Integrating Knowledge in Pipeline Risk Assessment – A Bayesian Network Approach

PHMSA workshop

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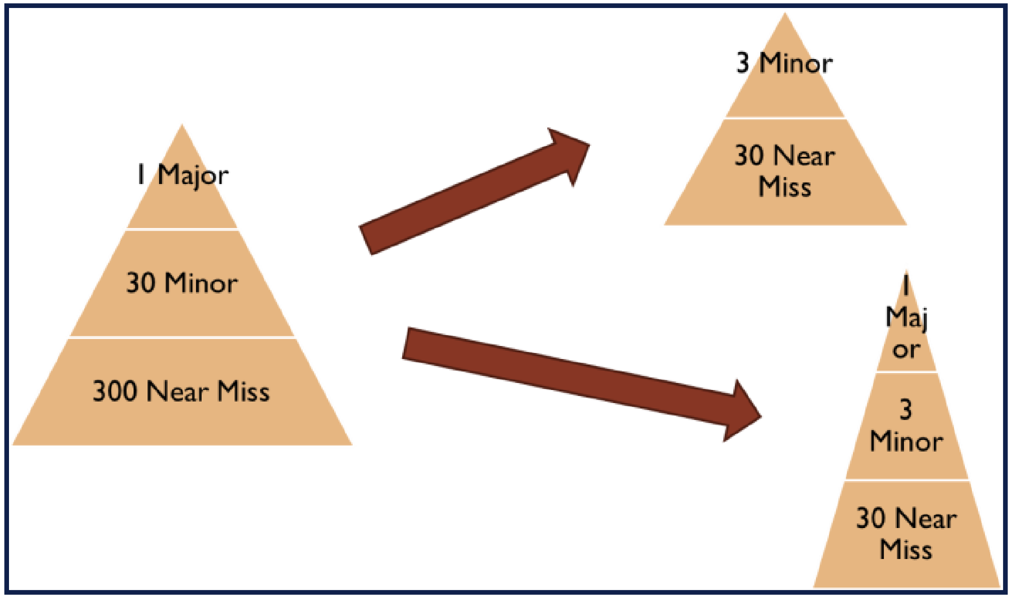
Our purpose
To safeguard life, property, and the environment

Process Safety Differs from Occupational Safety



Process Safety Events are Low Frequency and High-Consequence

- Process safety mostly (low-f/high-C) events
  - Pipeline failures are mostly low frequency
    - ~600/y PHMSA reportable; f-analyses can have role (e.g., RBI, QRA, POE)
  - Catastrophic failures <1/y
    - f-analysis inadequate
- How to find probability of low-f failure
  - Not enough past events to learn from experience
  - Possibly, knowledge existed to prevent the failure but was not integrated

Mitigating Process Safety Risk

- Some historical events could have been prevented (or mitigated into simple failures) if the right available information had been uncovered, understood, and used to drive a risk management decision
- In some cases, we failed to look because we didn't account for uncertainty
- Models ideally enable the risk manager to
  1. Collect large amounts of available information
  2. Sensibly assemble/organize/process it
  3. Understand the effect of data uncertainty (including gaps)
  4. Calculate risk and estimate benefit of mitigative action to measure ROI

"It ain't what you don't know that gets you into trouble. It's what you know for sure that just ain't so."

\- Mark Twain

Pipeline Threats

- All threats can be included and integrated
  - e.g., Corrosion, SCC, Fatigue, Excavation, Soil Movement, Theft/Security
  - No artificial distinctions between threat types
    - e.g., time dependent and independent threats are integrated
- All consequences can be included
  - e.g., impact/plume/spill estimates, service interruption, repair/replace, litigation, reputation, injury/fatality (constrained by safety)

S. Jain, F. Ayello, J. A. Beavers and N. Sridhar, “Probabilistic Model for Stress Corrosion Cracking of Underground Pipelines using Bayesian Networks”, paper 2616, CORROSION 2013, Orlando, Fl, USA.

