Probabilistic Risk Models for Plastic Piping Systems

Ernest Lever
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GTI Risk Modeling Approach

- **Lifetime Prediction** (Prediction of Failure) dependent on:
  - Stress distribution, and
  - Material properties
- **System Simulation** dependent on:
  - System components
  - Boundary conditions
  - End of life metrics
- **Understanding of interactions** dependent on:
  - System configuration
  - Environment
  - Known influencing factors
  - Unknown influencing factors

- **Policy evaluation** dependent on:
  - **Risk governance** framework
    - Risk appetite
    - Risk tolerances
  - Business process
    - **Goals**
    - **Situations**
    - **Assessors**
    - **Metrics**

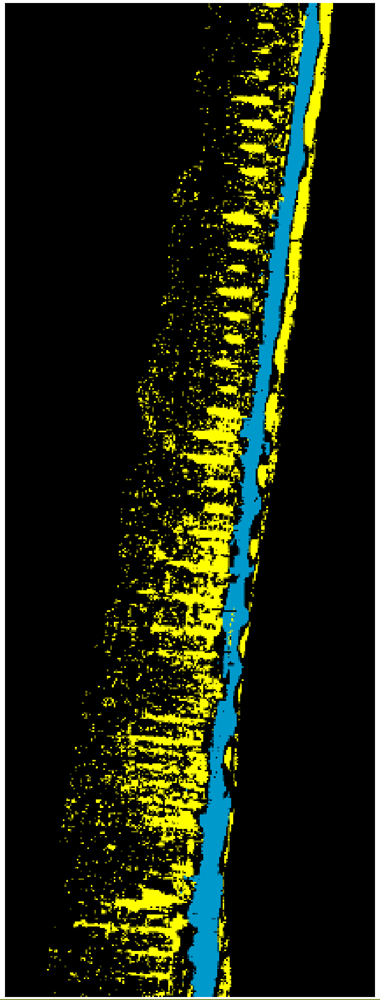
GTI Incorporation of Ground Movement in Risk Models

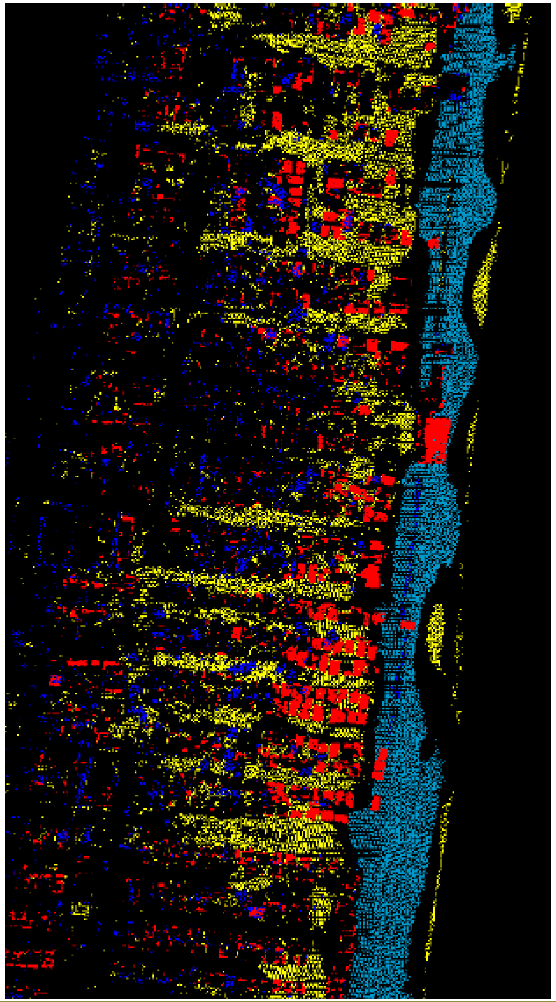
- GTI is heavily focused on Causal Modeling to drive risk models
- GTI executed a project with Rutgers University to evaluate damage to gas distribution systems after Hurricane Sandy
  - Ground movement measured by LiDAR
  - Causal model + Bayesian network developed for pipeline strain due to ground movement
- The Bayesian network was modified for general pipeline risk models
  - Pipeline displacements induce bending moments on pipeline components
  - Bending moment induced stresses converted to Stress Intensification Factors (SIF)
  - All factors impacting pipeline lifetime converted to equivalent SIF
- SIF acting on pipeline become normalizing factor
  - Distributions of SIF due to various components developed from empirical data, historic data, analysis
  - Distributions of SIF fully express uncertainty
  - Distributions of SIF express quality of various pipeline attributes
  - Reductions in uncertainty in SIF distributions are a measure of program effectiveness
- The general pipeline risk model was adapted to address highly transient loading due to blasting activity adjacent to distribution system

Analysis of Natural Gas System After Hurricane Sandy

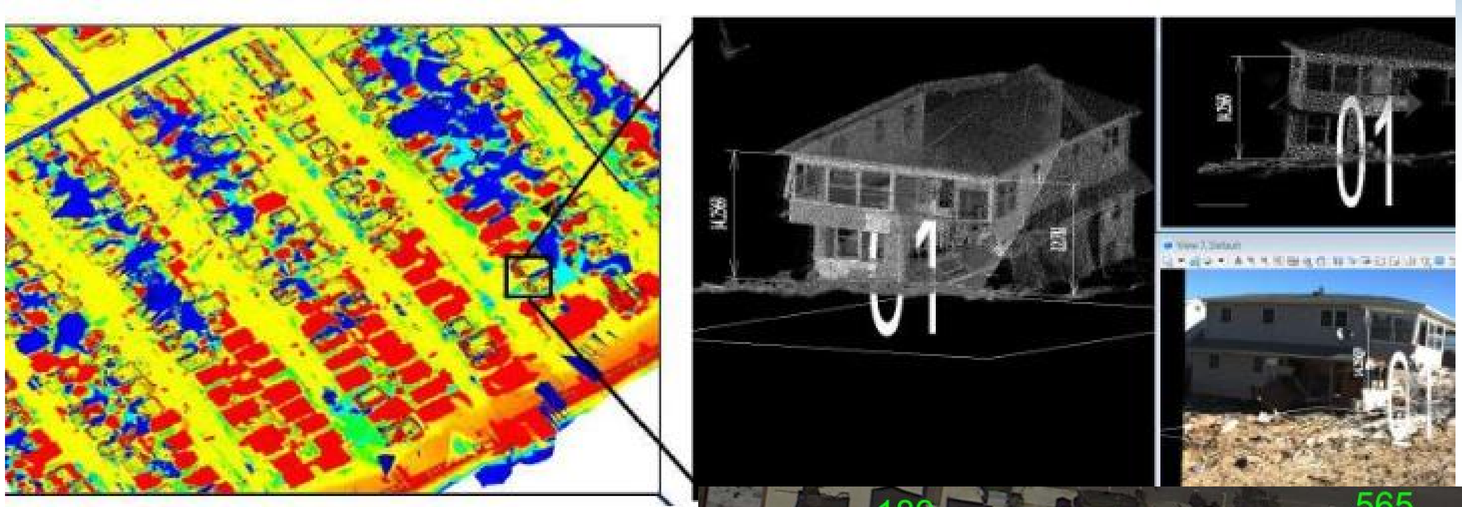
Worked with Rutgers U. in Post-Hurricane Sandy Study

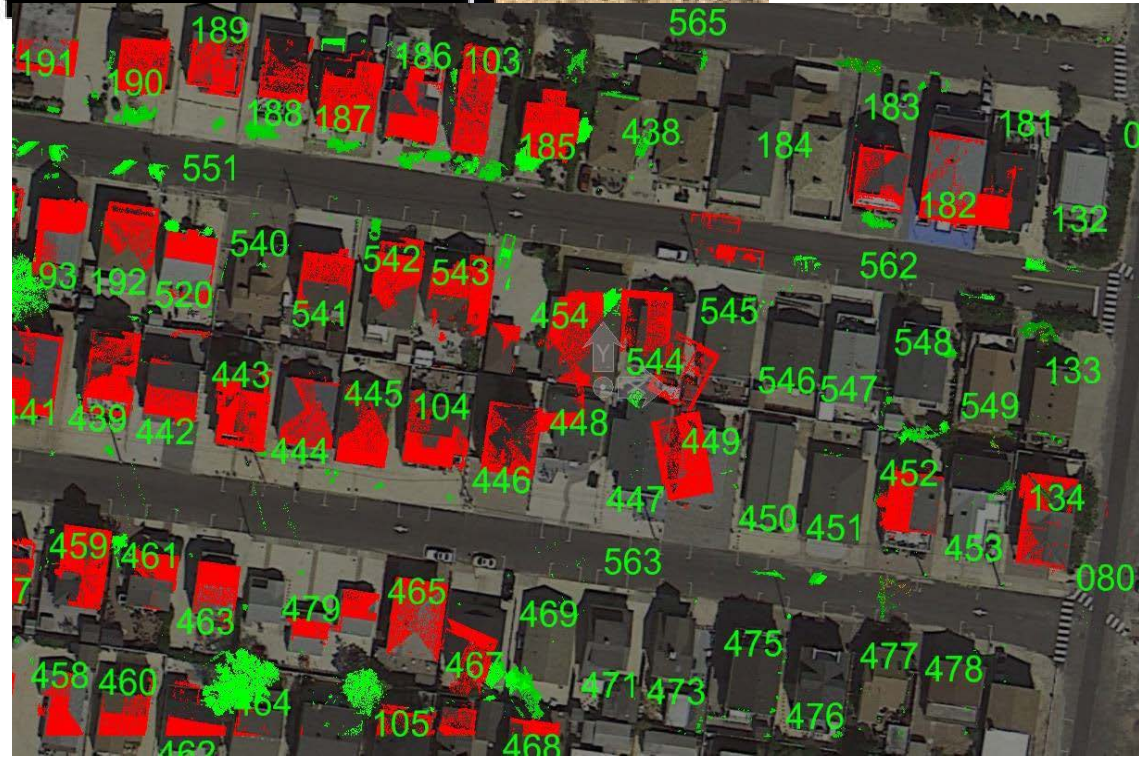
LiDAR Data of Debris Field and Flow





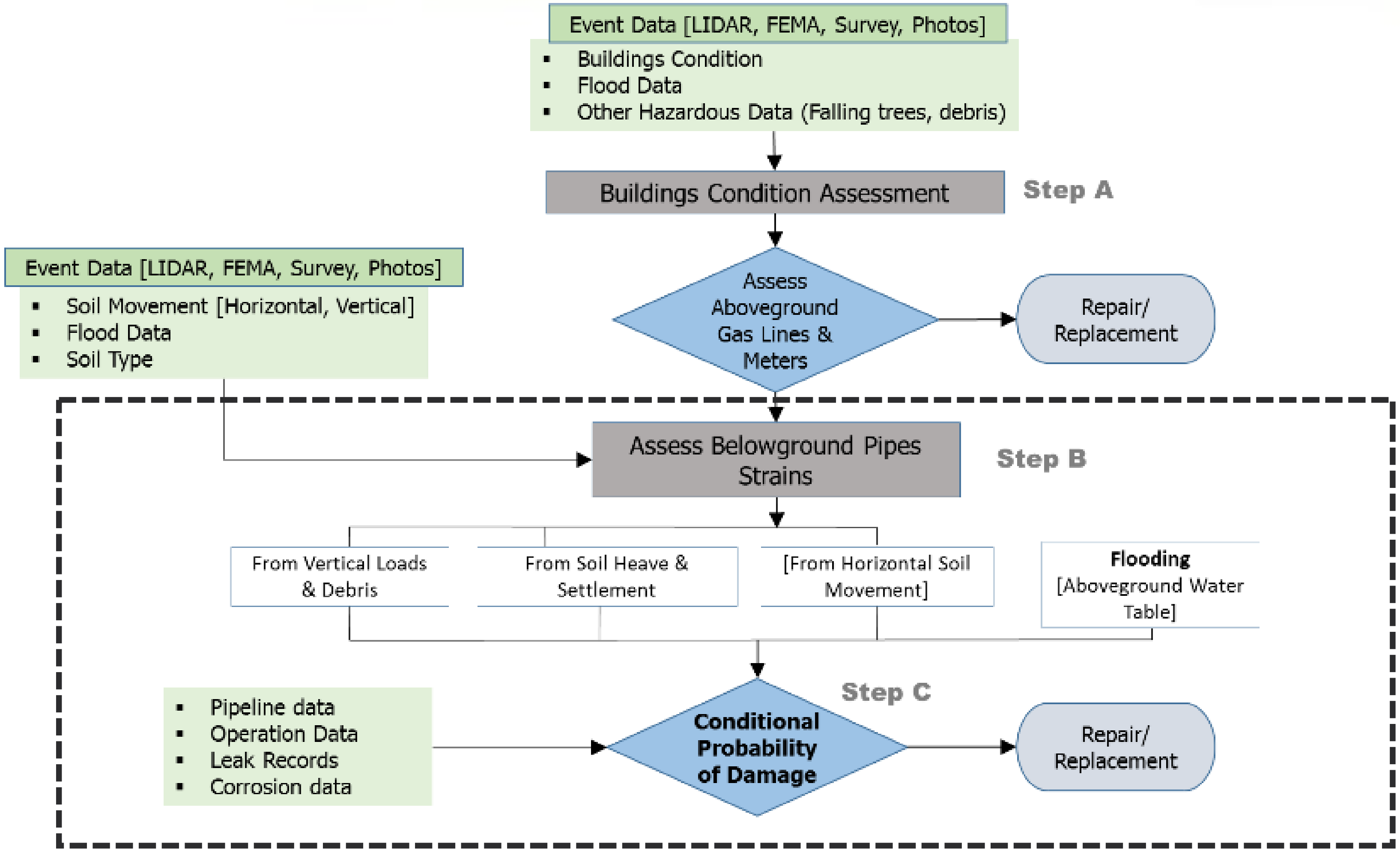
- **Yellow:** Sand Debris
- **Cyan:** Erode Dunes
- **Red:** Destroyed Buildings
- **Blue:** Building Debris or Changes





