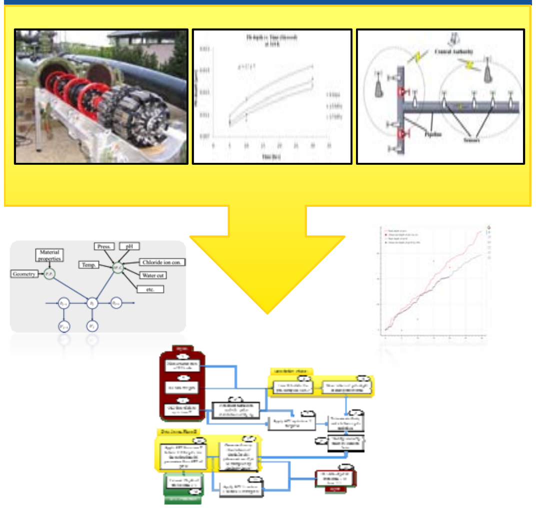
Assumptions

- ILI or pigging data (infrequent, discrete and low quality information) for most segments of the pipeline are available.
- Online inspection (OLI) data (continuous, discrete, and high quality information) and human inspection (infrequent, discrete, and high quality information) for some pipeline segments are available.



[Wan et al., 2011]

- The pipeline is aged and piggable (with some non-piggable segments).
- Pits are not interacting with each other.
- All pits are under similar operational condition at each time.
- Details about the sensor layout, the NDT equipment and the methods (coverage area, probability of detection and measurement errors, etc.) are known.



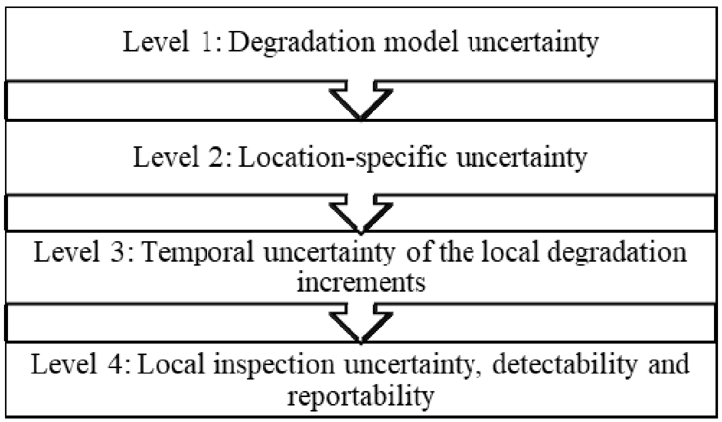
Literature review

- On data fusion algorithms
- On pitting corrosion degradation models

Literature review on data fusion algorithms on pipeline degradation

- Maes et al., (2009) fused multiple ILIs data in a hierarchical Bayesian framework to predict defect growth. They did not consider the variation in pits' initiation times.
- Zhang and Zhou (2013) considered corrosion initiation times within the previous work. Both of these works just used the ILI data.
- Rabiei et al. (2016) used augmented particle filtering to fuse two types of sensor data (i.e., acoustic emission and modulus of elasticity) from a damage in a metallic alloy under fatigue to estimate the degradation level.
- **Gaps**: **None of these works fused ILI and online sensor data from different objects (pits). The similarity between objects should be estimated which requires a physics-based degradation model**.

Literature review on pitting corrosion degradation models was used to identify six requirements for a proper model

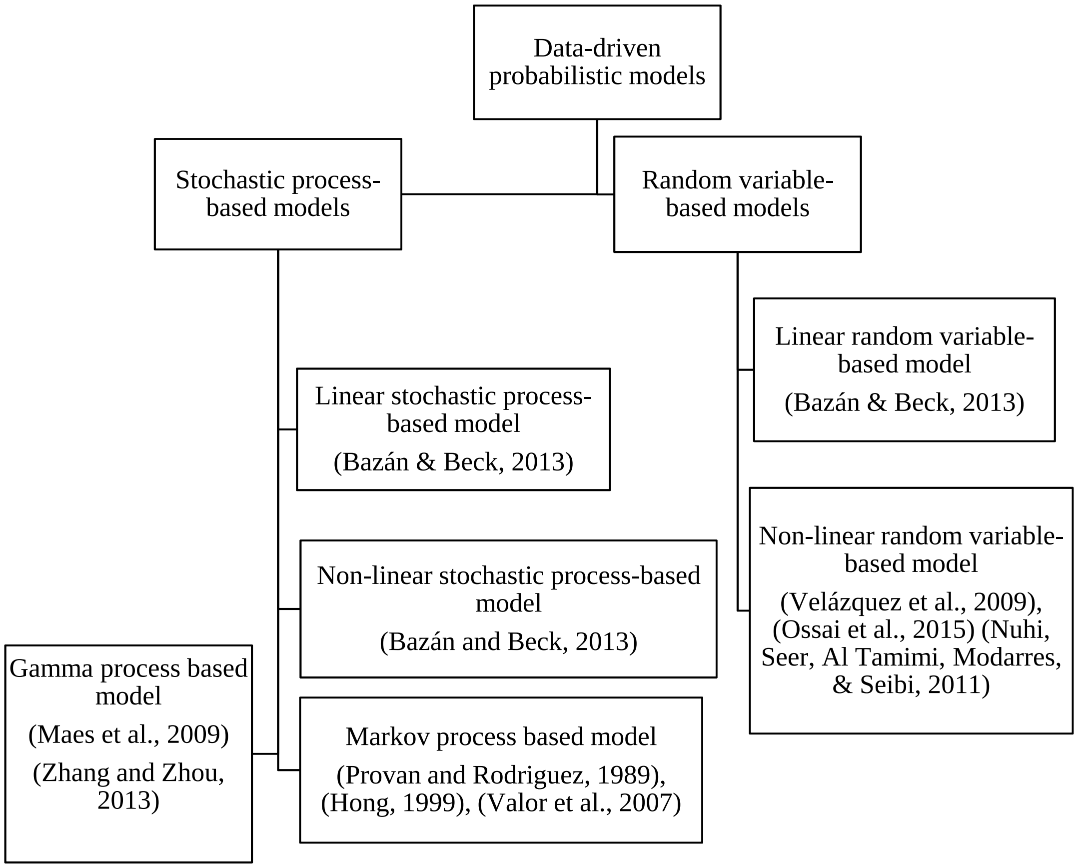


Hierarchical levels of uncertainty in degrading systems (Maes et al, 2009)

- Characteristic I: the corrosion rate of a deeper pit is greater than the corrosion rate of a shallower one (Rivas et al., 2008)

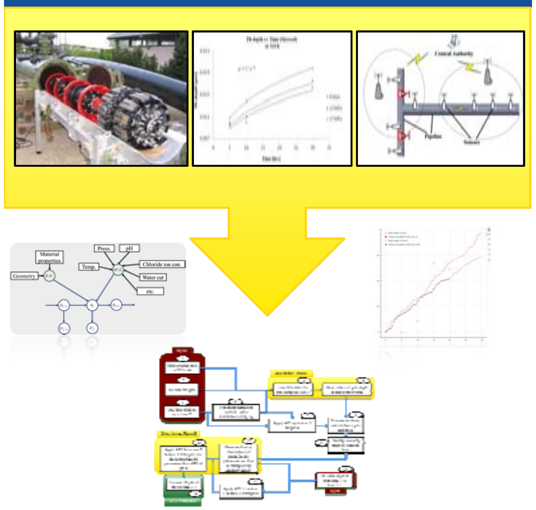
- Characteristic II: the corrosion rate decreases over time and this declining behavior follows a power-law model with a less than one positive exponent ((Velázquez et al., 2009) (Ossai, Boswell, & Davies, 2015) (Nuhi, Seer, Al Tamimi, Modarres, & Seibi, 2011))

Literature review on pitting corrosion degradation models; helped point to the correct modeling framework



Evaluation of current available models

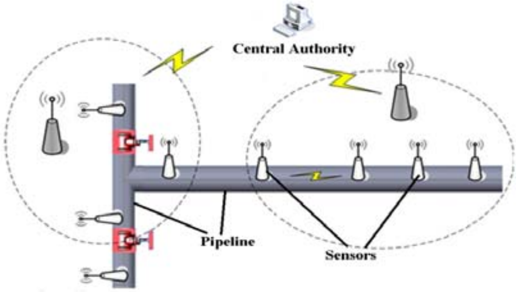
Model	Level 1	Level 2	Level 3	Level 4	Characteristic I	Characteristic II	Practicality
Linear Random variable models	√						**PI 1**
Nonlinear Random variable models	√					√	**PI 1**
Linear Stochastic Process models	√		√				**PI 2**
Nonlinear Stochastic Process-based models	√		√			√	**PI 2**
Markov process-based models	√		√		√	√	**PI 3**
Gamma process-based models	√	√	√	√		√	**PI 3**



Proposed approach

Fusing ILI and OLI data and physics of the failure

[iecetech.org]



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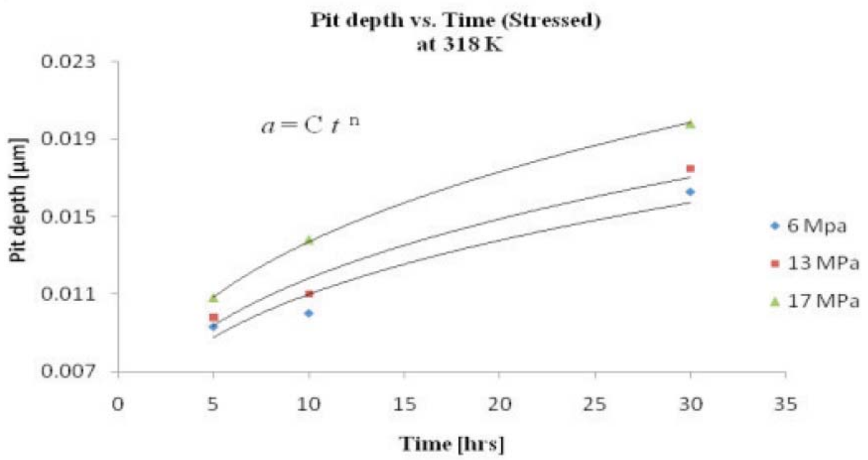