Pros of Bayesian network

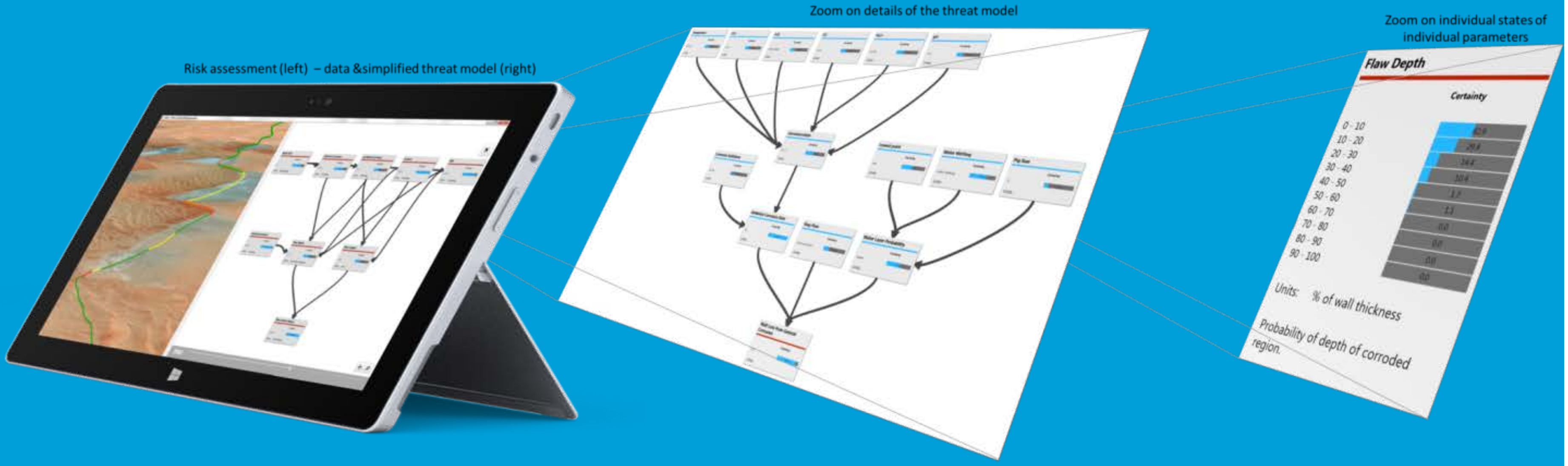
- **Accounts for uncertainties in data and knowledge**
- **Transparent; no ‘black box’**
- Can be validated using past failure data or new information
  - (i.e., how do you know the model works?)
- Includes available information in forms of statistical data, mechanistic models, and expert opinions
  - Updates predictions using new data (e.g., monitoring and inspection)
- Uses cause-effect relationships within the system
- Links probabilities to consequences
- Pictorially represents whole-system knowledge

F. Ayello, S. Jain, N. Sridhar, and G.H. Koch, Corrosion, 70(11), 1128 – 1147, 2014.

Cons of Bayesian Network

- Change
  - Satisfaction with current models
    - But how do we know they work?
  - Initial investment to populate model with data
- Integrating much data requires collecting lots of data
- Currently goes beyond minimum regulatory requirements
  - Must find value in risk management beyond compliance
- Tolerance of residual risk
  - ALARP
  - Exercise model to determine if residual risk is optimized and/or minimized
    - Both data collection and maintenance activities
    - Estimate new risks of maintenance activities (e.g., excavation)
- Might reveal unintuitive risk (i.e., it hasn't failed that way before)
  - Highly networked systems difficult to comprehend (despite transparency)

Case Study #1
CNPC Pipeline External Corrosion



Multi Analytic Risk Visualization (MARV)