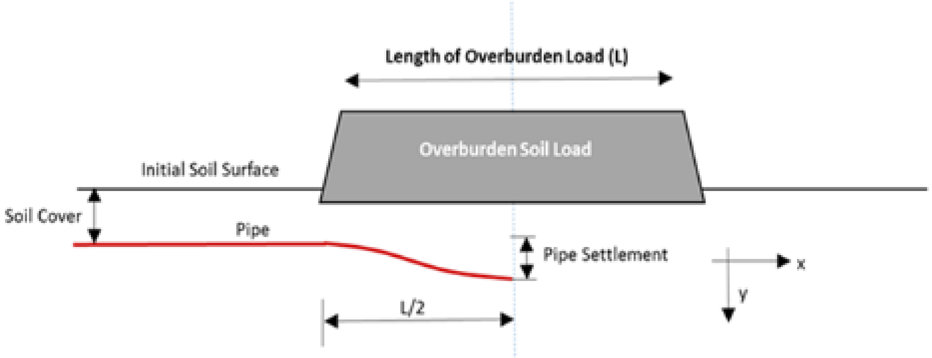
LiDAR Data of Building Displacements

GTI Integrated Infrastructure Analysis

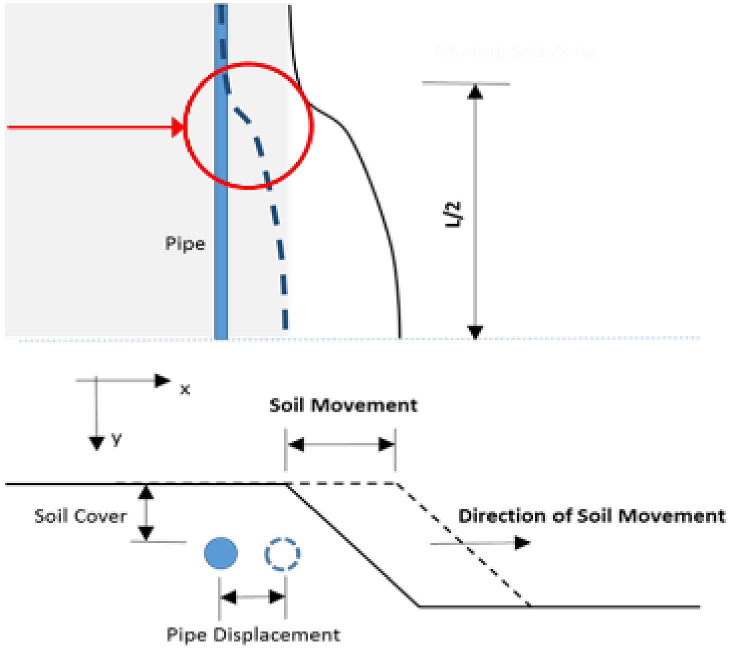


Natural Forces Threats – Belowground Pipe Strains

Belowground pipelines may experience high longitudinal and axial strains due to soil movement resulting from slope instability, soil subsidence, seismic activity, and flooding.



Vertical Displacement



Horizontal Displacement

Natural Forces Threats – Belowground Pipe Strains

- Pipe deformations are not necessarily equal to soil displacements. Various factors: pipe type, size, depth of pipe, soil type, length of displaced section along the pipe affect soil-pipe interaction
- FE program* was used to estimate pipe strains corresponding to the ranges of soil deformations.

Procedures used:

- *ASCE Committee on Gas and Liquid Fuel Lifelines, Guidelines for the Seismic Design of Oil and Gas Pipeline Systems, 1984.*
- *Guidelines for the Design of Buried Steel Pipe, American Lifelines Alliance (ALA), American Society of Civil Engineers, July, 2001.*
- *Guidelines for the Seismic Design and Assessment of Natural Gas and Liquid Hydrocarbon, PRCI, 2004.*
- *PIPLIN, Computer Program for Stress and Deformation Analysis of Pipelines, Version 4.59, SSD Inc., December 2013.*

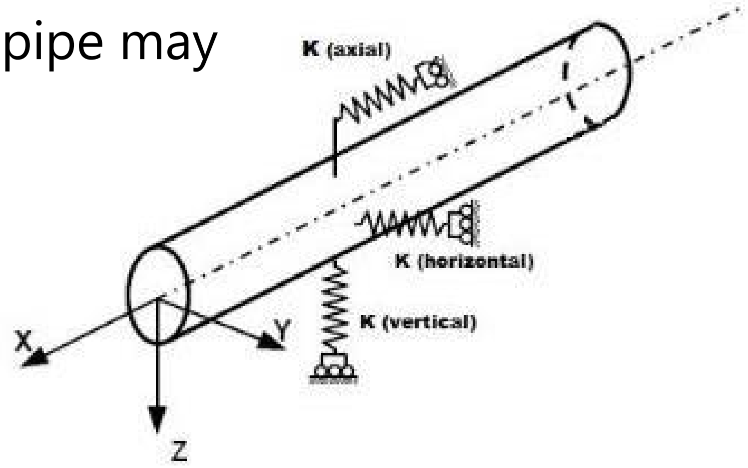
Natural Forces Threats – Belowground Pipe Strains

FE Analysis of Pipe Strains

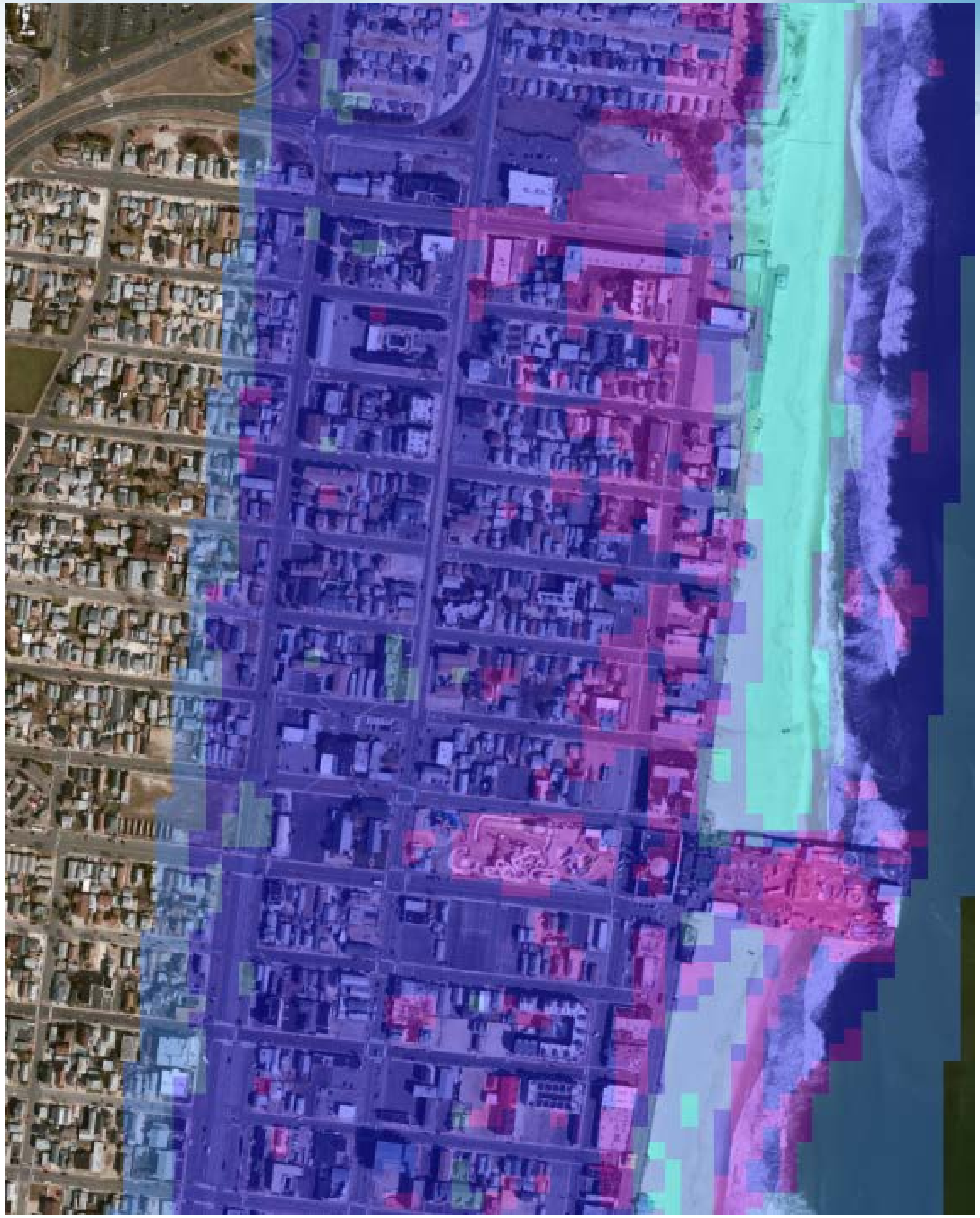
The pipe is represented as a structural beam with the soil as spring elements in the axial (longitudinal), transverse horizontal, and transverse vertical directions. The axial strains on the pipe result mainly from the friction caused by soil shear stresses around the pipe circumference.

As the ground displacement is progressively increased, the pipe may reach their specified compressive or tensile strain limits.

The soil may yield and continue to move past the pipe with no increased pipe deformations.



Soil Movement, [LiDAR DATA]



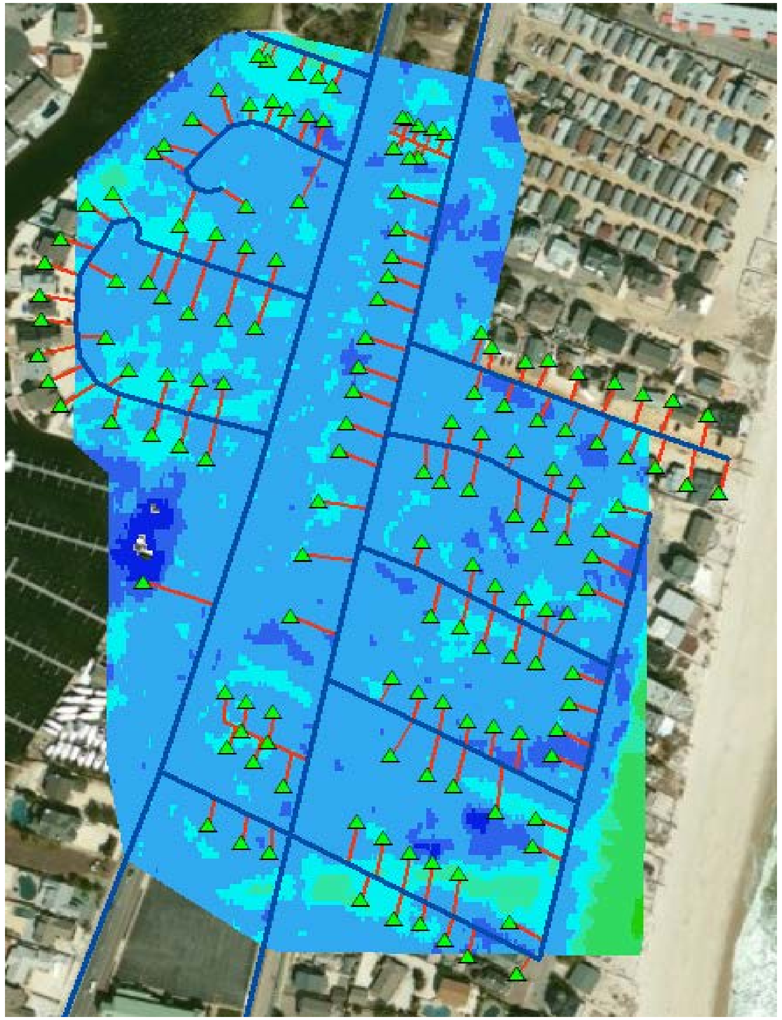
Data Tabulated in 50-ft Grids, Change of Soil Elevation

- -4.8 – -1.0 ft
- -1.0 – 0.10
- 0.10 – 0.55
- 0.55 – 2.50
- 2.50 – 6.00

Belowground Pipes Assessment – Input Data

Spatial Changes in soil elevation before and after Sandy.