[Nuhi et al., 2011]

[Bazán & Beck, 2013; Ossai et al., 2015; Velázquez et al., 2009]

Pros and cons of In-Line Inspection (ILI)

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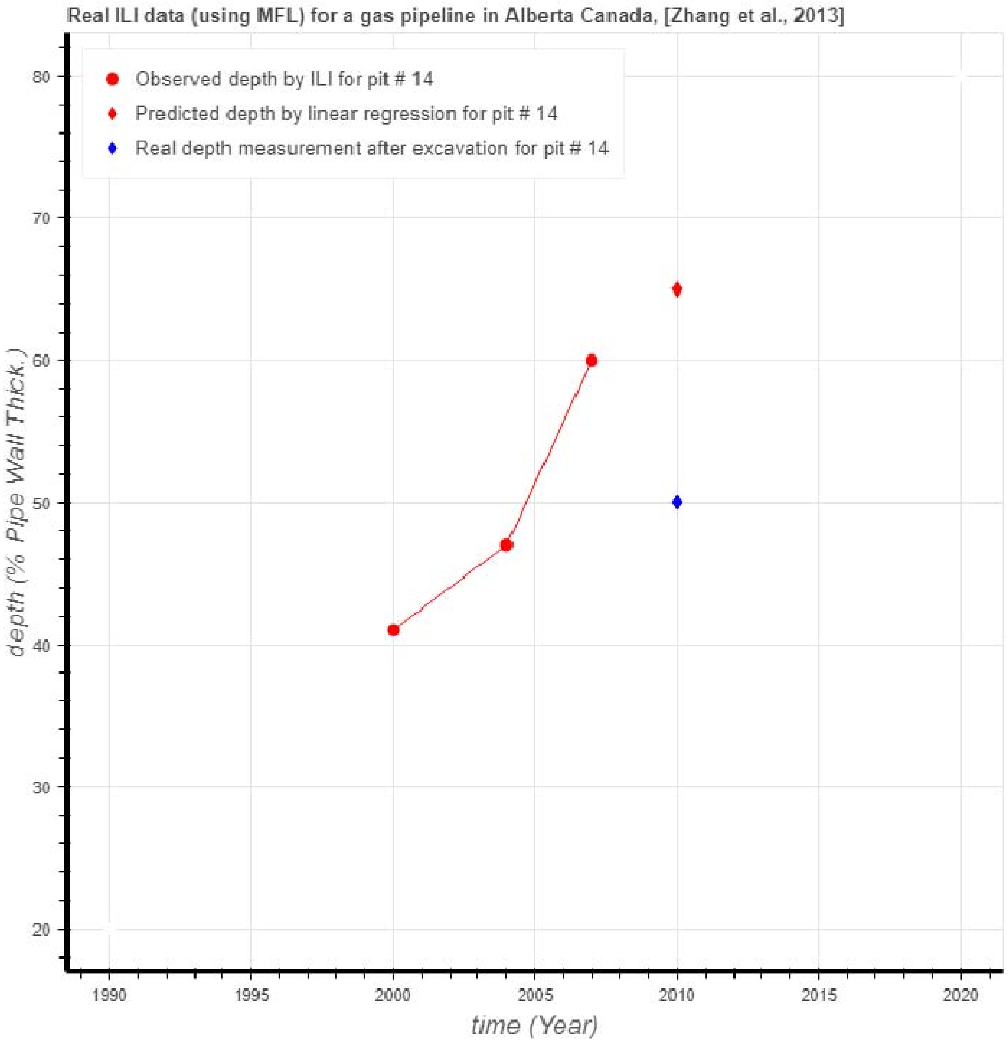
Pros:
- Comprehensive (Covers a long distance)

Cons:
- Expensive
- High measurement error
- Low frequency (e.g., every five years)



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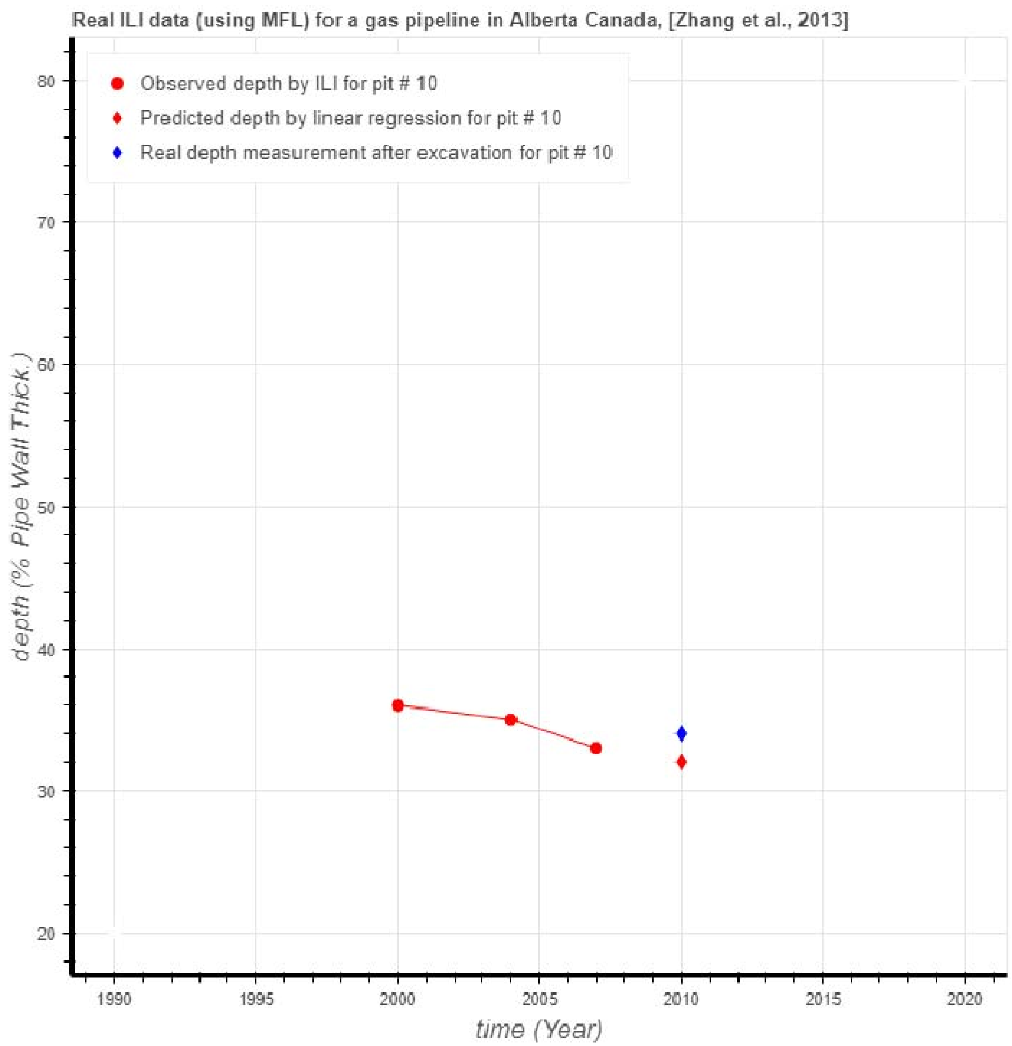

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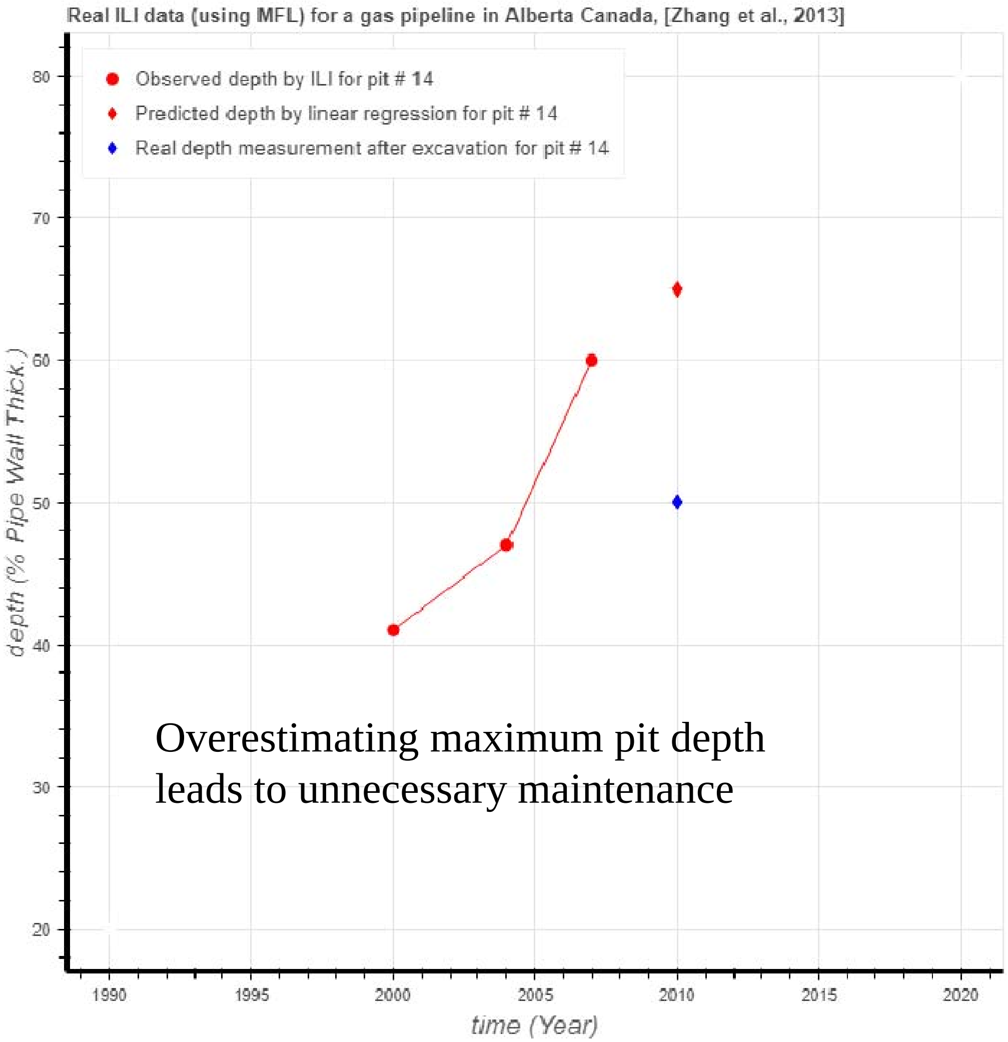