Example of Data Input

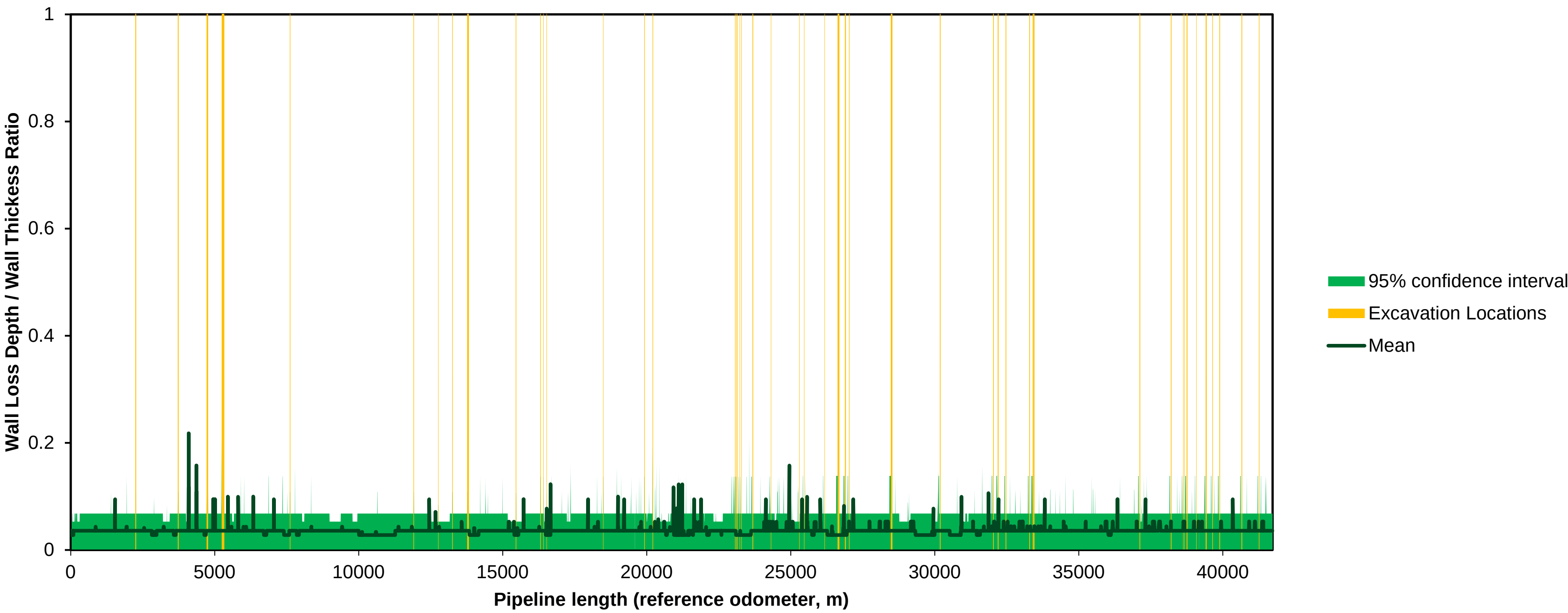
Known Uncertain Unknown

Simulation Parameters	Value	Certainty %
Soil type	Sand	0
	Coastal Saline Soil	100
	Clay	0
	Loam	0
Soil Porosity	0 - 0.1	0
	0.1 - 0.2	0
	0.2 - 0.45	100
	0.45 - 0.6	0
Dent	Yes	0
	No	100
Area affected by weld	Affected	0
	Not Affected	100
Surface preparation	Blasting	33
	Brushing	33
	No Preparation	33
Sulfates	0 ppm to 50 ppm	0
	50 ppm to 100 ppm	0
	100 ppm to 150 ppm	0
	150 ppm to 200 ppm	0
	200 ppm to 1,000 ppm	100
Chlorides	0 ppm to 150 ppm	0
	150 ppm to 1,500 ppm	100
	1,500 ppm to 10,000 ppm	0
MIC	Yes	0
	No	100