[Note: Z in this figure is in meters]

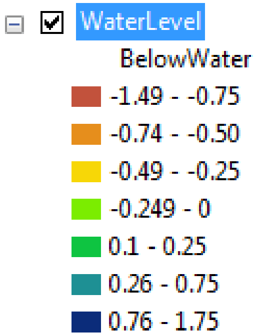


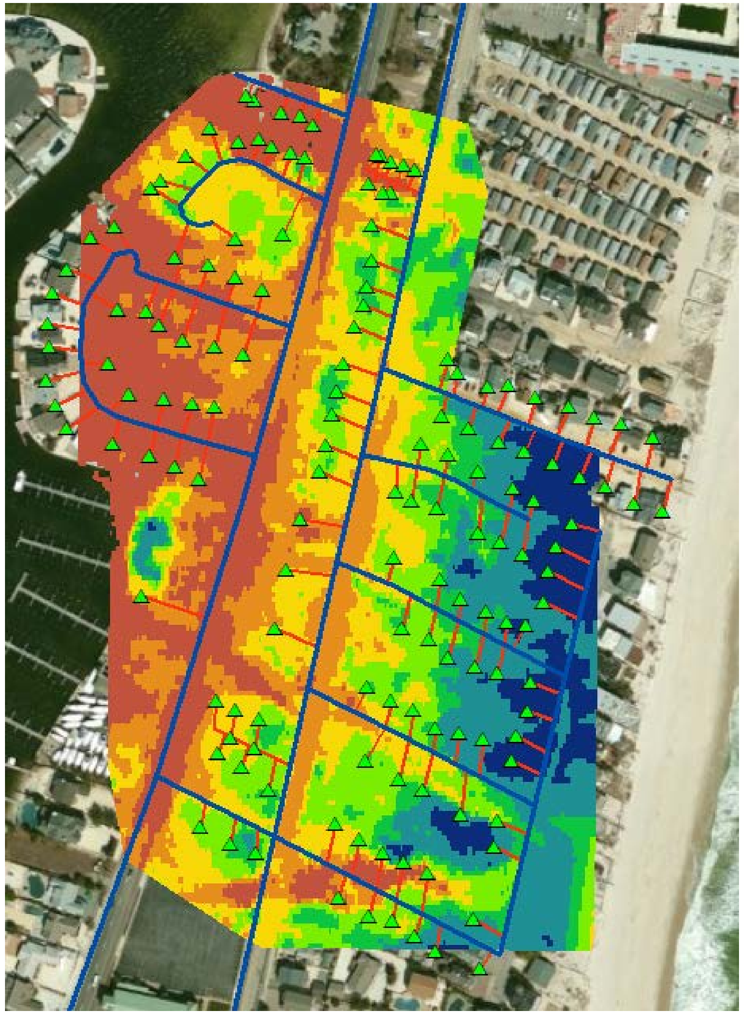
SoilChange
ZDifference
-5.25 - -4.00
-3.99 - -1.00
-0.99 - -0.50
-0.49 - 0
0.01 - 0.50
0.51 - 1.00
1.01 - 1.75

Belowground Pipes Assessment – Input Data

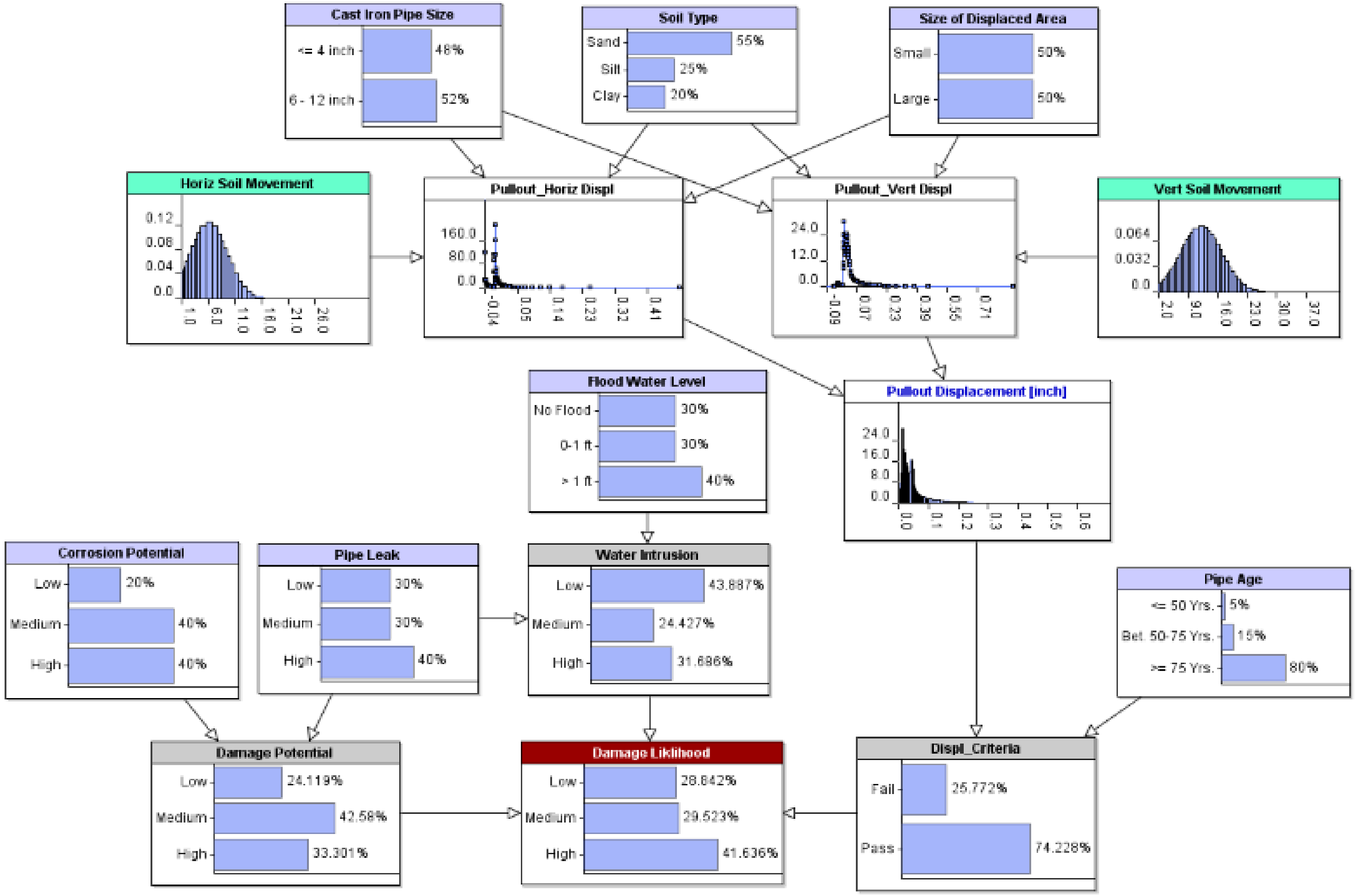
Spatial Changes in water elevation before and after Sandy.

[Note: Z in this figure is in meters]

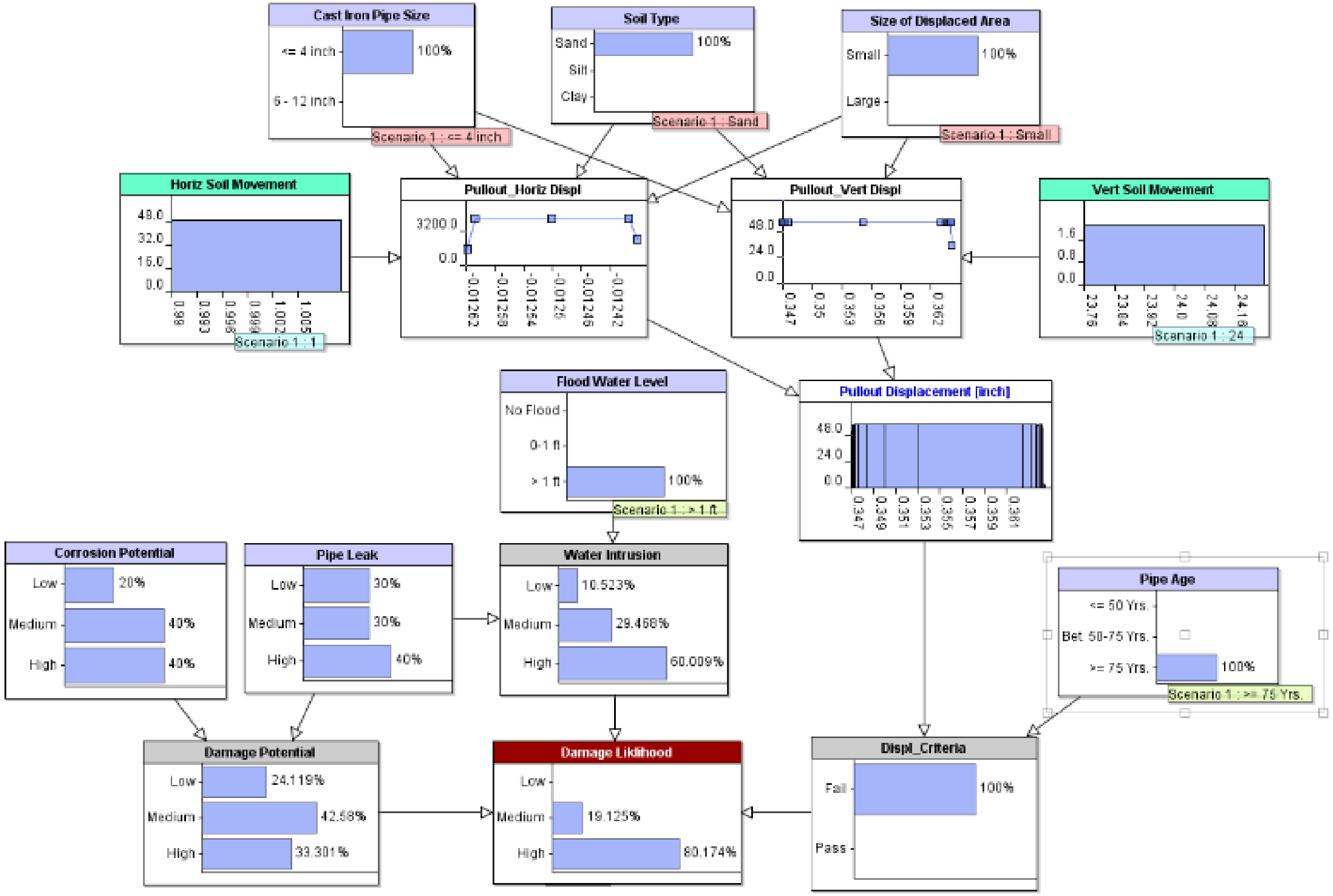




Integrated Risk Model, Bayesian Network



Integrated Risk Model, Bayesian Network.

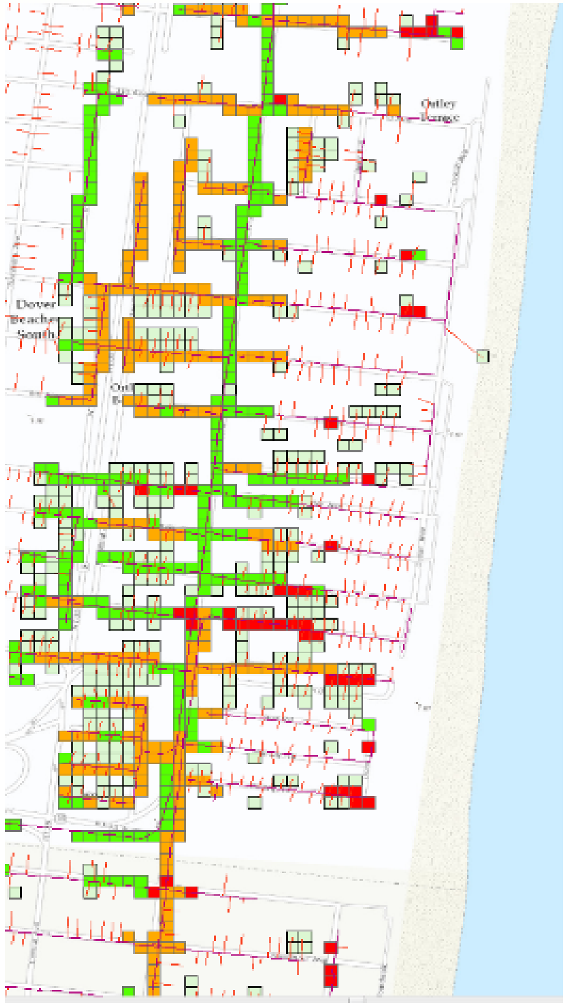


Integrated Risk Model, Bayesian Network.