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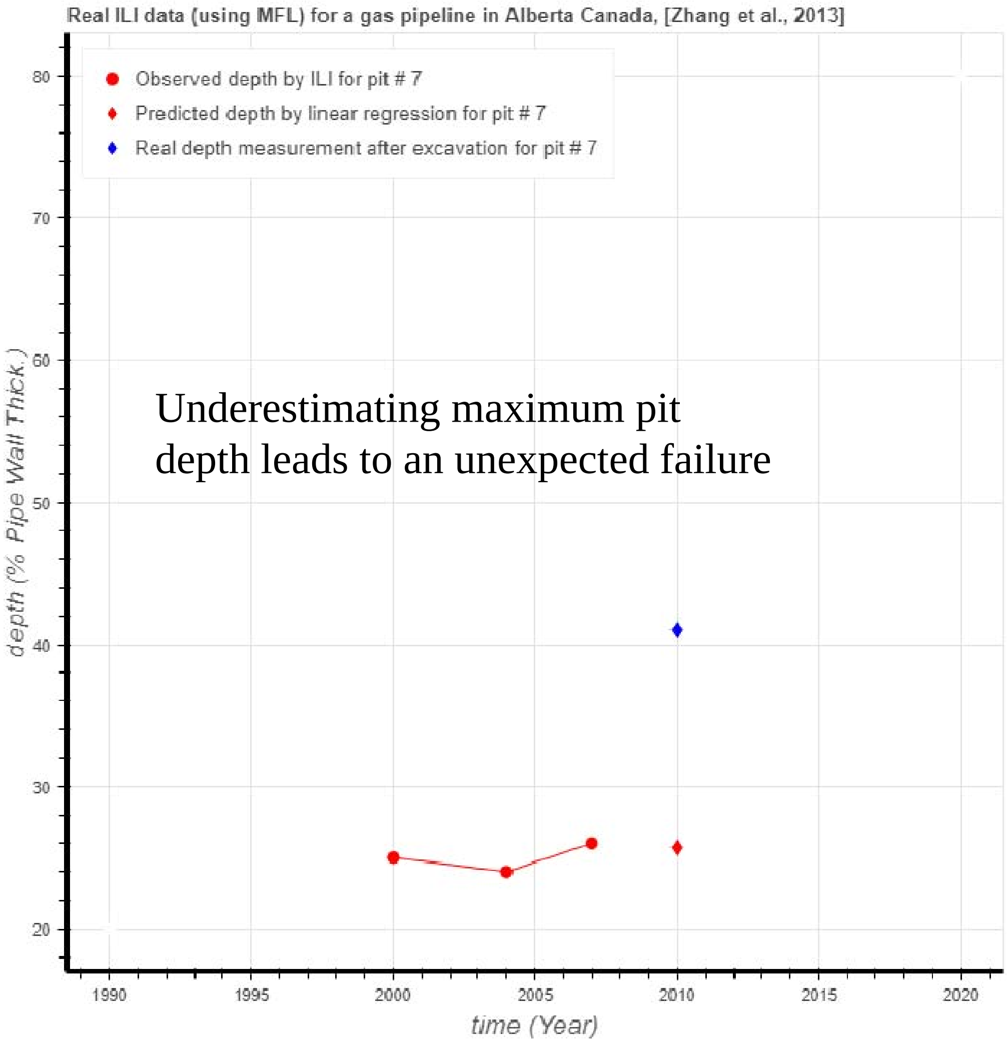
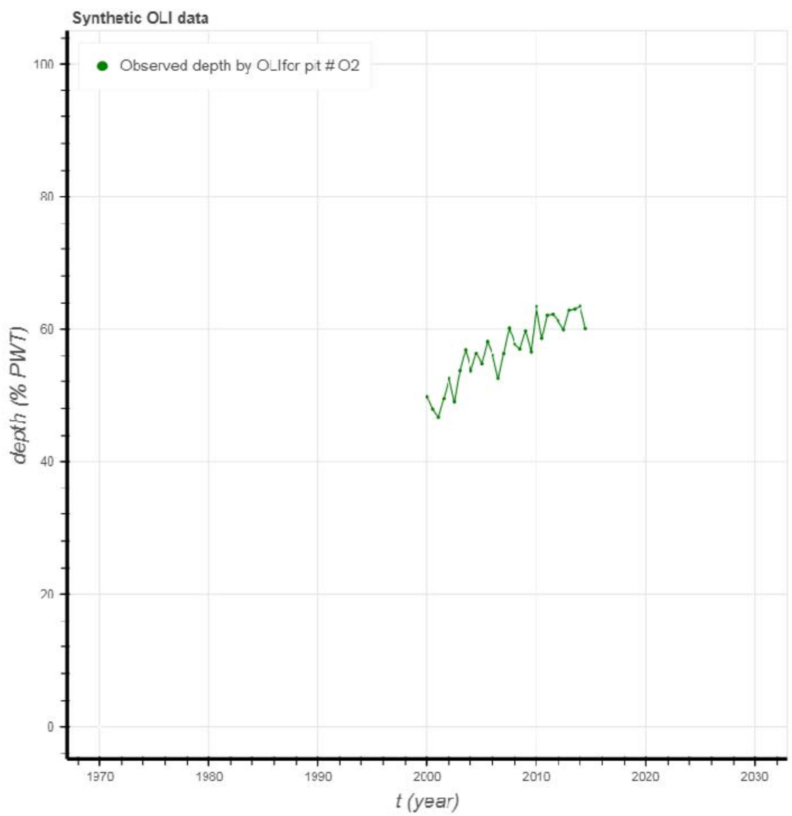
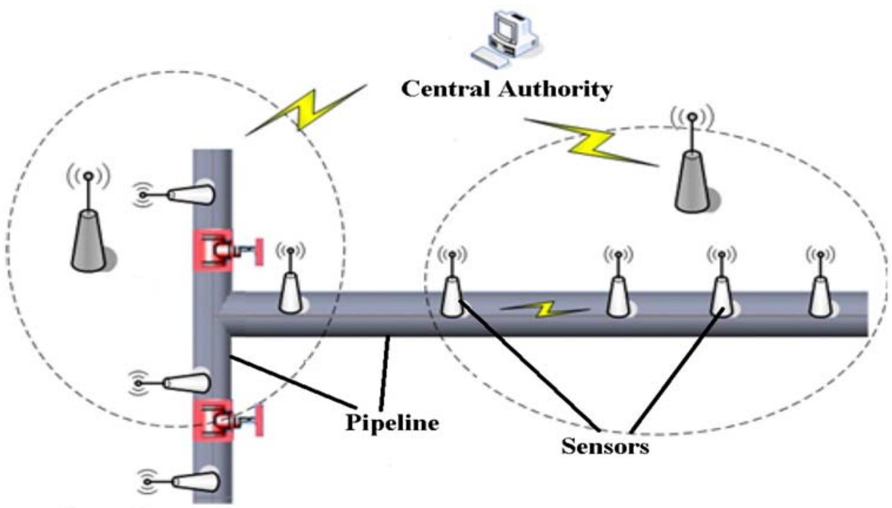


Pros and cons of Online Inspection (OLI)





[Wan et al., 2011]

Pros:

- Low measurement error
- High frequency (e.g., near continuous)