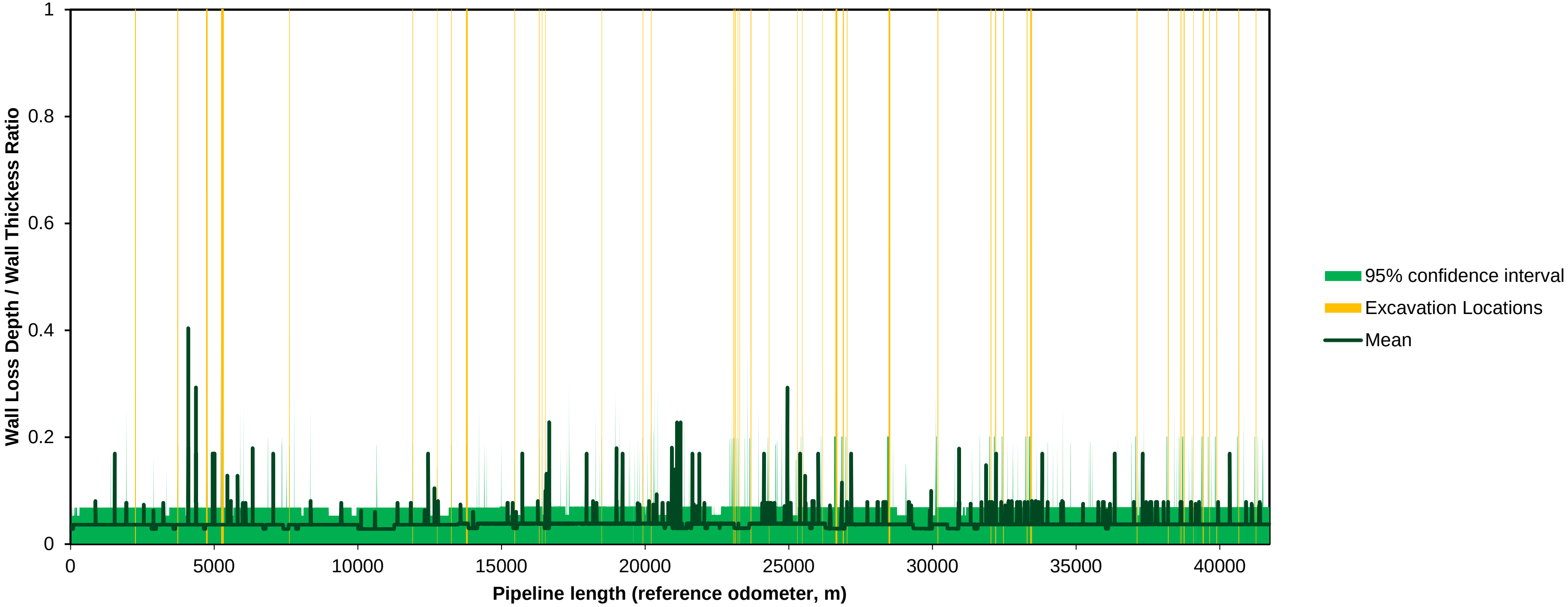
Simulation Parameters	Value	Certainty %
Temperature	80°C-70°C	0
	70°C-60°C	25
	60°C-50°C	25
	50°C-40°C	25
	40°C-30°C	25
	30°C-20°C	0
	20°C-10°C	0
Applied CP	-500 to -650	0
	-650 to -700	0
	-700 to -750	0
	-750 to -800	0
	-800 to -850	0
	-850 to -950	25
	-950 to -1200	75
	-1200 to -1500	
Natural Potential	-500 to -650	6
	-650 to -700	30
	-700 to -750	40
	-750 to -800	20
	-800 to -850	4
	-850 to -950	0
	-950 to -1200	0
Coating type	Asphalt	0
	Coal Tar	0
	3PE	100
	FBE	0
	PVC	0
	Tar Glass	0