Risk model output in a sample GIS grid:

Damage Likelihood:

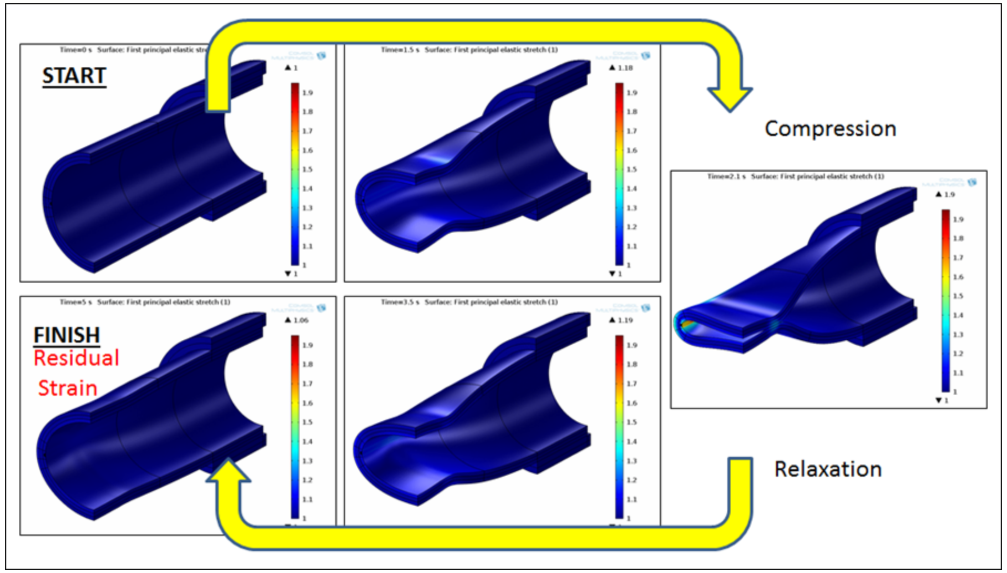
- High
- Medium
- Low



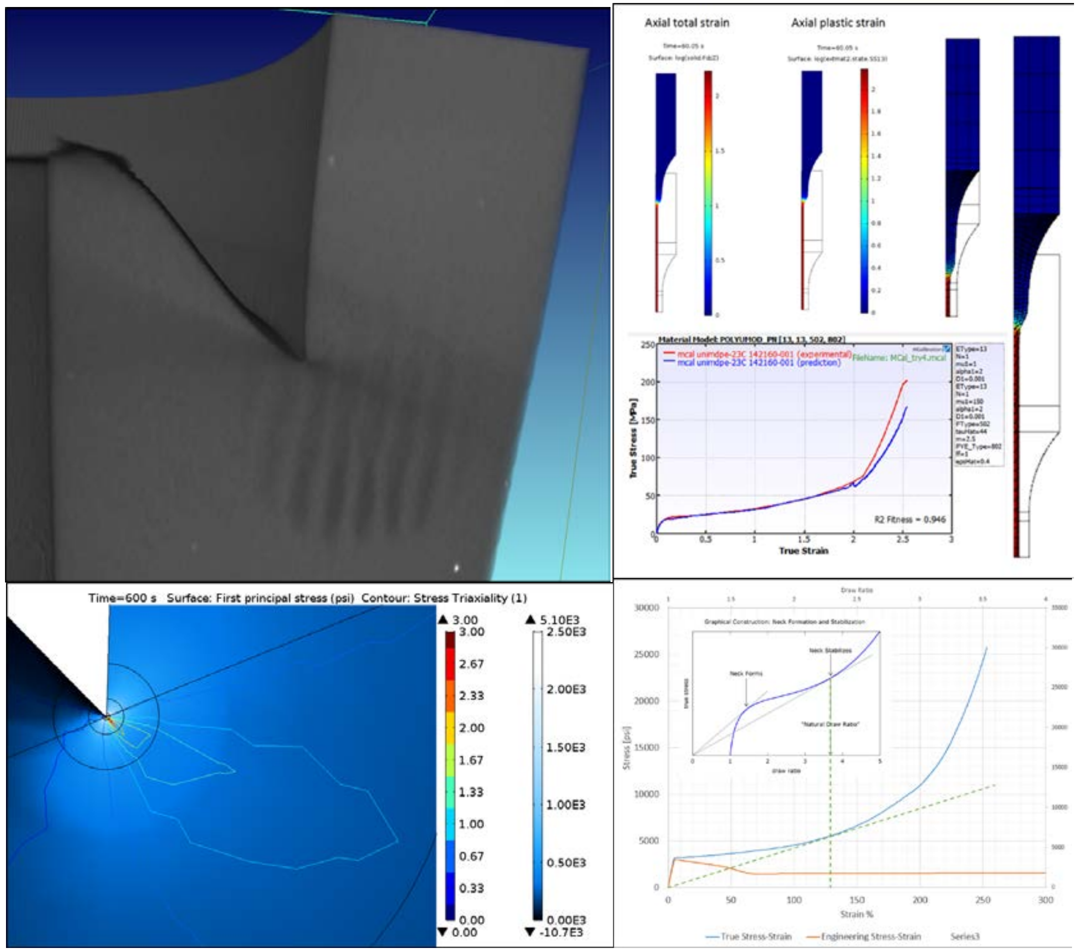
GTI Material Models

- GTI has progressively been improving the modeling tools it applies to risk analysis over the past eight years
- Models have been developed for:
  - Polyethylene
    - Aldyl A
    - MDPE
    - HDPE
  - Steels
    - Leak Rupture Boundary
    - FEM based FAD from 2D and 3D crack propagation modeling
    - Critical flaw curves to allow ILI as an alternative to a hydrotest
    - Currently working on reducing uncertainty due to damage interactions, NDE uncertainties and material uncertainties
  - Cast Iron
    - Line breaks due to frost heave
    - Line breaks due to graphitic corrosion

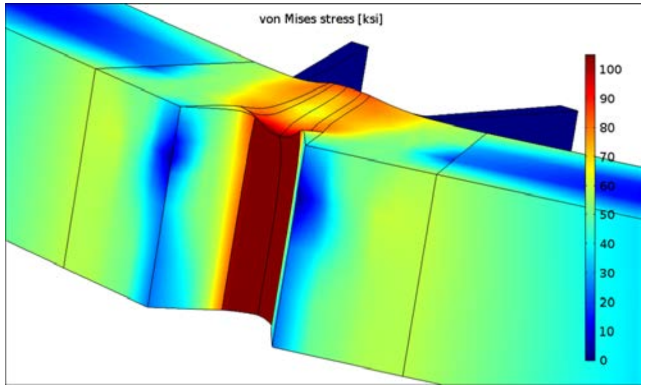
Material Models for Polyethylene

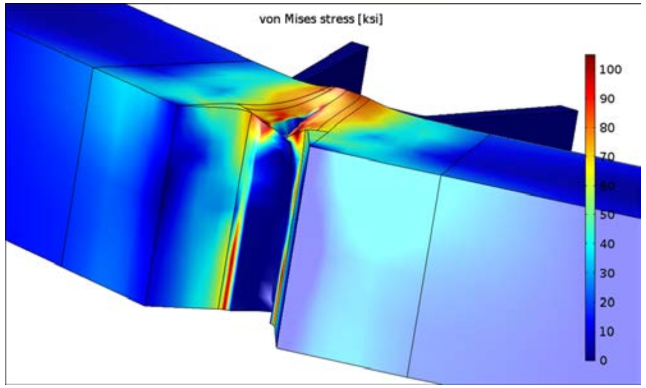


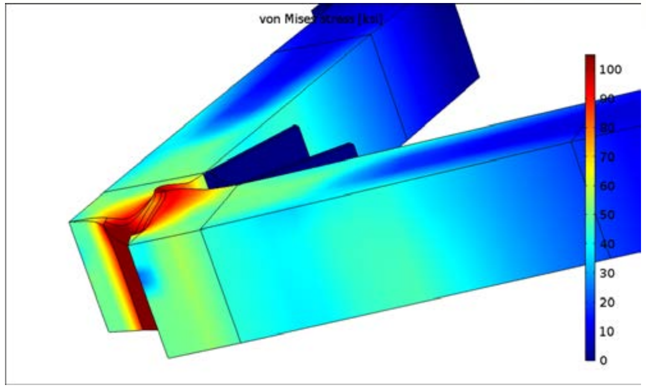
> Fully viscoelastic/plastic material models
> Capture large strains in compression and tension across wide temperature and strain rate ranges
> Accurately predict damage propagation

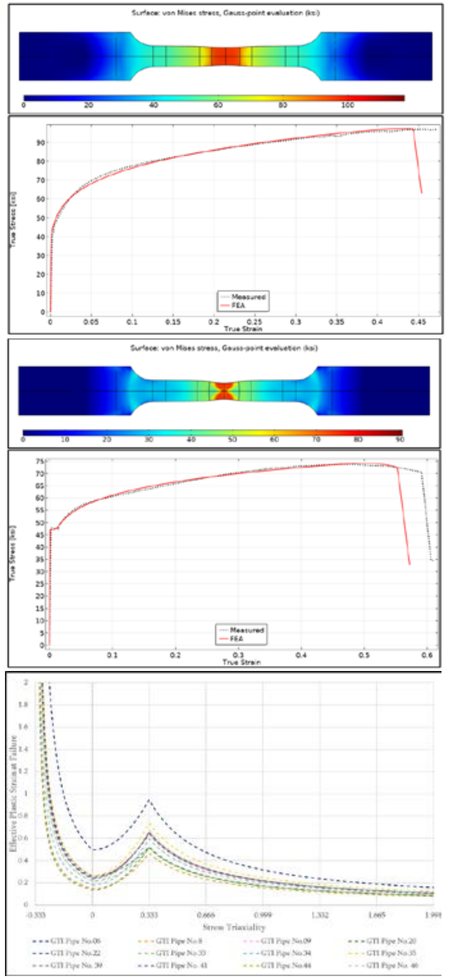


Material Models for Steel



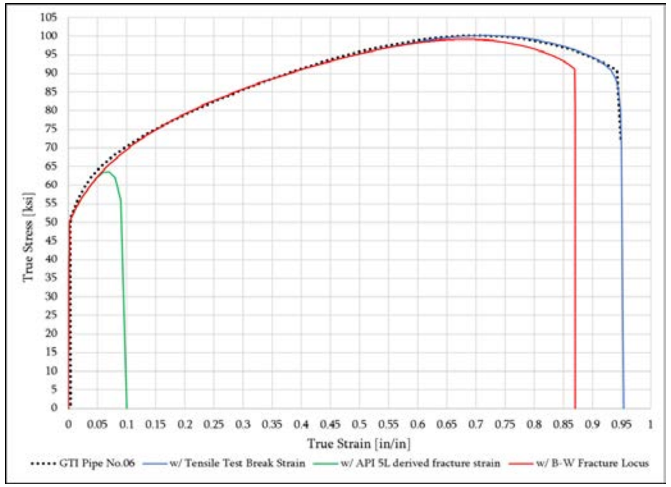


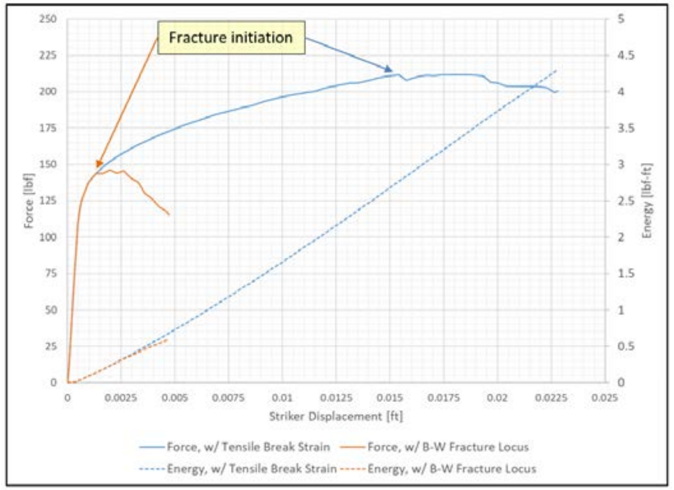


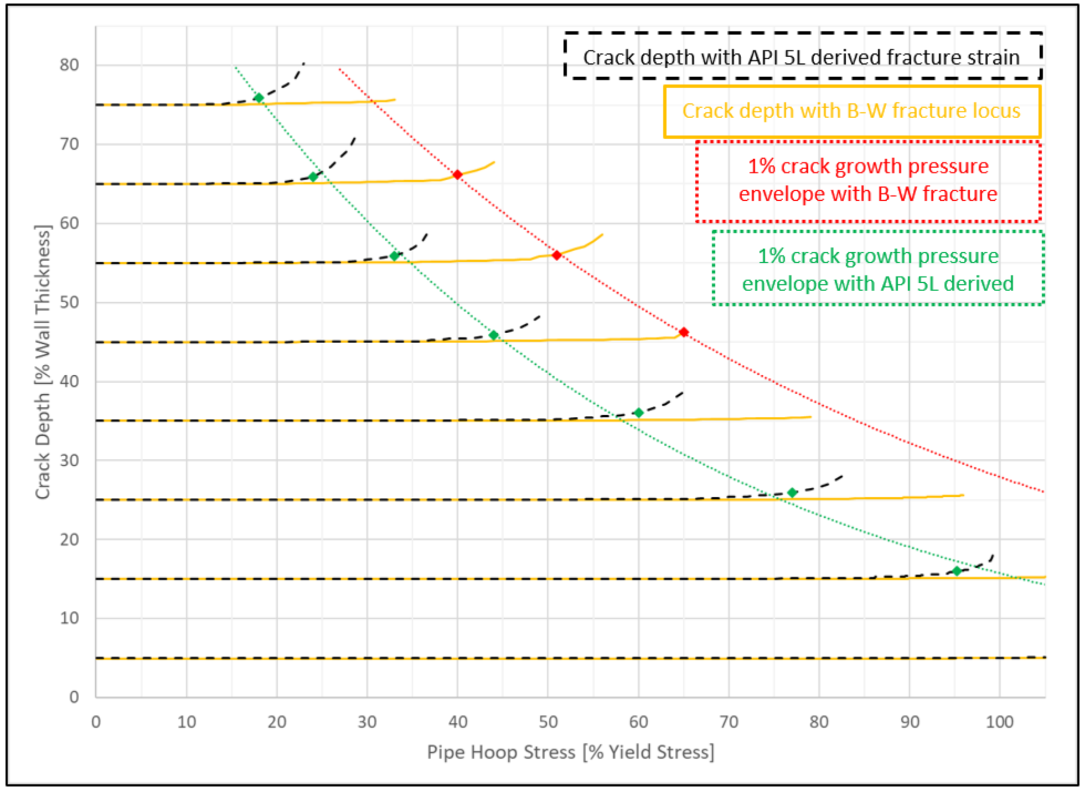


- GTI models capture yield point offset, strain hardening and plasticity
- State-of-the-art Bao-Wierzbicki ductile damage models incorporated
- Models capable of simulating impact loading with large displacements, plastic deformation and damage propagation