Cons

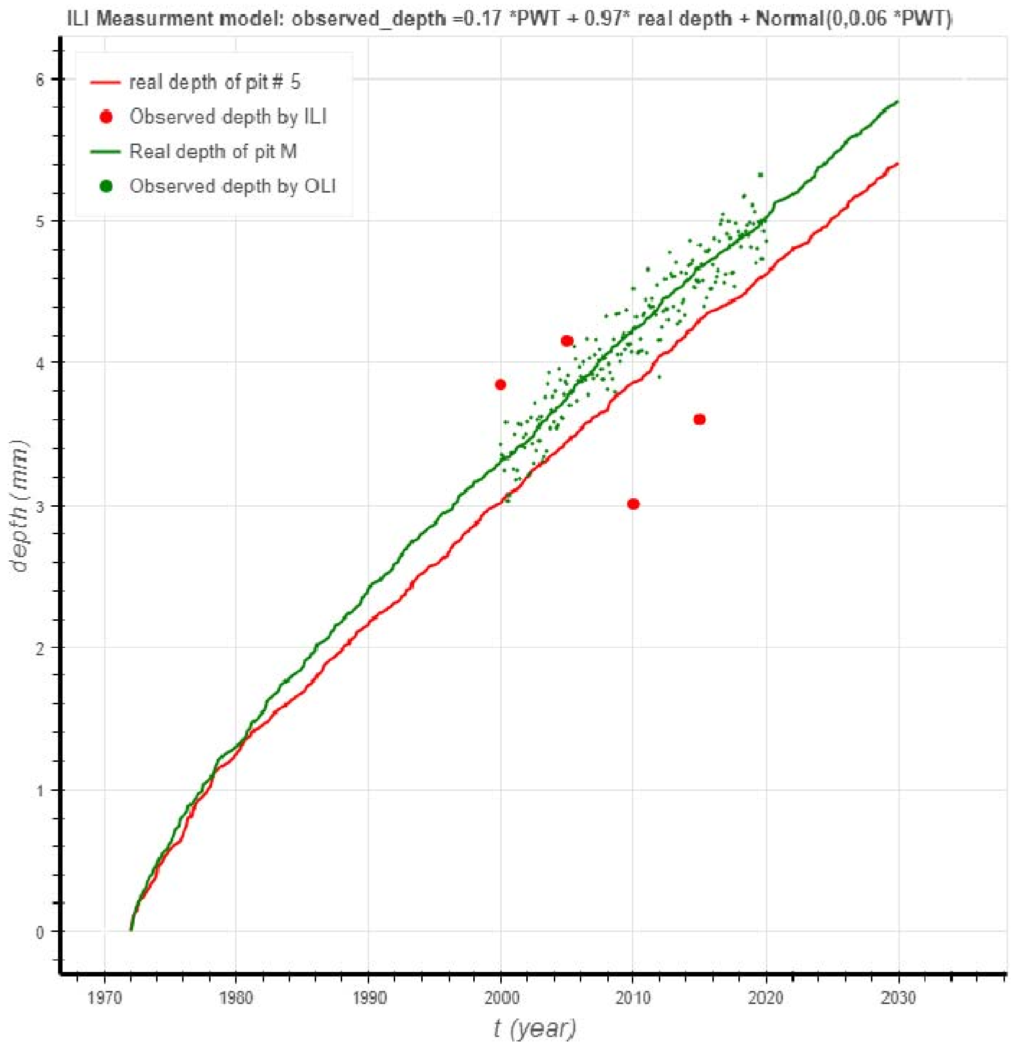
- Requires power
- Discrete in location
- They rarely cover a large area of the pipelines

OLI helps to decrease the epistemic uncertainty

Developed data fusion framework

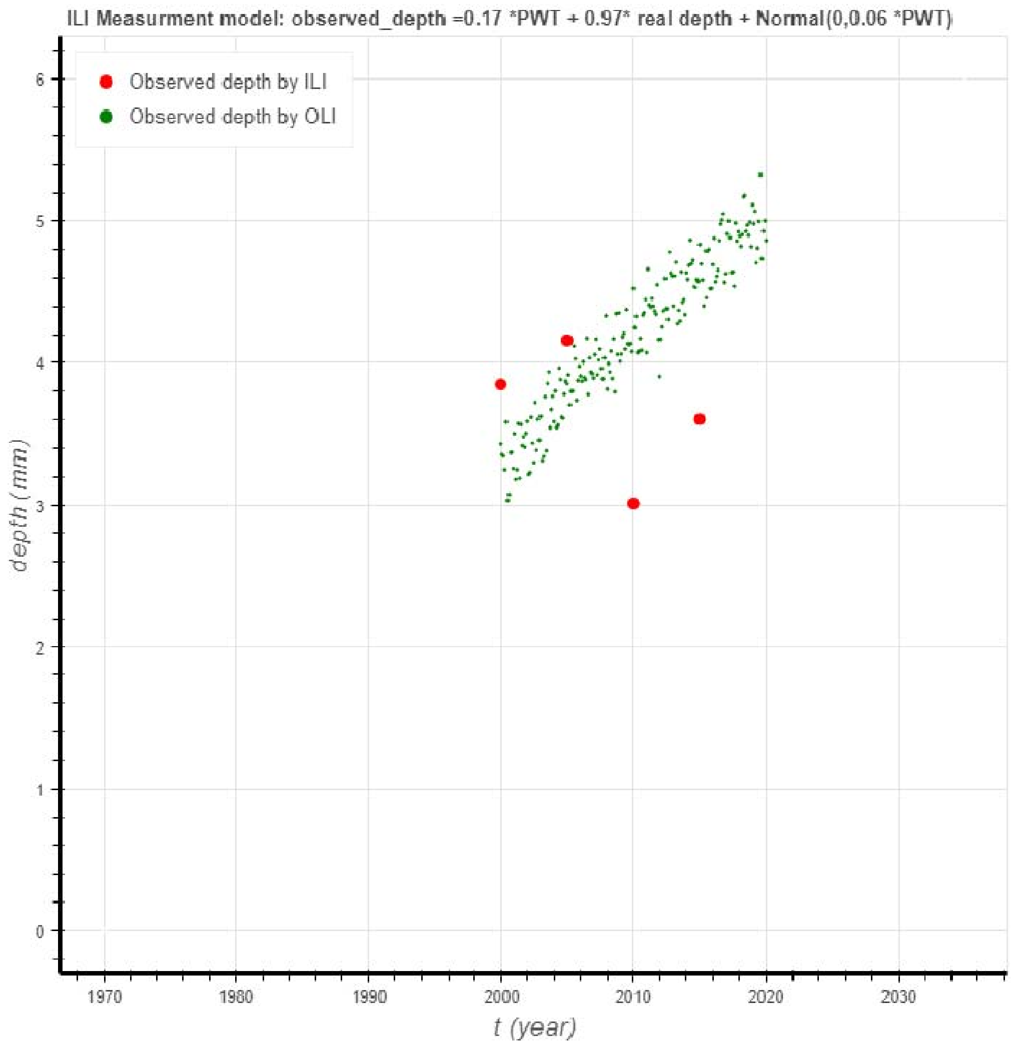
- Estimating prior values for model parameters by non-linear regression analysis. $d = \theta_1(t_k - t_0)^{\theta_2}$
- Estimating maximum pit depth of ILI pits by using a hierarchical Bayesian-non-homogeneous gamma process (HB-NHGP)
- Estimating maximum pit depth of OLI pits by augmented particle filtering (APF)
- Defining similarity index between each ILI pit and each OLI pit
- Generating dummy observations of pit depth for ILI pits
- Using APF to estimate maximum pit depth of ILI pits by using the generated dummy observation
- Estimating RUL

Developed data fusion framework



Answering the question:
How to fuse more frequent OLI data with less frequent ILI data of different pits at different locations?

Developed data fusion framework



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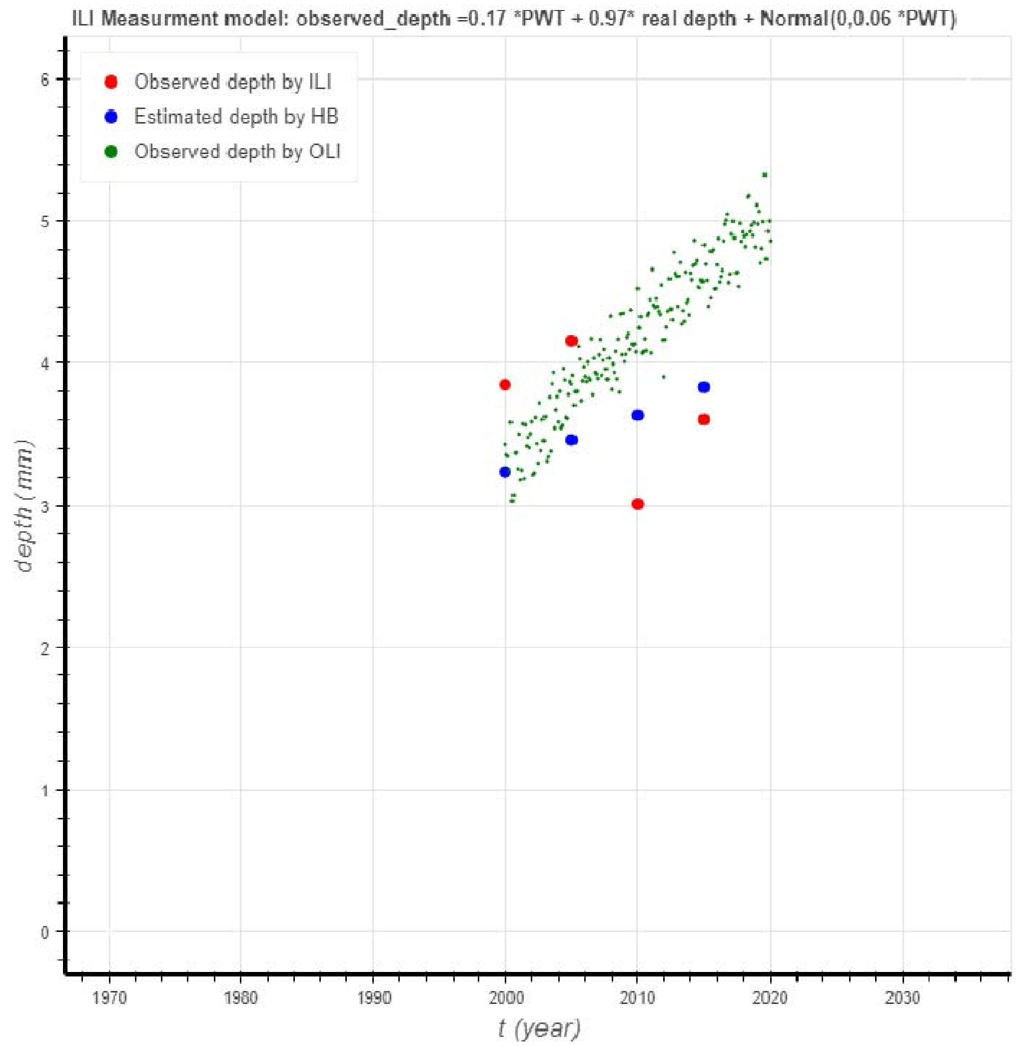