Update with ILI data

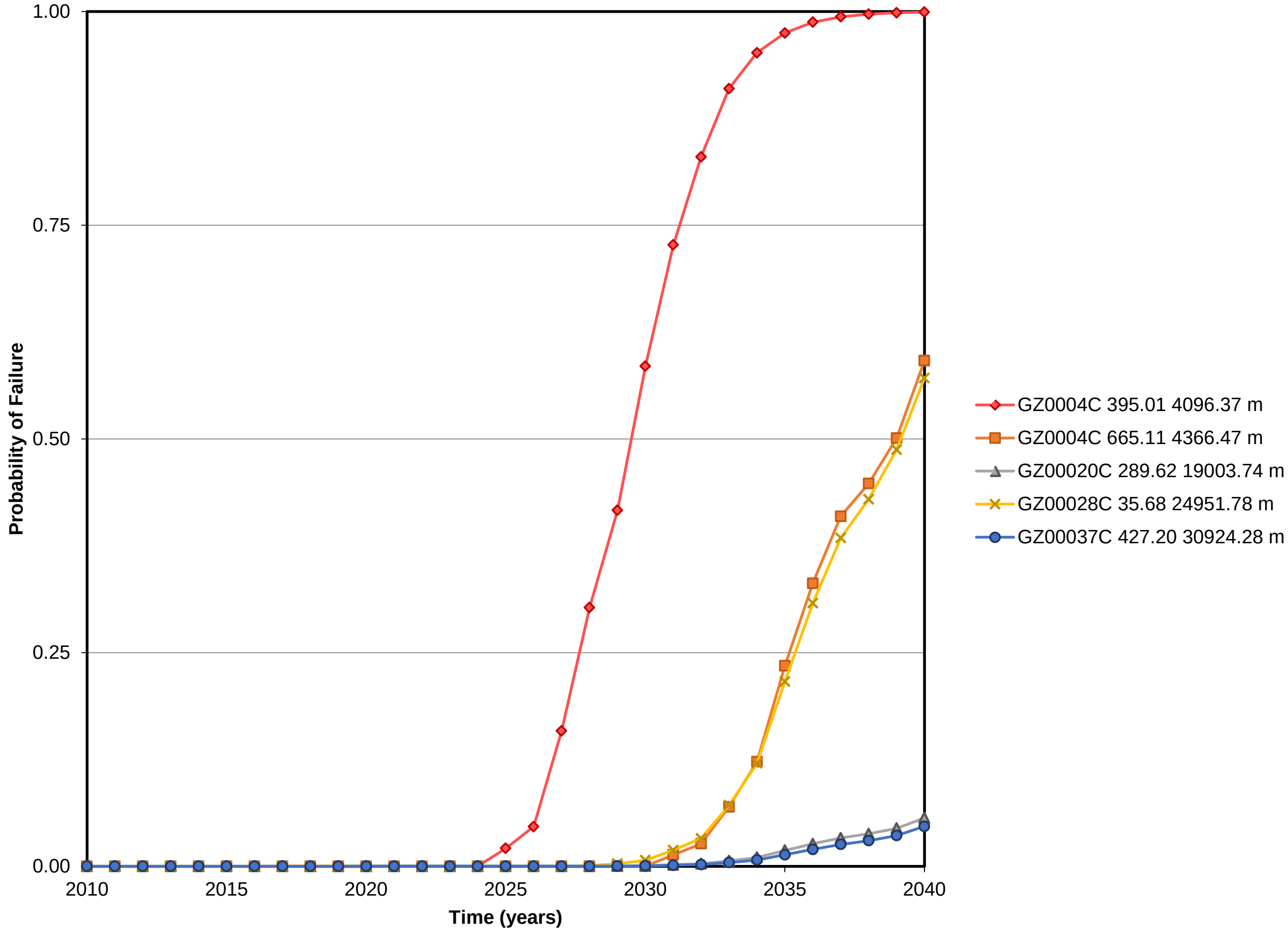
- Year: **2014**
- External metal loss used to estimate corrosion rates (localized and uniform)
- Corrosion rates adjusted for locations where the ILI measured metal loss
- Dents and bends were incorporated to the model