Influence of Toughness on Critical Crack Depth



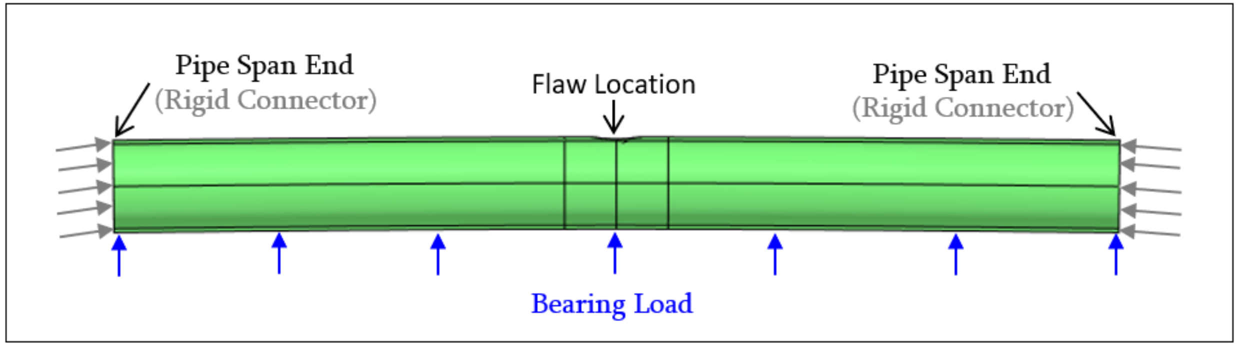


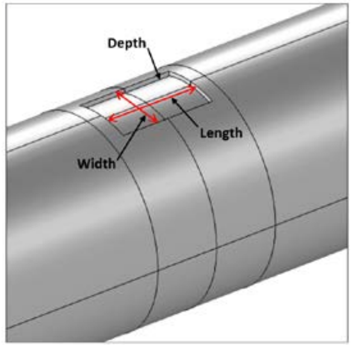


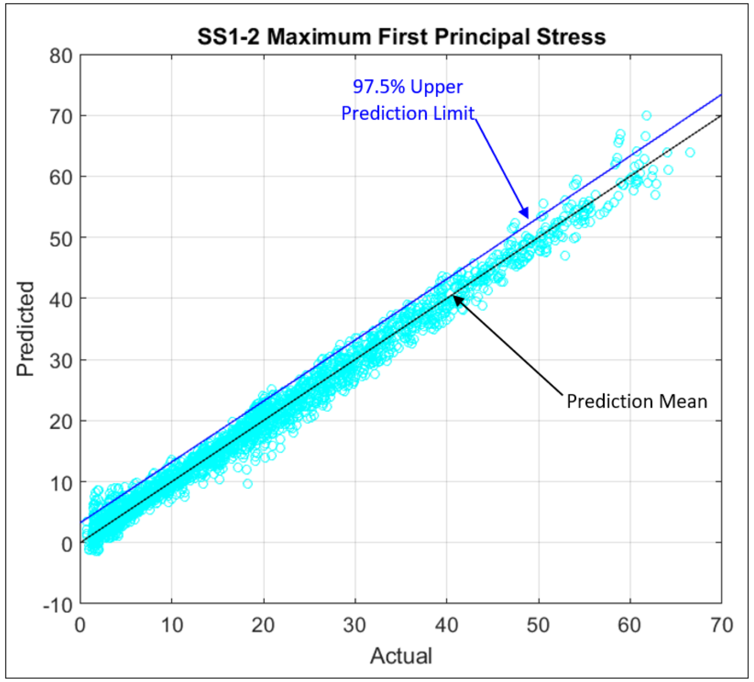
- GTI material models are capable of capturing stress/strain toughness
- Damage propagation models introduce the capability of calibrating toughness to strain rate, morphology and chemistry

4” IPS, 0.25” Wall

FEM Coupled with DoE







- GTI routinely runs several thousand FEM analyses to fully capture wide ranges of asset geometries, flaw geometries, material properties and boundary conditions
- ANOVA analysis of the results provides closed form equations for system response given different levels of input parameters
- Prediction limits at any desired confidence level can be specified to suit particular decision support needs.

	Units	Lower Value	Upper Value
Class	-	10	60
Outer Diameter	in	4.8	15.65
Pipe Span	ft	12	18
Temperature Change	degC	-20	0
Vertical Load Pressure	psi	0	80

Stress Intensity Factor (SIF) from FEM Coupled with DoE

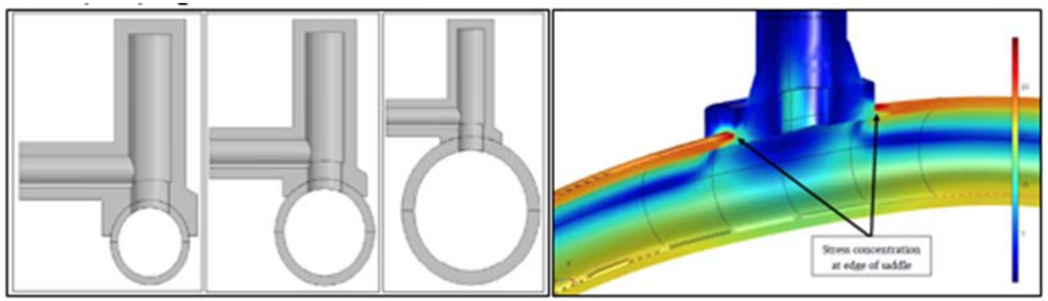
Configuration	a	b	c
Pipe without Saddle Tee	4453.0	-1.0657	-0.744
Pipe with Saddle Tee Positive Bending	5310.7	-0.9654	-0.7251
Pipe with Saddle Tee Negative Bending	9364.1	-1.0757	-0.7789
Pipe with Saddle Tee Lateral Bending	3476.7	-1.0059	-0.5593
Pipe with Coupling	4285.0	-0.676	-0.9252

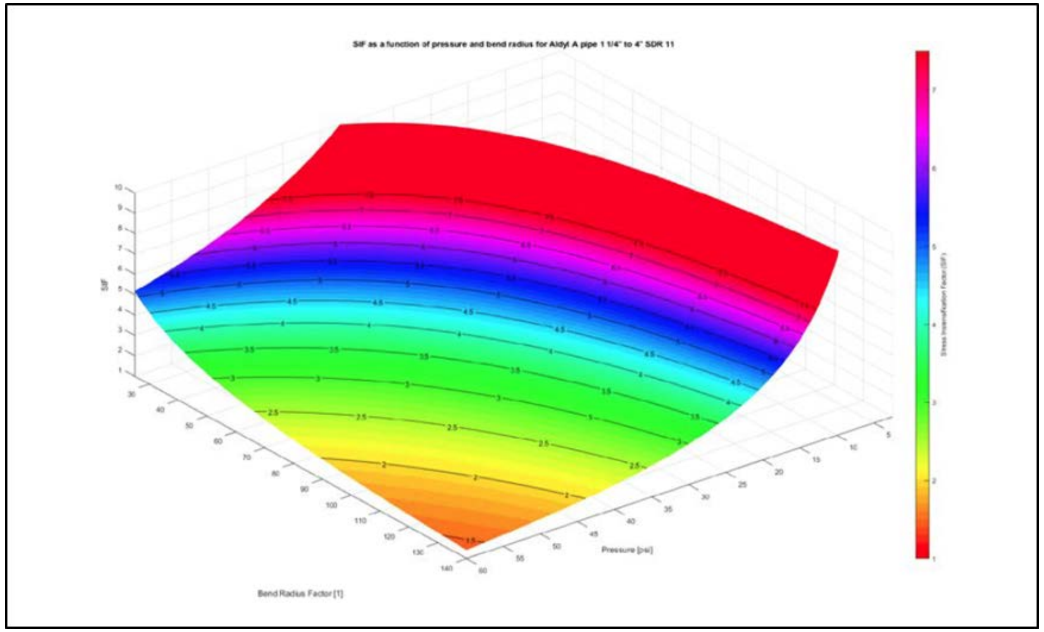
SIF – Stress Intensity Factor

P – Pressure[psi]

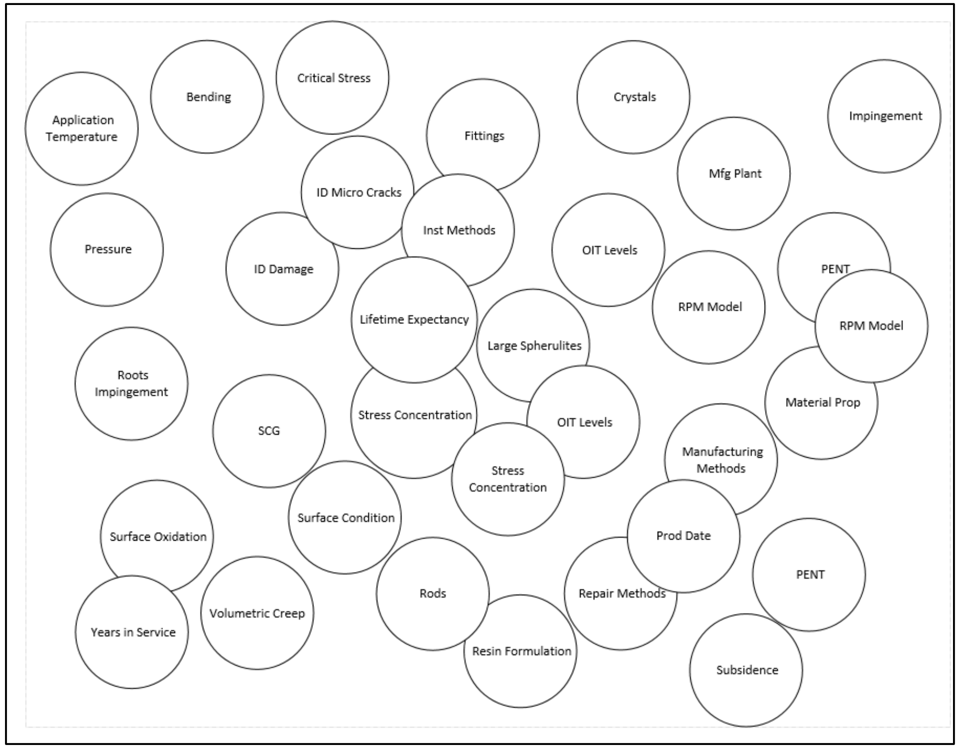
BRF – Bend Radius Factor expressed as multiples of the pipe diameter