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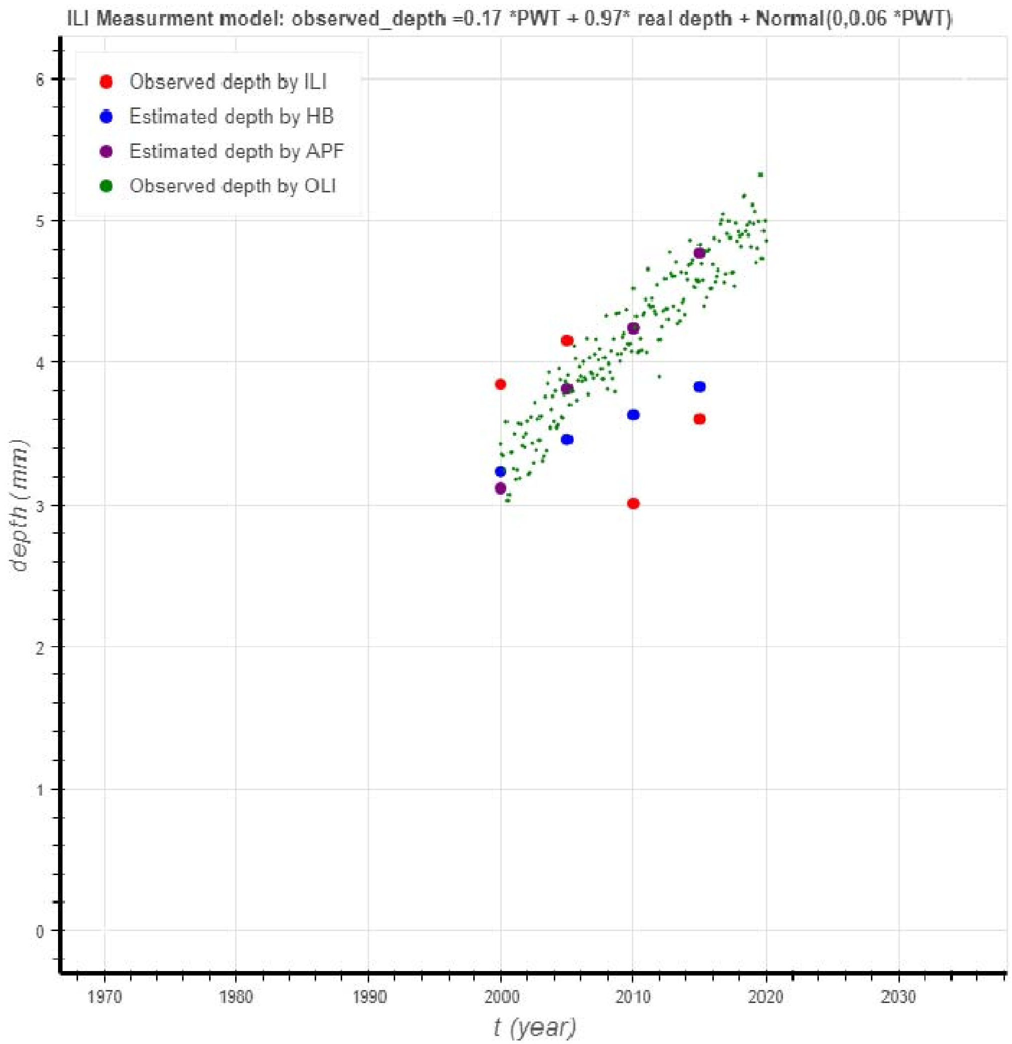

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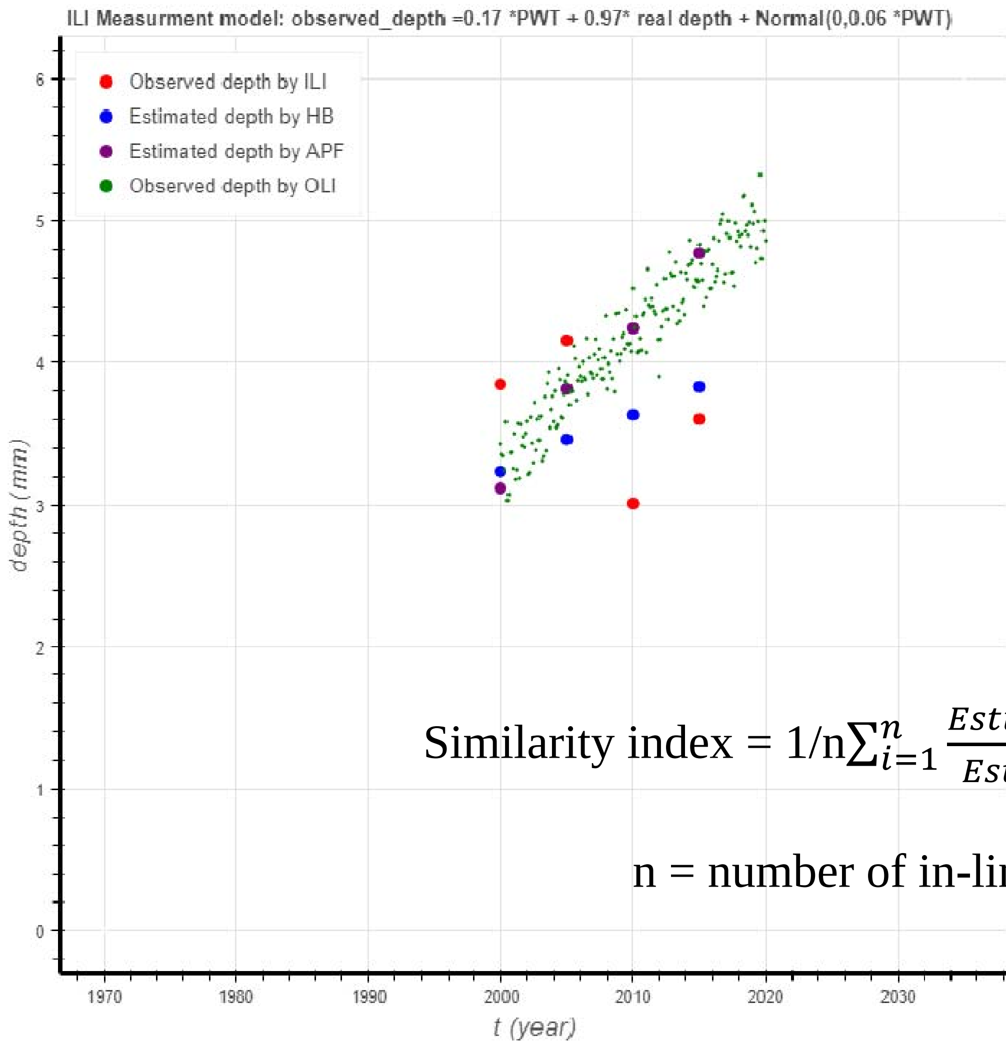

Answering the question:
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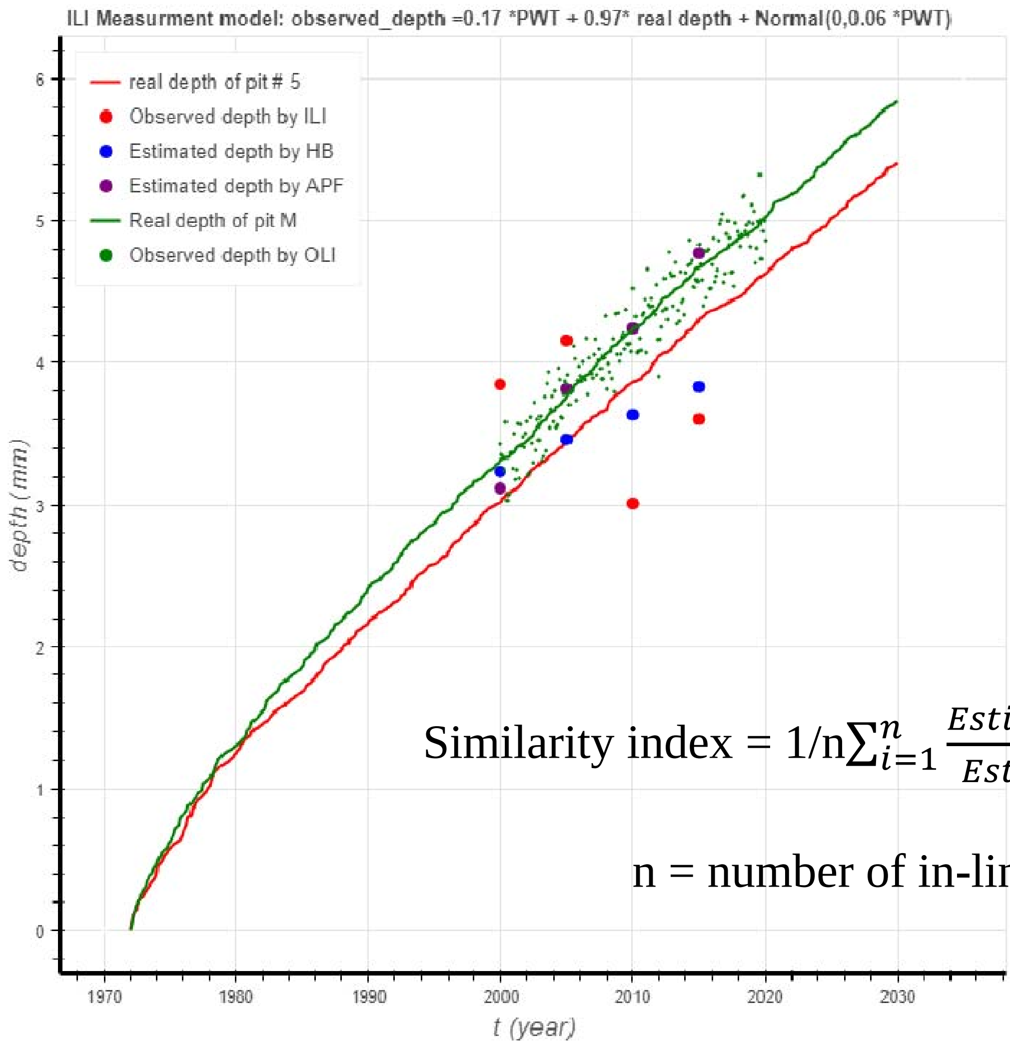
Similarity index = $1/n\sum_{i=1}^{n} \frac{Estimated\ depth\ of\ an\ OLI\ pit\ by\ APF}{Estimated\ depth\ of\ an\ ILI\ pit\ by\ HB}$