Updated Prediction for Year 2020



Failure Probability for 5 Locations

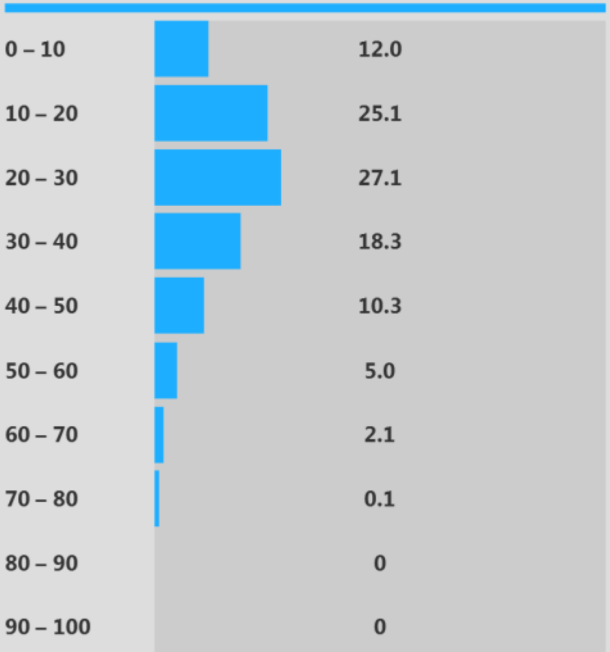


Case Study #2
KOC Pipeline Internal Corrosion

Case Study # 2 - KOC

KOC, internal corrosion model, 2004 to 2010 forward projection

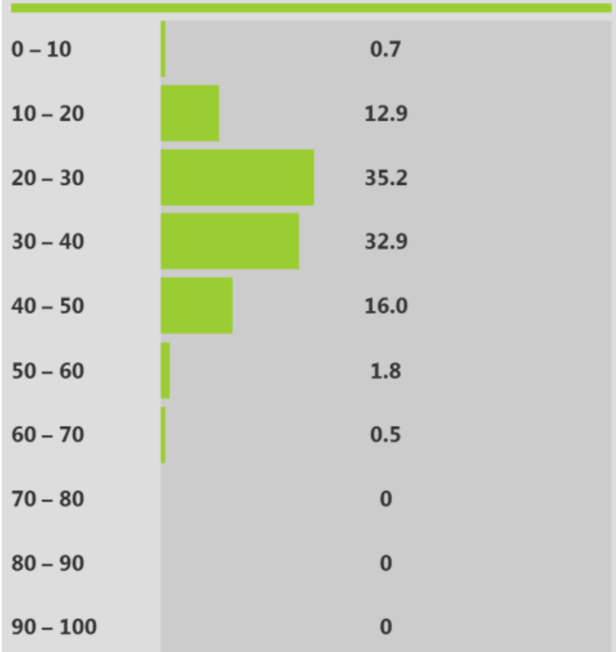
Flaw depth – 7 years projection



Unit: Percentage of wall thickness

Probability of corrosion flaw depth, amount of corrosion in % of total wall thickness