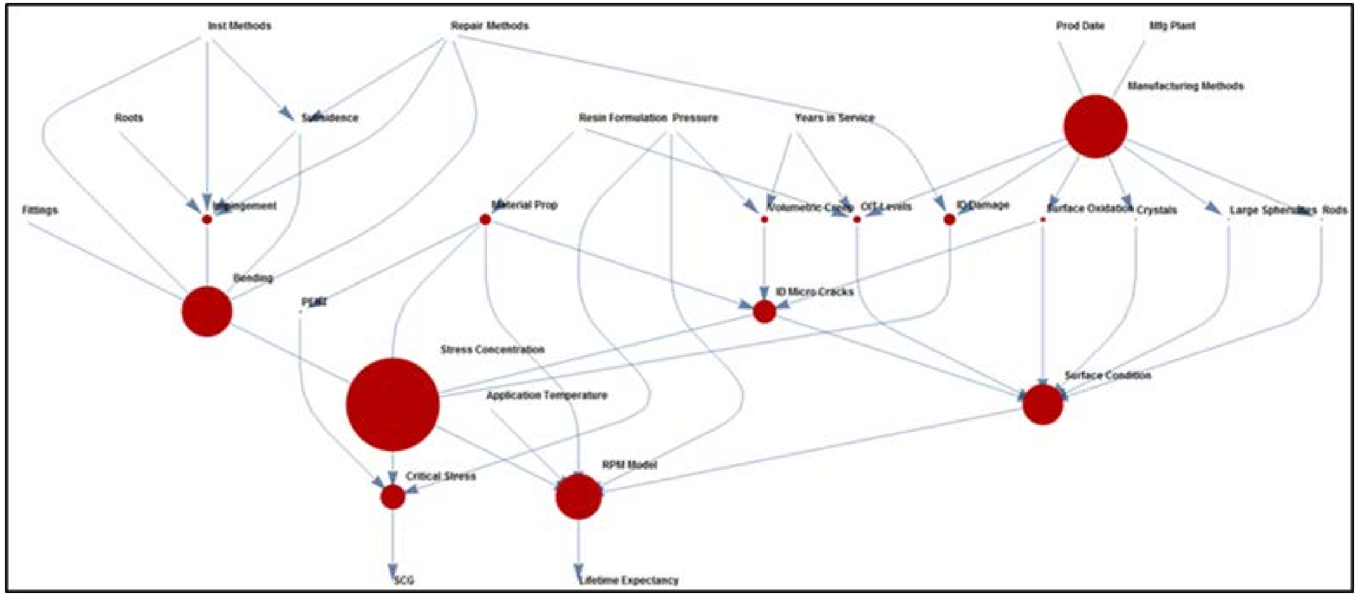
a, b, c – Regression Coefficients





GTI Causal Model for Vintage Aldyl-A Pipeline Risk

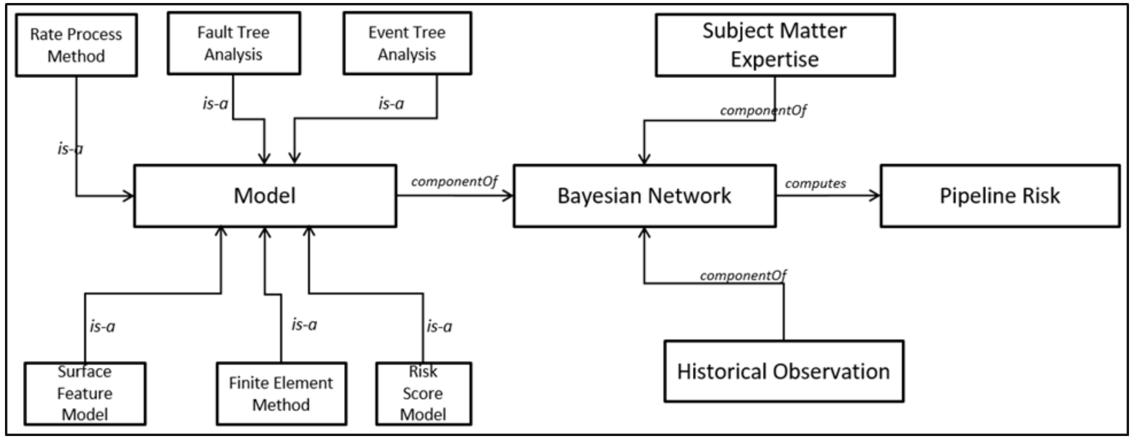


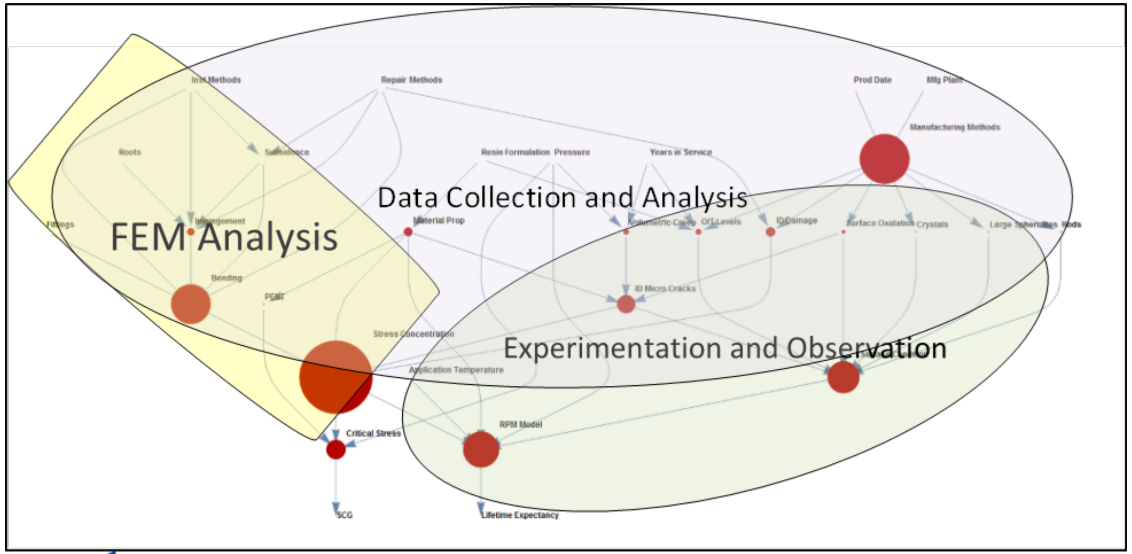


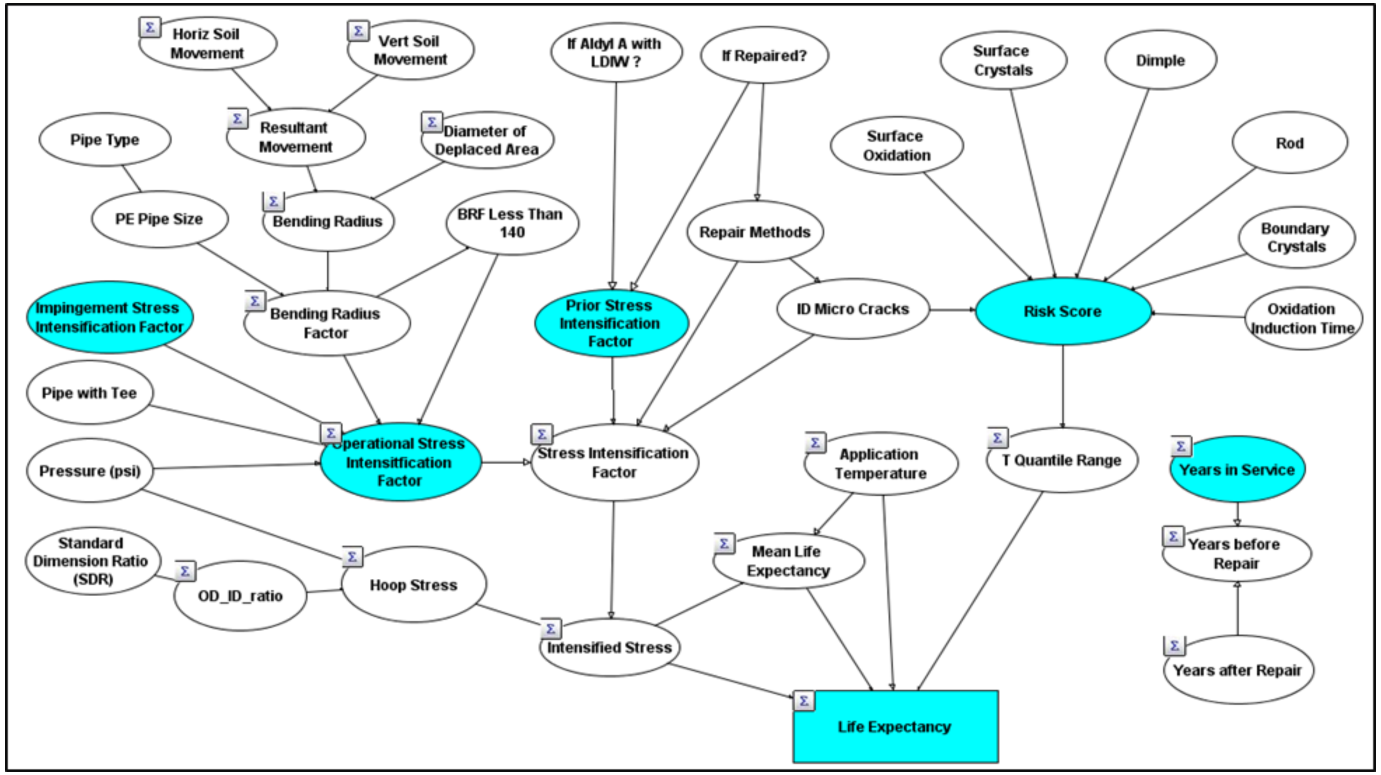
32 factors impacting vintage pipeline performance

Interaction reduction and quantification using Directed Acyclic Graph

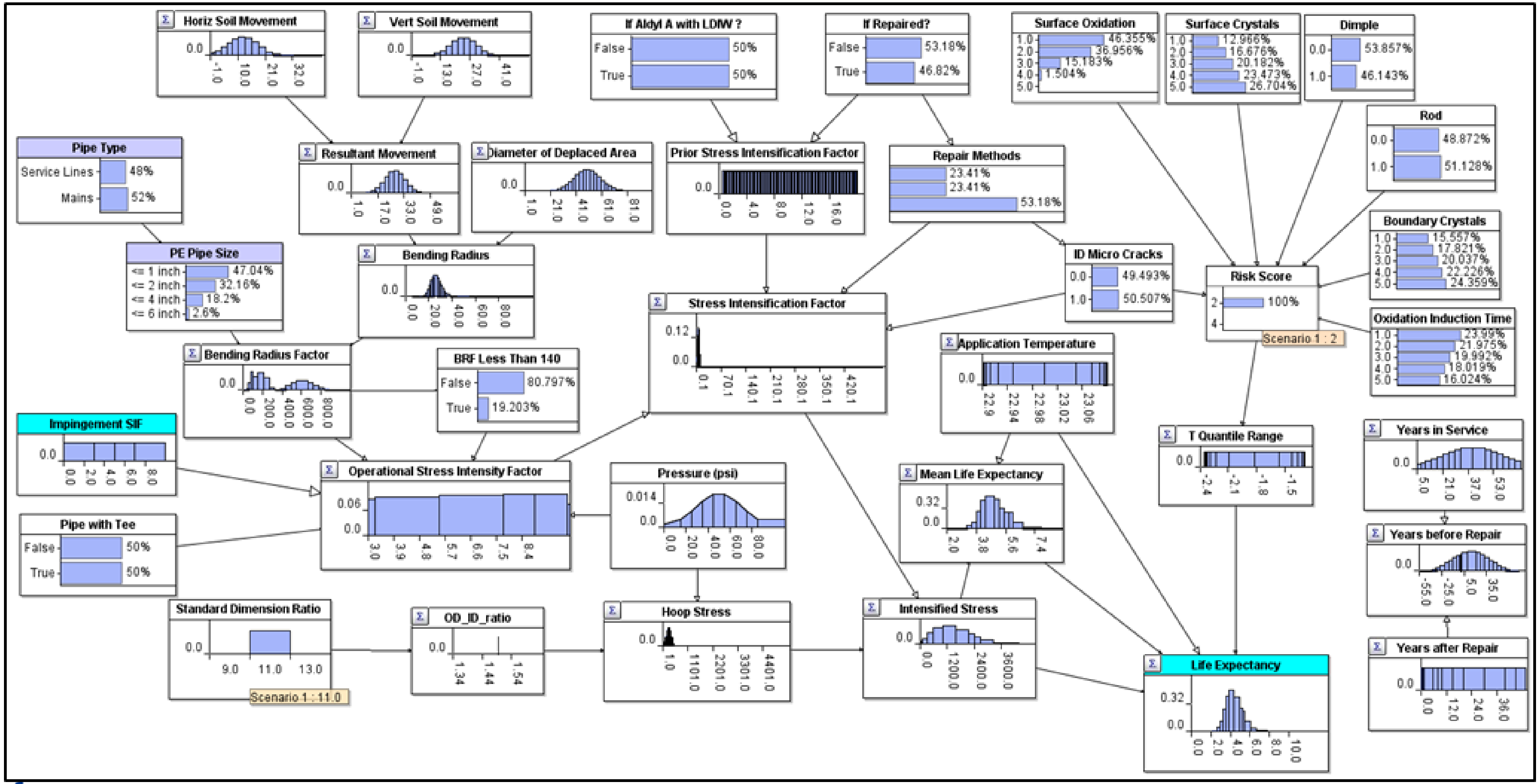
Constructing the Bayesian Network





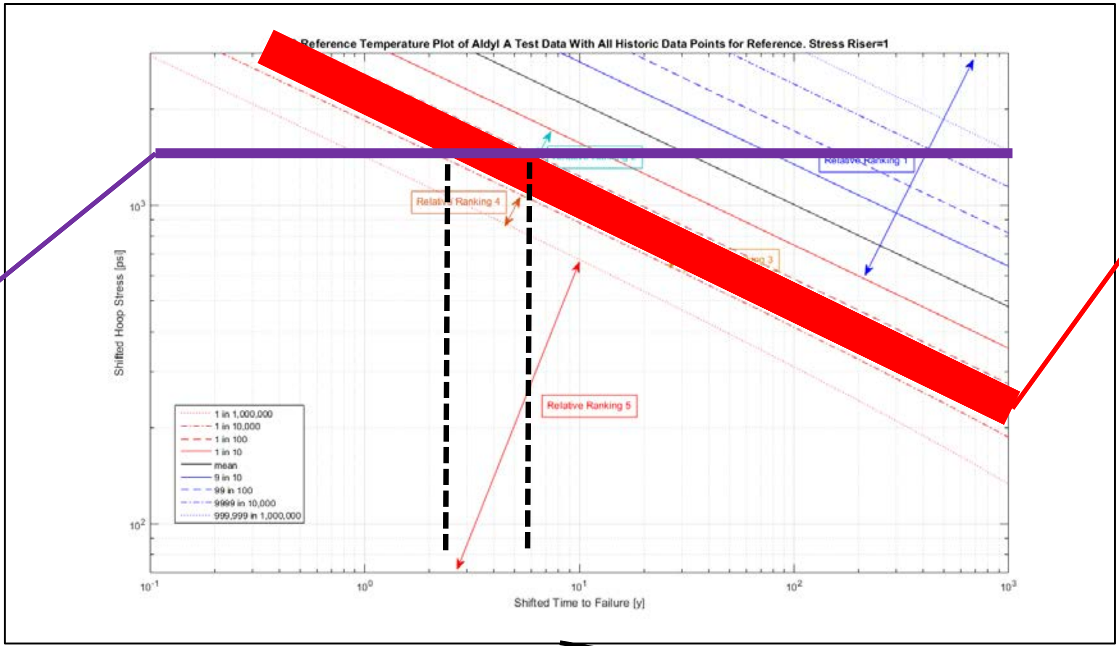


Bayesian Network Probabilistic Model for Lifetime Expectancy



How does the Bayesian Network (BN) work?

$$\log(t) = C_1 + C_2 \frac{1}{T} + C_3 \log(\sigma) + C_4 \frac{log(\sigma)}{T}$$