n = number of in-line inspections

Developed data fusion framework



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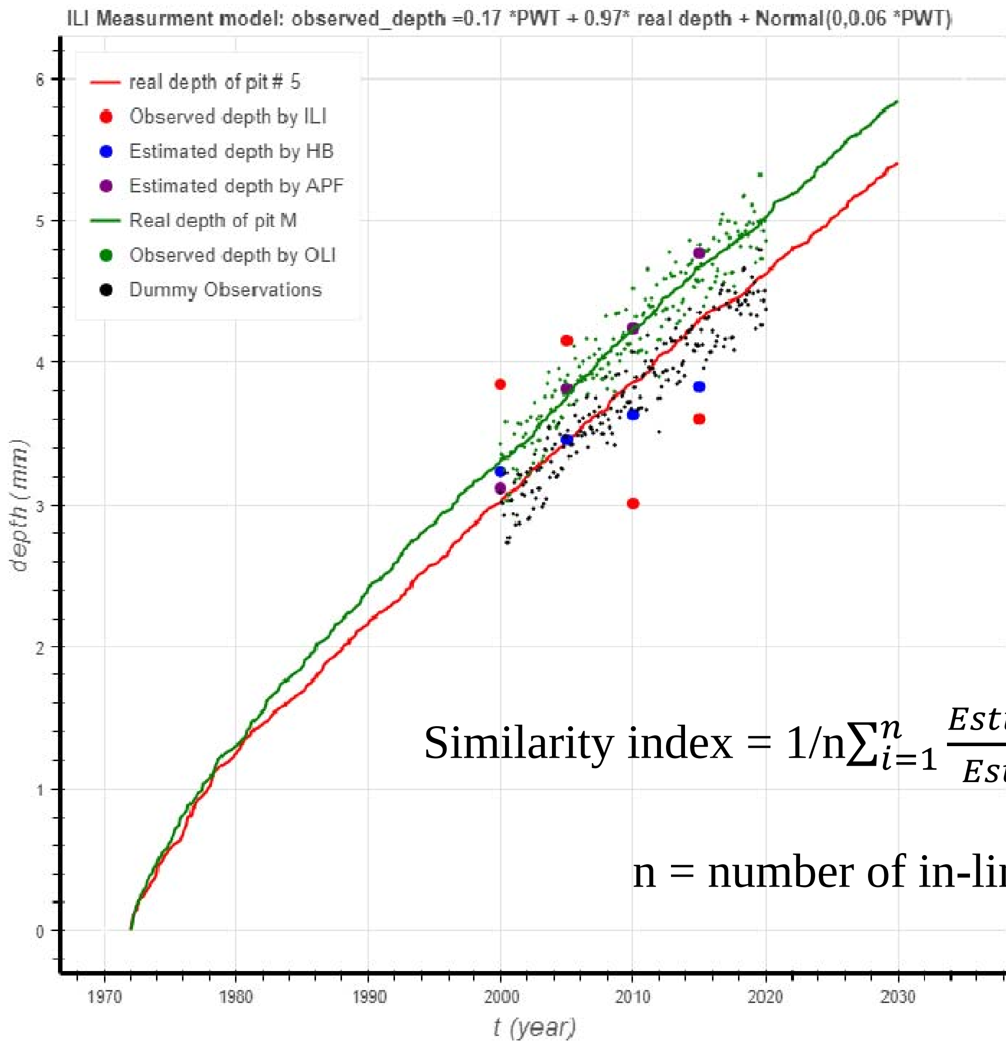

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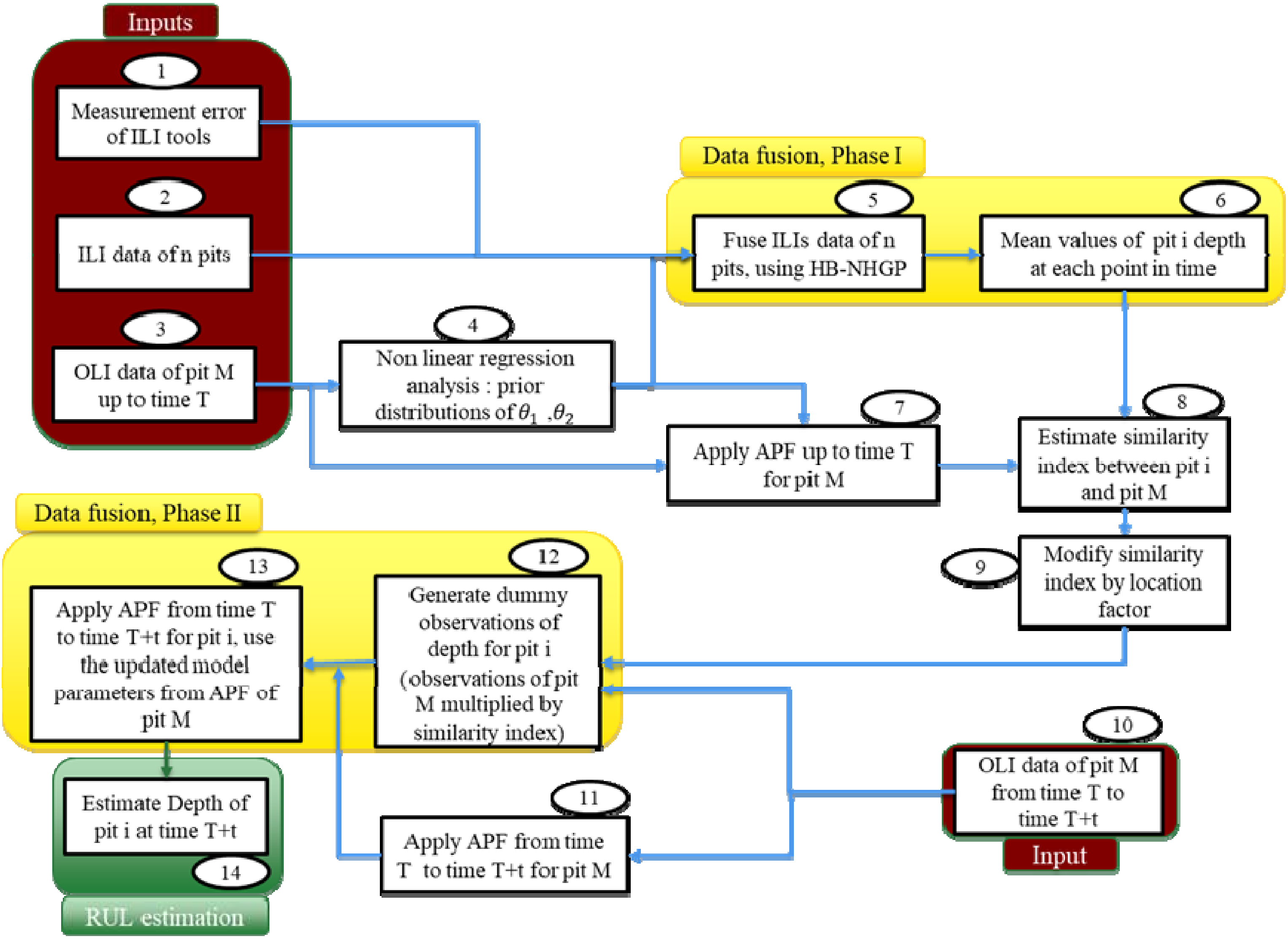
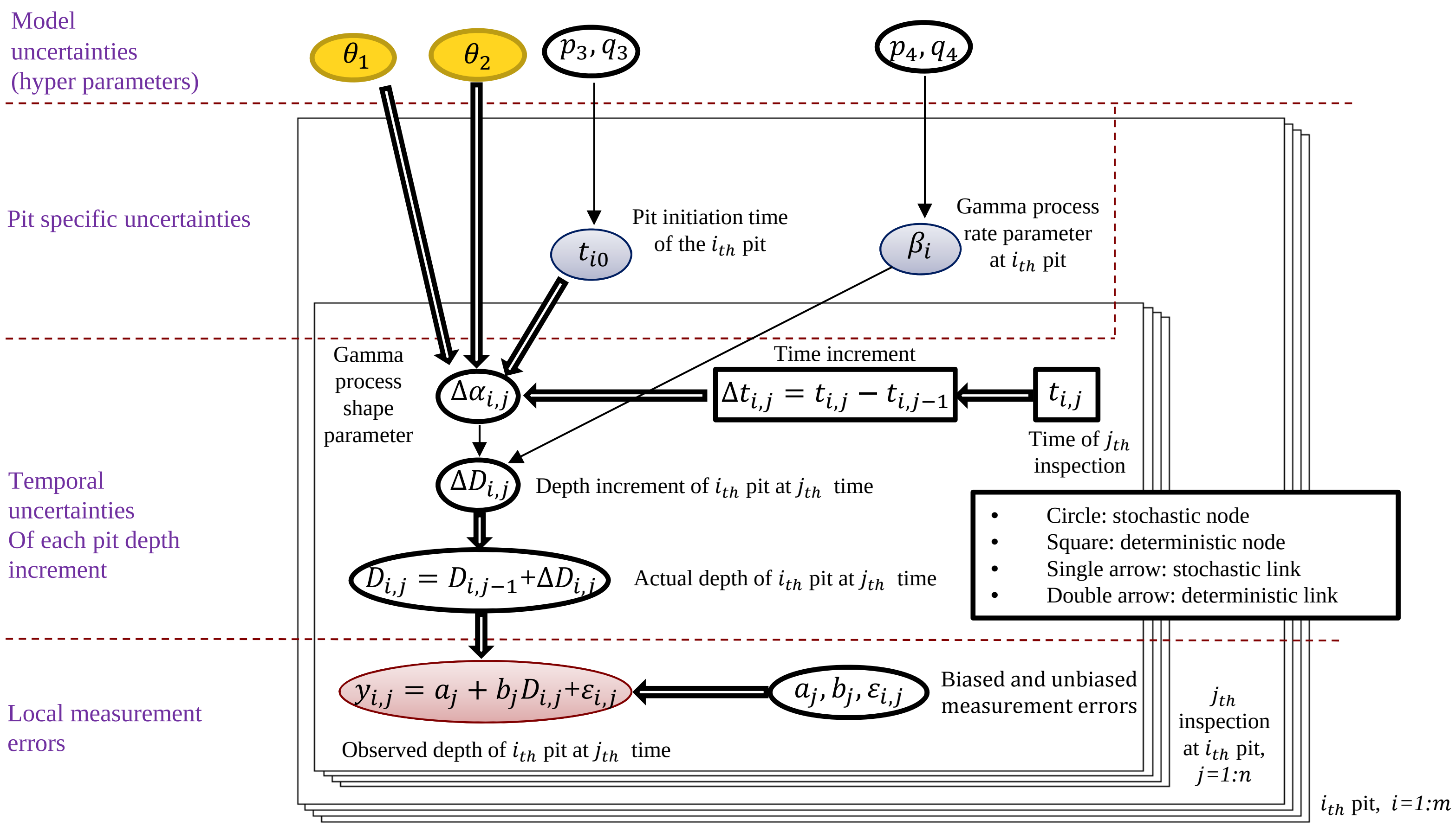