Flaw depth – Inspection results

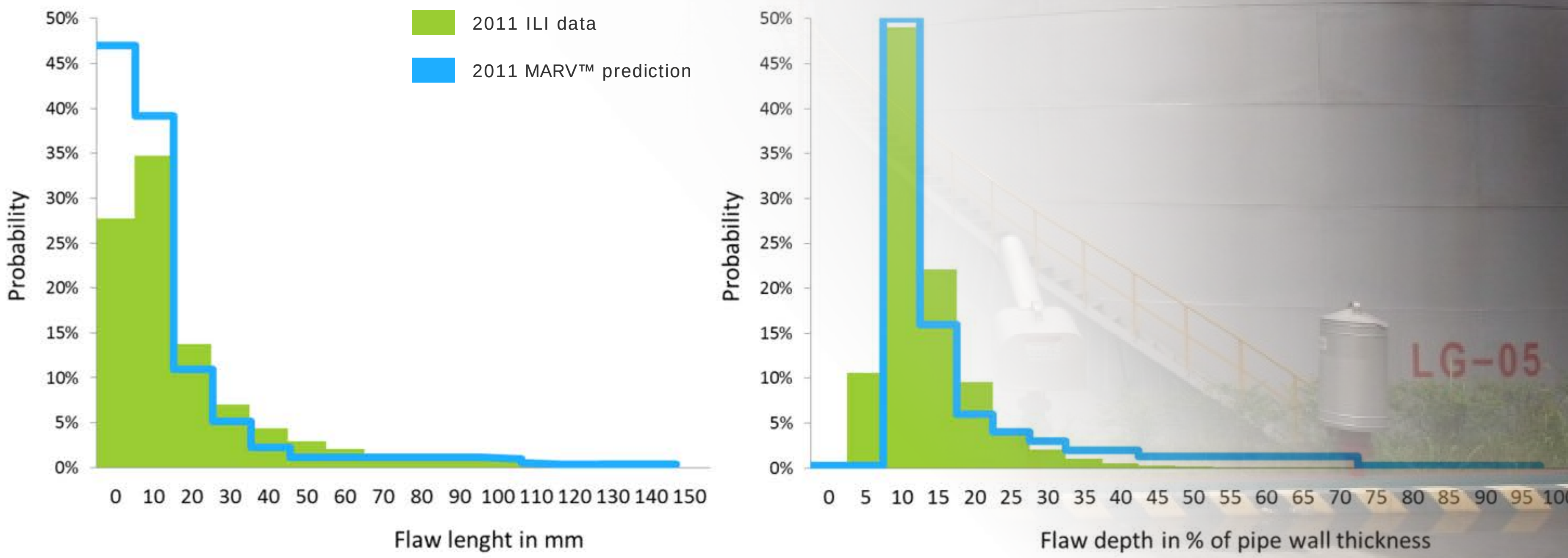


Unit: Percentage of wall thickness

In–line inspection results

Case Study #3
CNPC Langfang Pipeline External Corrosion

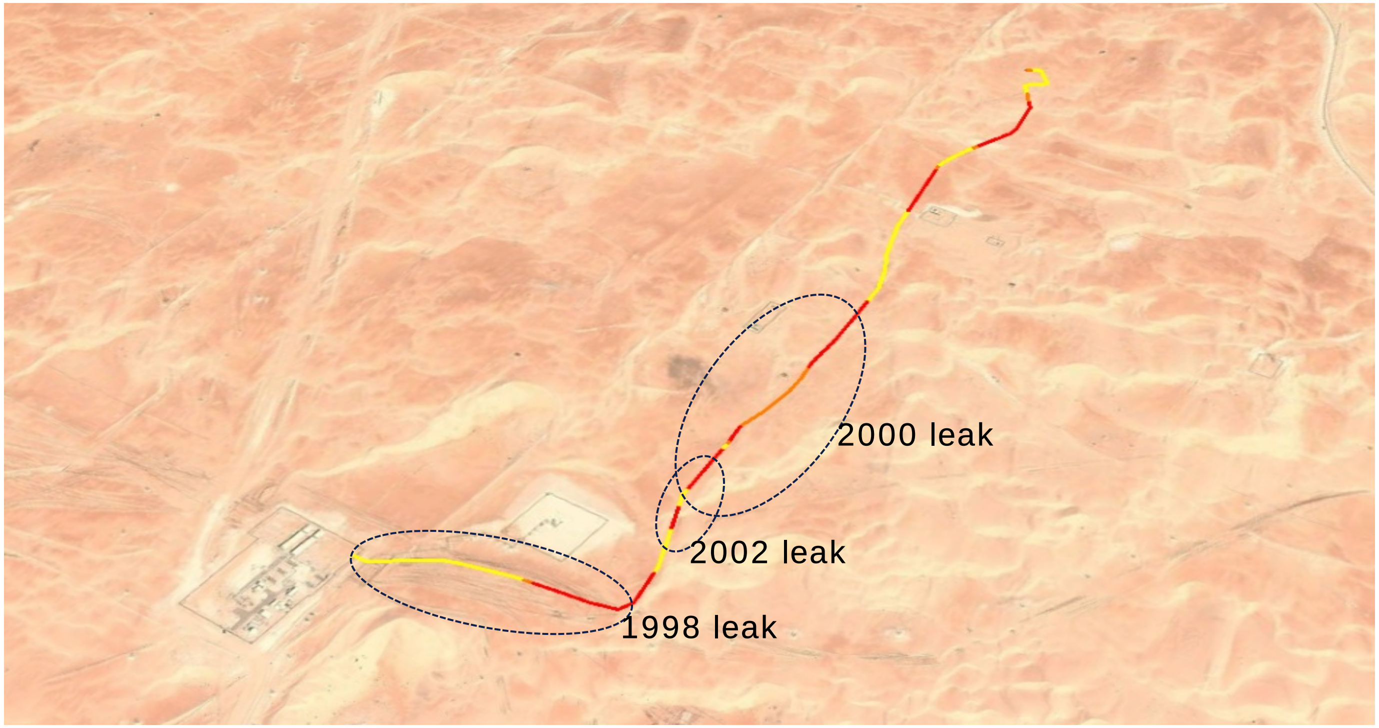
CNPC External Corrosion Model



Case Study #4
ADCO Pipeline External Corrosion

Case Study 4 - 25 years prediction 1988-2013

- Predicted locations of high external corrosion consistent with leak history
- Predicted low internal uniform corrosion rate consistent with leak histor



G. Koch, F. Ayello, V. Khare, N. Sridhar, and A. Moosavi, Corrosion Engineering, Science and Technology, 50 (3), pp. 236 – 247, 2015.

Summary

- Serious pipeline events are low-f and high-C
  - Most commonly used models are not suited to identify and prevent them
    - They are built around learning from past experience
  - Bayesian networks directly address this problem
    - Probabilistic, use all data, account for gaps & uncertainties, can be validated, and have output that drives business decisions (i.e., perform activities that have both lowest cost and greatest benefit)
    - In addition to learning from the past, they predict the future

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