Surface Conditions

Logistic Regression Model

Internal Pressure

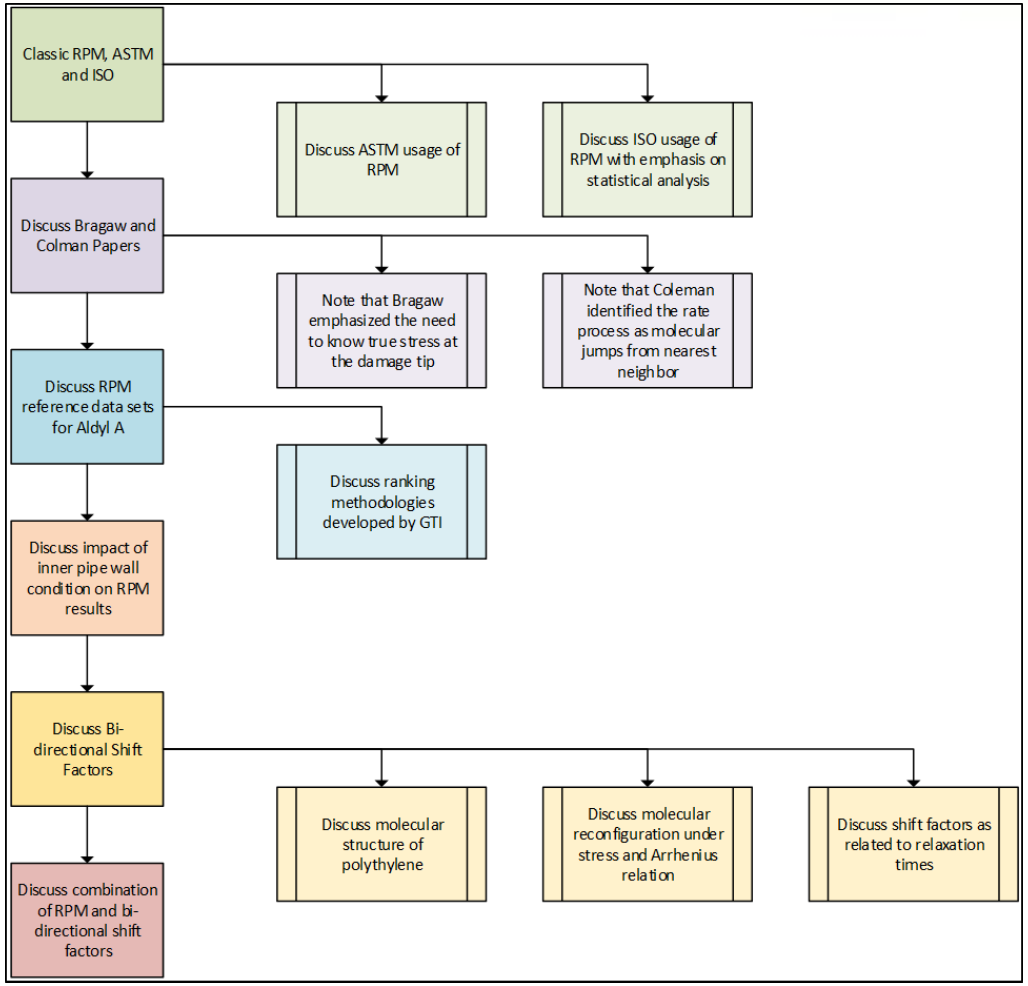
Stress Riser

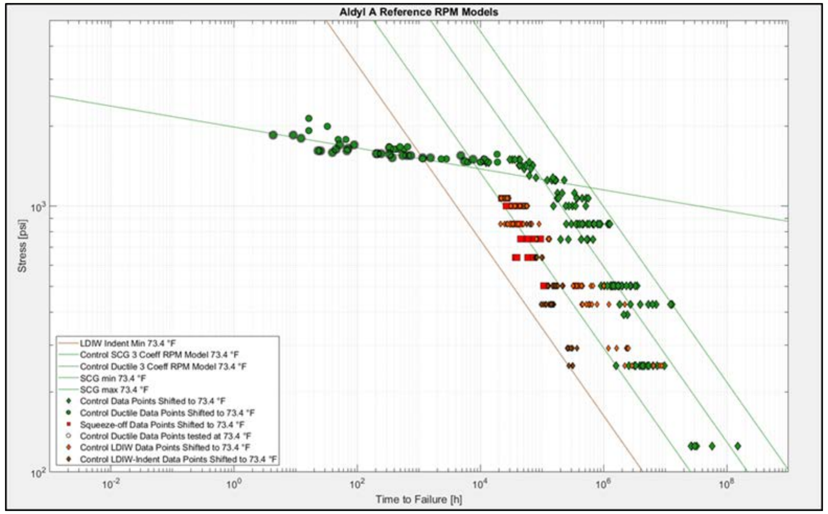
RPM Model

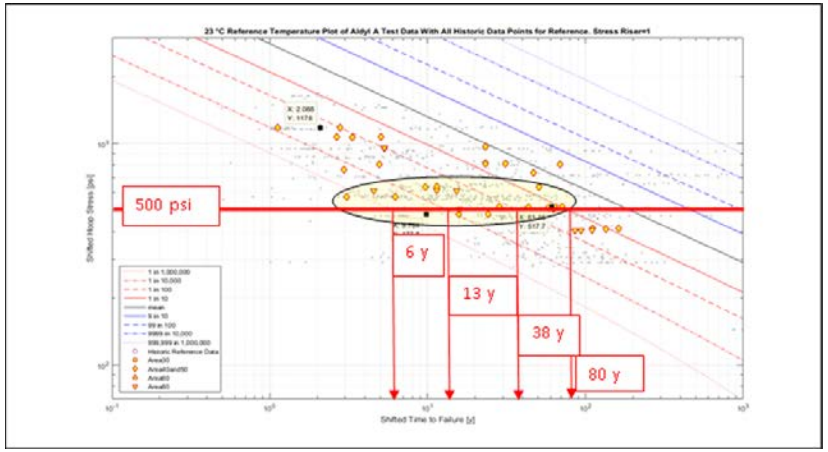
Material, Temperature

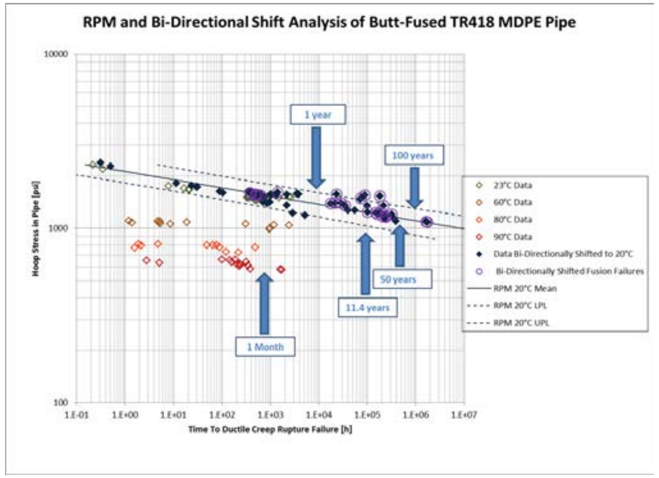
> RPM and logistic regression models have been implemented in the Bayesian network