Hierarchical Bayesian-non-homogeneous gamma process (HB-NHGP)

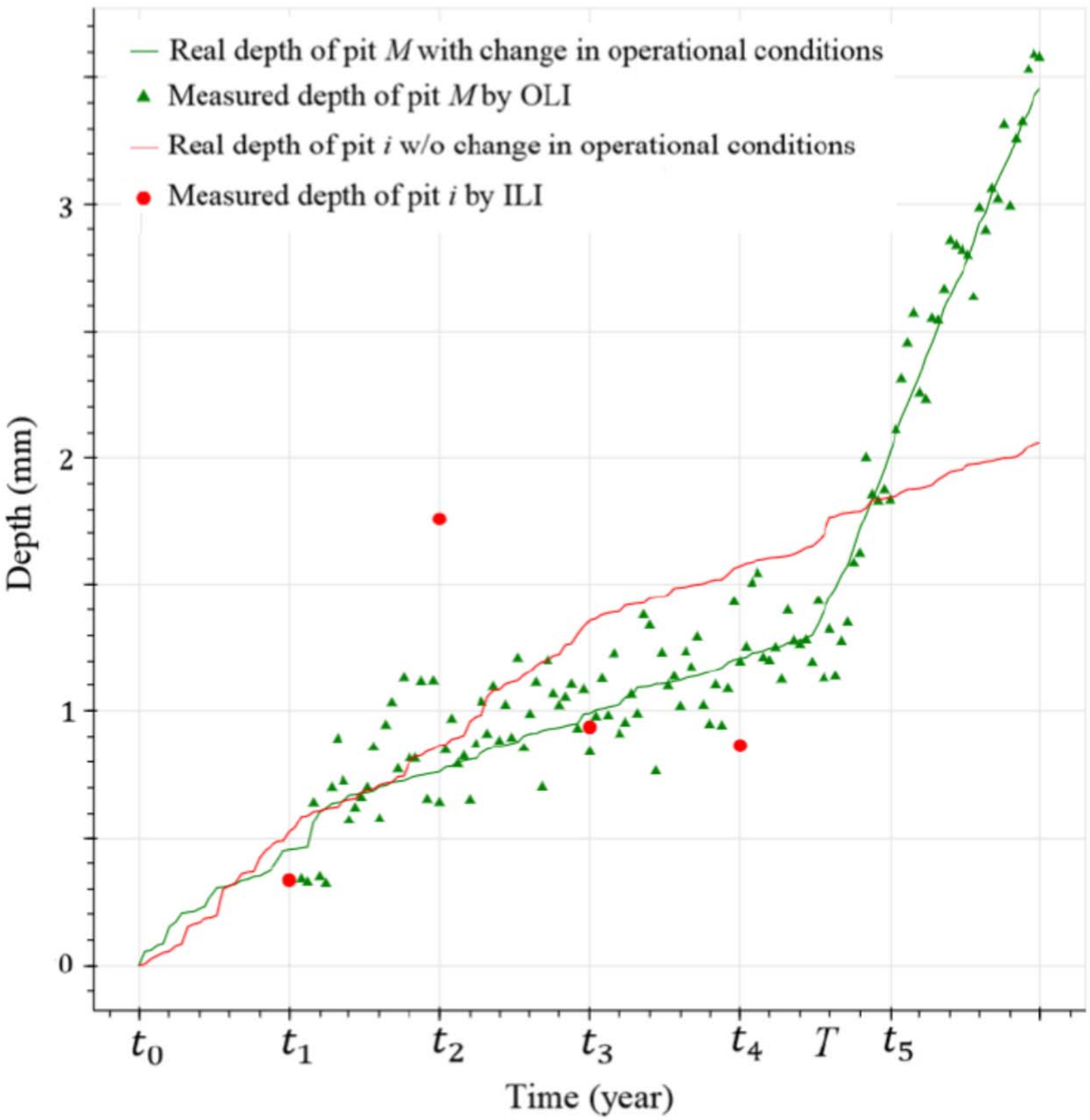


Modified from (Maes, Dann, Breitung, & Brehm, 2008)

$$\alpha(t) = \theta_1 (t - t_0)^{\theta_2}$$

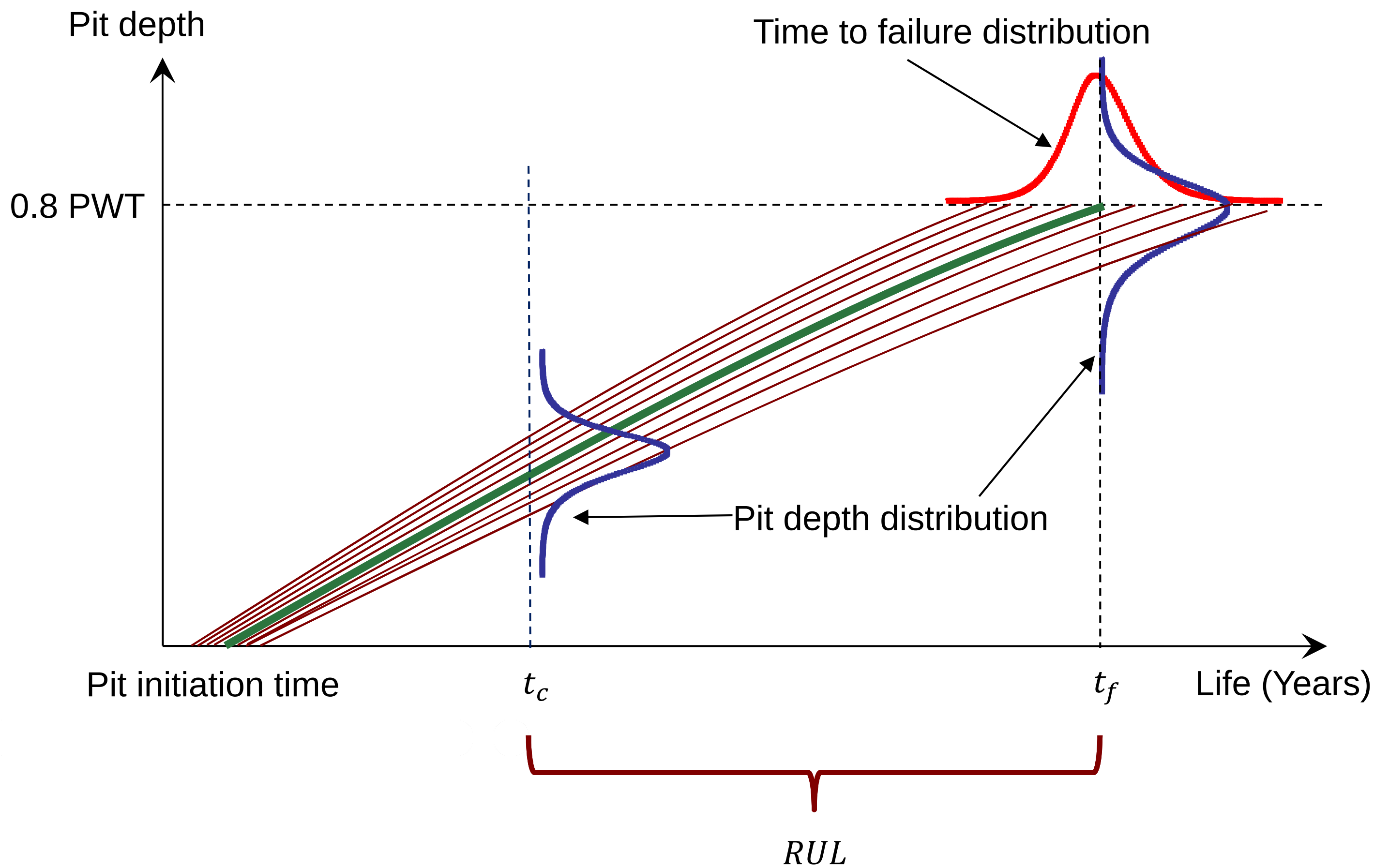
$$f(\Delta D(t)) = Ga(\Delta D | \Delta\alpha(t), \beta) = \frac{\beta^{\Delta\alpha(t)}}{\Gamma(\Delta\alpha(t))} \Delta D^{\Delta\alpha(t)-1} \exp(-\beta \Delta D)$$

Using this framework to consider change in operational condition in RUL estimation



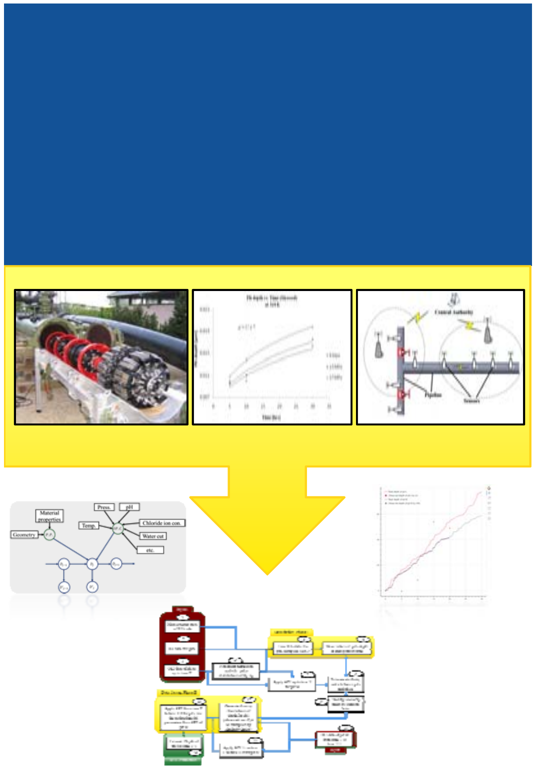
By using this framework and taking advantage of having online sensors, change in operational condition is considered in RUL estimation of the pipeline segment.

RUL estimation



Summary

- **Objectives**
  - RUL estimation of a segment of a pipeline
- **Approach**
  - Fusing ILI data and OLI data of different pits
- **Results**
  - Framework is developed
  - Synthetic data is generated
  - HB-NHGP code is developed
- **Future works**
  - Adding variation of pits initiation times
  - Considering POD in modeling
  - Validating the proposed framework by finding real degradation data (not necessarily pipeline data)



Thank You!

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Acknowledgement

This work is being carried out as a part of the Pipeline System Integrity Management Project, which is supported by the Petroleum Institute, Khalifa University of Science and Technology, Abu Dhabi, UAE

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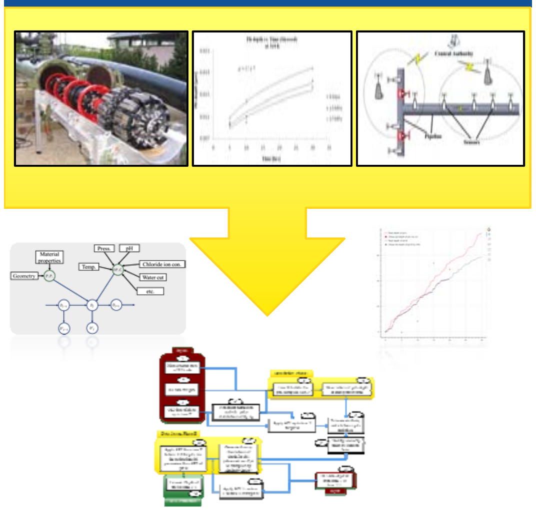

Back up slides

SYRRA

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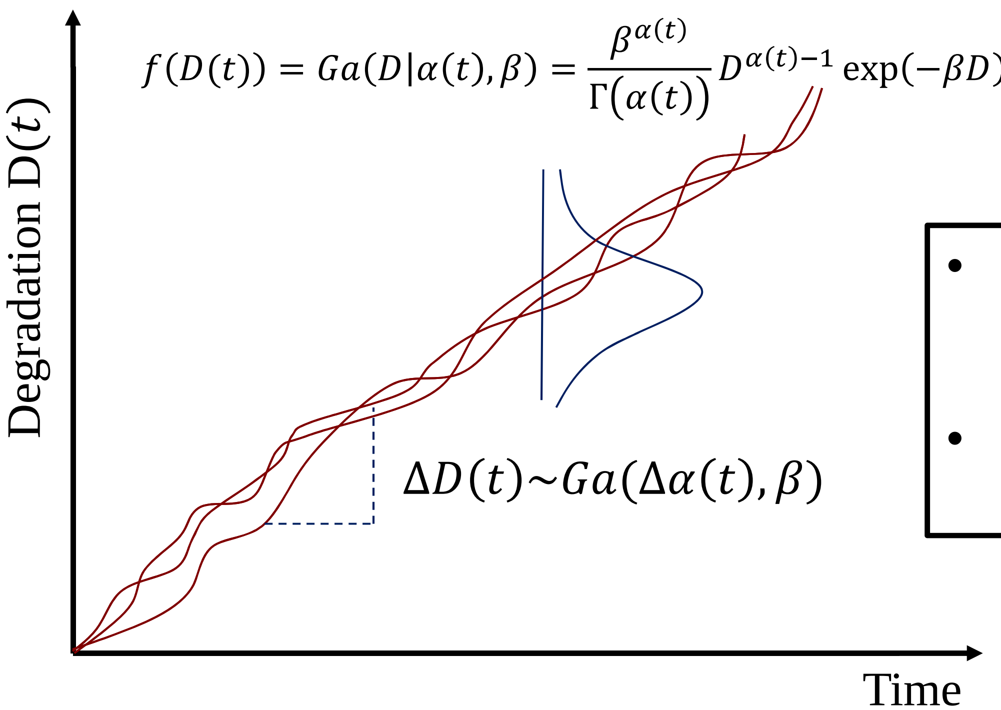
Non-homogenous gamma process for degradation modeling



- Temporal variability of stochastic degradation processes can be modeled properly by a gamma process.
- It is appropriate to model monotonic and gradual degradation processes.

$E(D(t)) = \alpha(t)/\,\beta$

Based on the physics of failure:
$\alpha(t) = \theta_1(t-t_0)^{\theta_2}$

Particle Filtering

$$Pr(D_k|D'^k) = \frac{Pr(D'_k|D_k)Pr(D_k|D'^{k-1})}{Pr(D'^k|D'^{k-1})} \approx \sum_{i=1}^{N} w_k^i \delta(D_k - D_k^i)$$

sensor measurements $D'^k = \{D'_1, \dots, D'_k\}$

Process Model:

$$D_k = f(D_{k-1}, \omega_{k-1}) \rightarrow Pr(D_k|D_{k-1})$$

In which D_k is state at time step k, ω is called process noise and f is the evolution function.

$$D_k = \theta_1(t_k - t_0)^{\theta_2}$$

$$D_k = D_{k-1} + \theta_1\theta_2(t_k - t_0)^{\theta_2 - 1}\Delta t$$

Measurement Model:

$$D'_k = h(D_k, v_k) \rightarrow Pr(D'_k|D_k)$$

Where D'_k is measurement at time step k, v is called measurement noise and h is the measurement function.

$D'_k = D_k + measurement\ error$ (ILI or OLI)

Reliability analysis of the pipeline segment

Limit state functions
$$\begin{cases} f_1 = 0.8\,PWT - d \\ f_2 = P_b - P_{op} \\ f_3 = P_{rp} - P_{op} \end{cases}$$

Small leak	$f_1 \leq 0 \cap f_2 > 0$
Large leak	$f_1 > 0 \cap f_2 \leq 0 \cap f_3 > 0$
Rupture	$f_1 > 0 \cap f_2 \leq 0 \cap f_3 \leq 0$
Safe	Otherwise

$$P_b = X\frac{2\sigma_u t}{D}\left[1 - \frac{d}{t}\left(1 - exp\left(\frac{-0.1571}{\sqrt{\frac{D(\mathrm{PWT} - d)}{2}}}\right)\right)\right]$$ [Stephens & Leis, 2000]

$$P_{rp} = \frac{1.8t\sigma_u}{MD} \qquad M = \begin{cases} \sqrt{1 + 0.6275\frac{l^2}{D.PWT} - 0.003375\frac{l^4}{D^2\mathrm{PWT}^2}} & \frac{l^2}{DPWT} \leq 50 \\ 0.032\frac{l^2}{D.PWT} + 3.293 & \frac{l^2}{D.PWT} > 50 \end{cases}$$

σ_u: Ultimate tensile strength
D: Pipeline diameter
X: Model error
d: Pit maximum depth
PWT: Pipeline thickness
l: Pit length
P_{op}: operation pressure

[Kiefner et al., 1973]

Motivation

- Considering change in operational condition in RUL estimation of a segment of oil and gas pipelines
- All the available pitting corrosion degradation models assumed that operational conditions remain the same during the life of the pipeline.
- In some occasions operational conditions change over time:). [Regulations, PHMSA, 2014]
  - Flow reversal,
  - Product change (e.g. crude oil to refined products),
  - Conversion to service (e.g. convert from natural gas to crude oil)

Online monitoring data is required to consider change in operational conditions in RUL estimation, however, online monitoring of the whole pipeline is infeasible.
Proposed solution: fusing ILI and OLI data