RPM, Master Curves

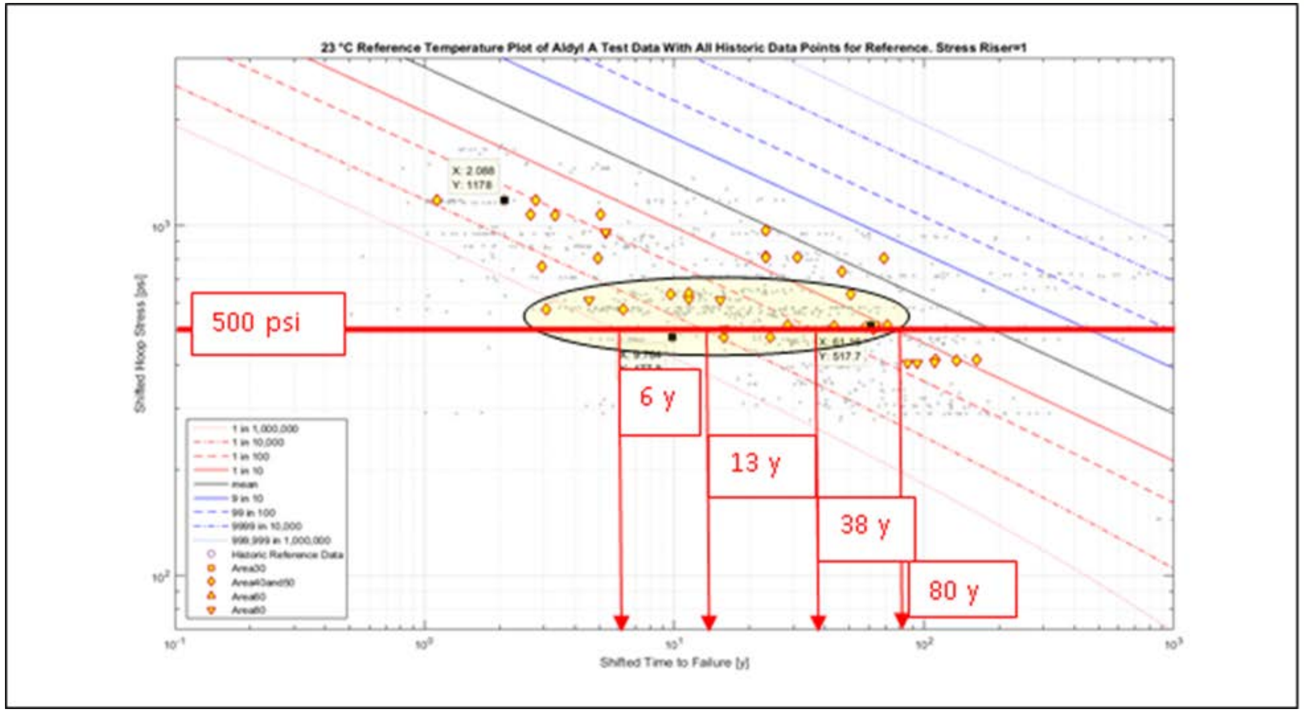


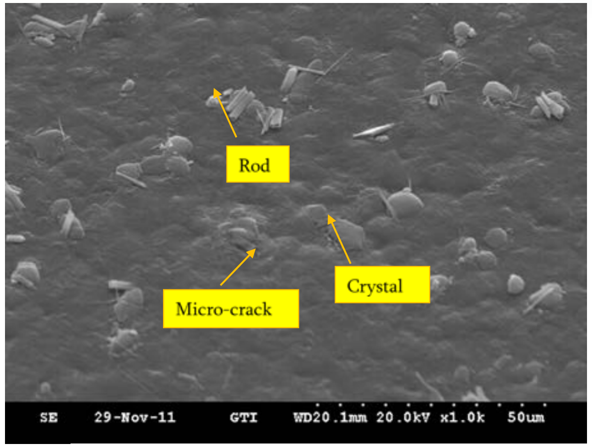


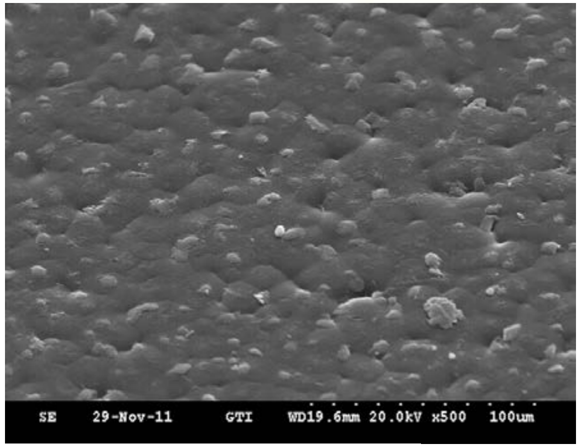




Material Morphology Impacting Lifetime Expectancy





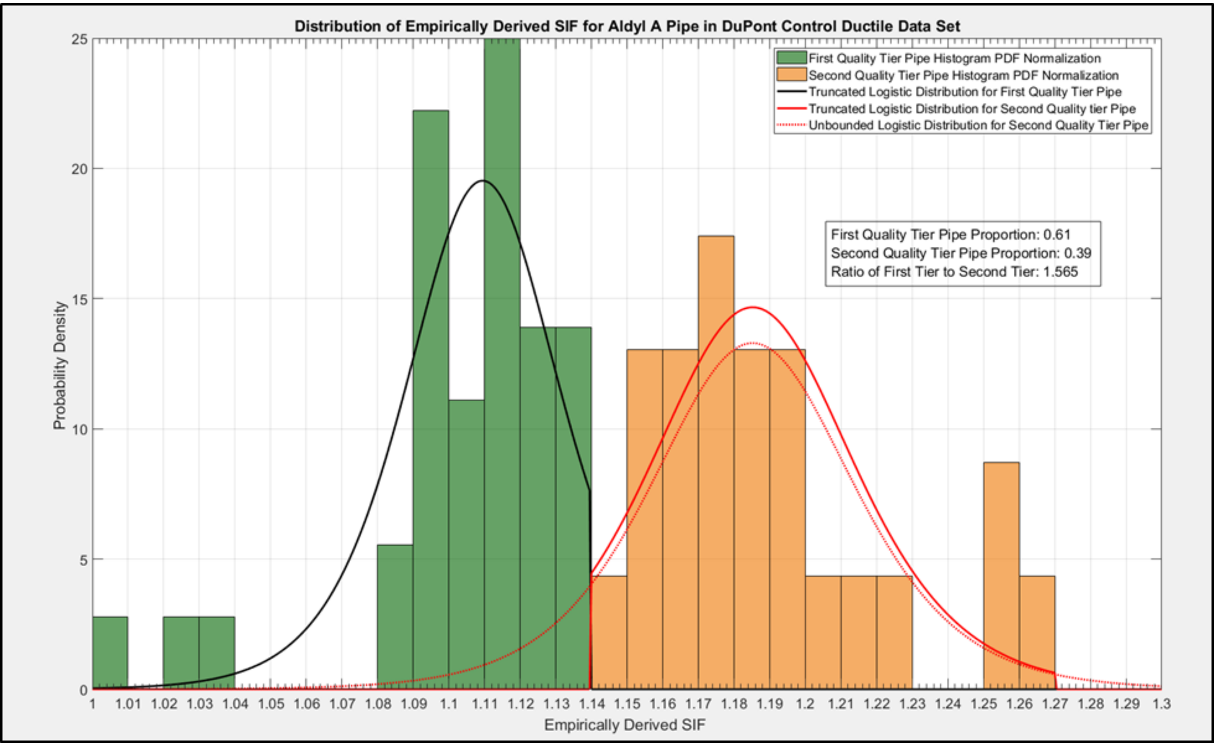


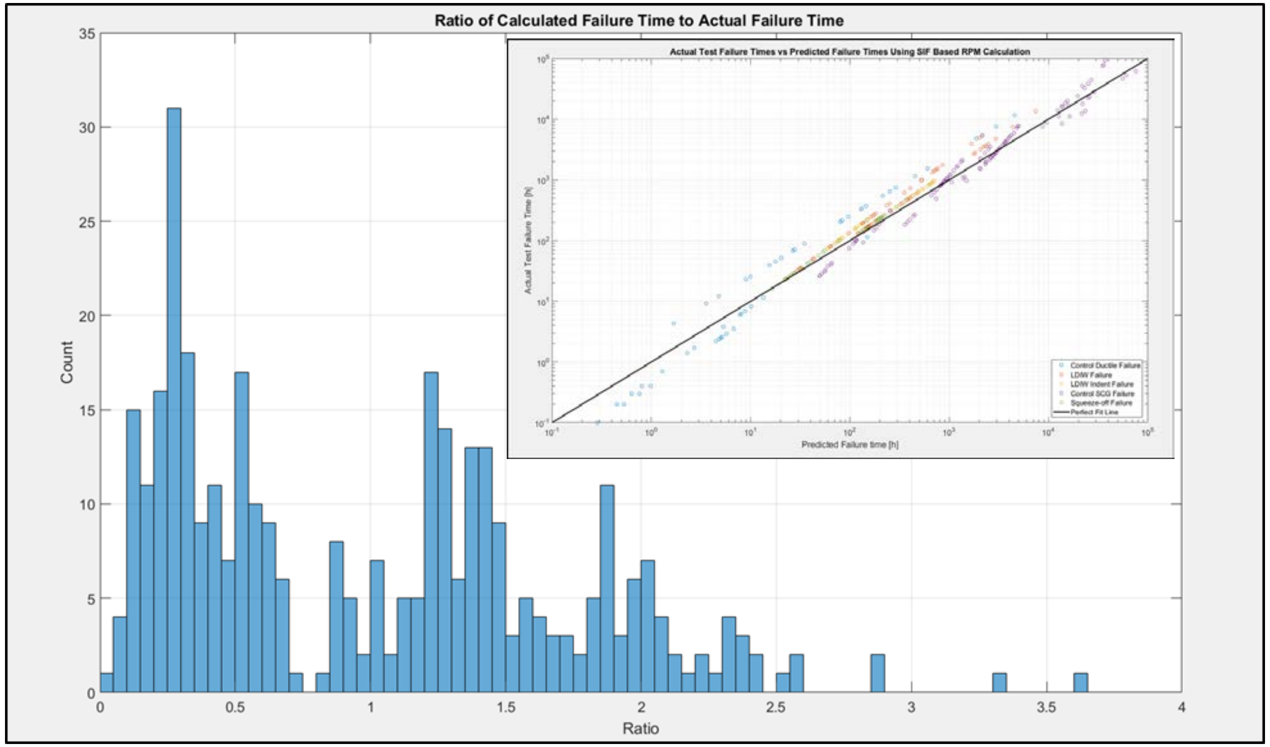
Dimple	Micro Crack	Rod	Boundary Crystals	Surface Crystals	OIT	FTIR - CI	RPM Ranking		Predicted RPM Ranking
1	1	0	1	2	3	5	3	✓	3
1	1	1	1	1	4	4	4	✓	4
1	0	1	1	1	2	3	3	✓	3
0	1	0	1	1	5	1	2	✗	3
1	1	0	1	1	5	1	3	✓	3
1	1	0	1	3	5	1	2	✓	2
0	1	0	1	1	5	1	3	✓	3
1	1	0	4	1	5	1	2	✓	2
0	1	1	1	1	3	1	2	✓	2
0	1	0	1	1	2	1	2	✓	2
1	1	0	3	1	1	2	2	✗	3
1	1	1	4	5	2	4	3	✓	3
1	1	0	3	2	1	3	3	✓	3
1	0	0	3	1	1	3	3	✓	3
1	1	0	3	1	1	2	3	✓	3
1	1	0	5	2	1	2	2	✓	2

Actual System Data

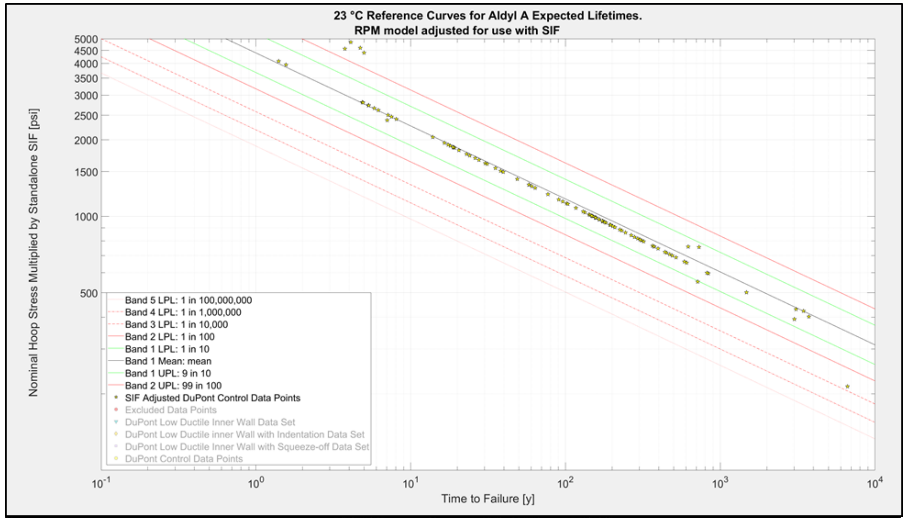
Not Theory

SIF – Reducing Uncertainty in Data Analysis

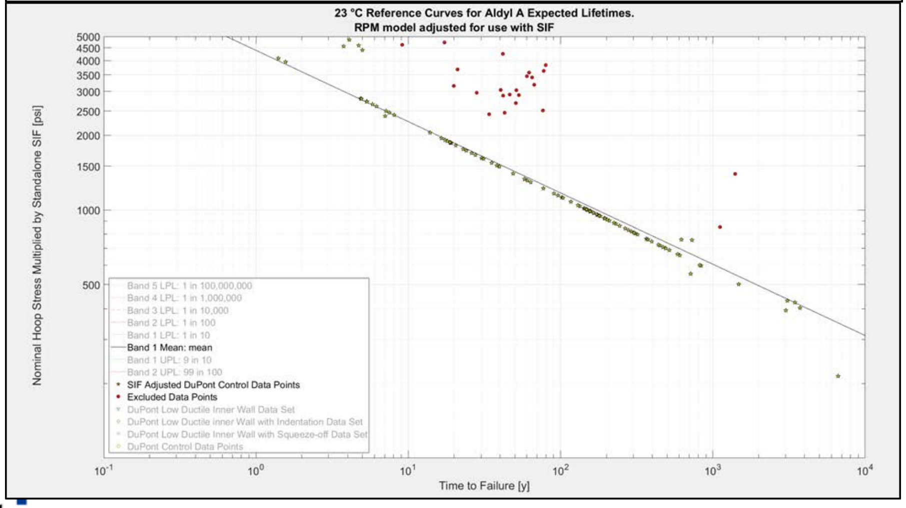


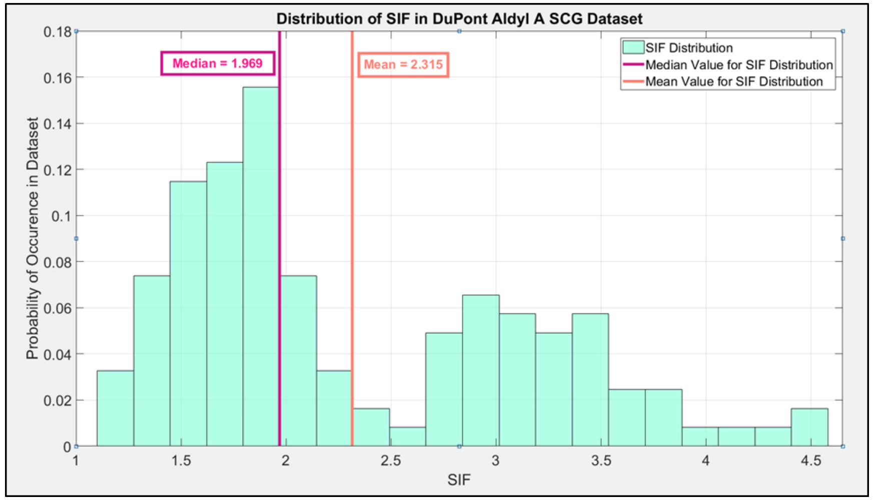


Adjusting RPM Models for Use with SIF: 2 order of magnitude reduction in uncertainty



Adjusted SIF for SCG Failure: Logistic Distribution Parameters for use with adjusted RPM model given in Table 3-1	Standalone SIF		Relative to baseline pipe SIF	
	Mu	sigma	Mu	sigma
Pipe Quality Tier 1 SCG – Baseline SIF	1.016	0.061	1.016	0.061
Use standalone SIF value for single SIF. Develop composite SIF by adding SIF referenced to baseline using Equation 2-5 for each independent SIF component acting on pipe component to the baseline SIF				
Pipe Quality Tier 2 SCG	1.117	0.067	0.461	0.028
Pipe Quality Tier 3 Severe Grooves SCG	1.524	0.091	1.136	0.068
Pipe Quality Tier 4 LDIW SCG	2.936	0.176	2.755	0.165
LDIW Squeeze-off SCG	3.401	0.204	3.246	0.195
LDIW Impingement SCG	4.367	0.262	4.247	0.255



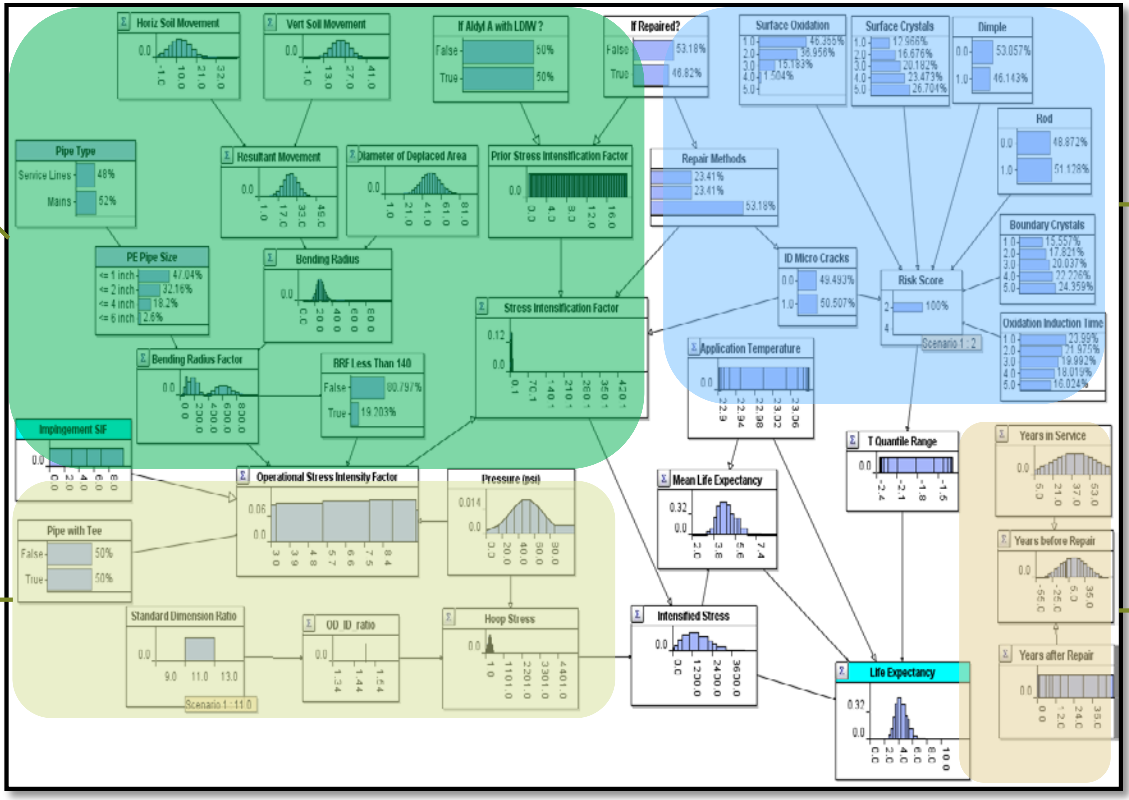


- Normalizing measured system data to historic data sets yields unique SIF distributions.
- These SIF distributions become an objective measure of system quality

Quantified Bayesian Network

Soil
- Soil movement
- Soil type
- Bending
- Impingement

Pipe & pressure
- Pipe geometry
- Fitting
- Hoop stress

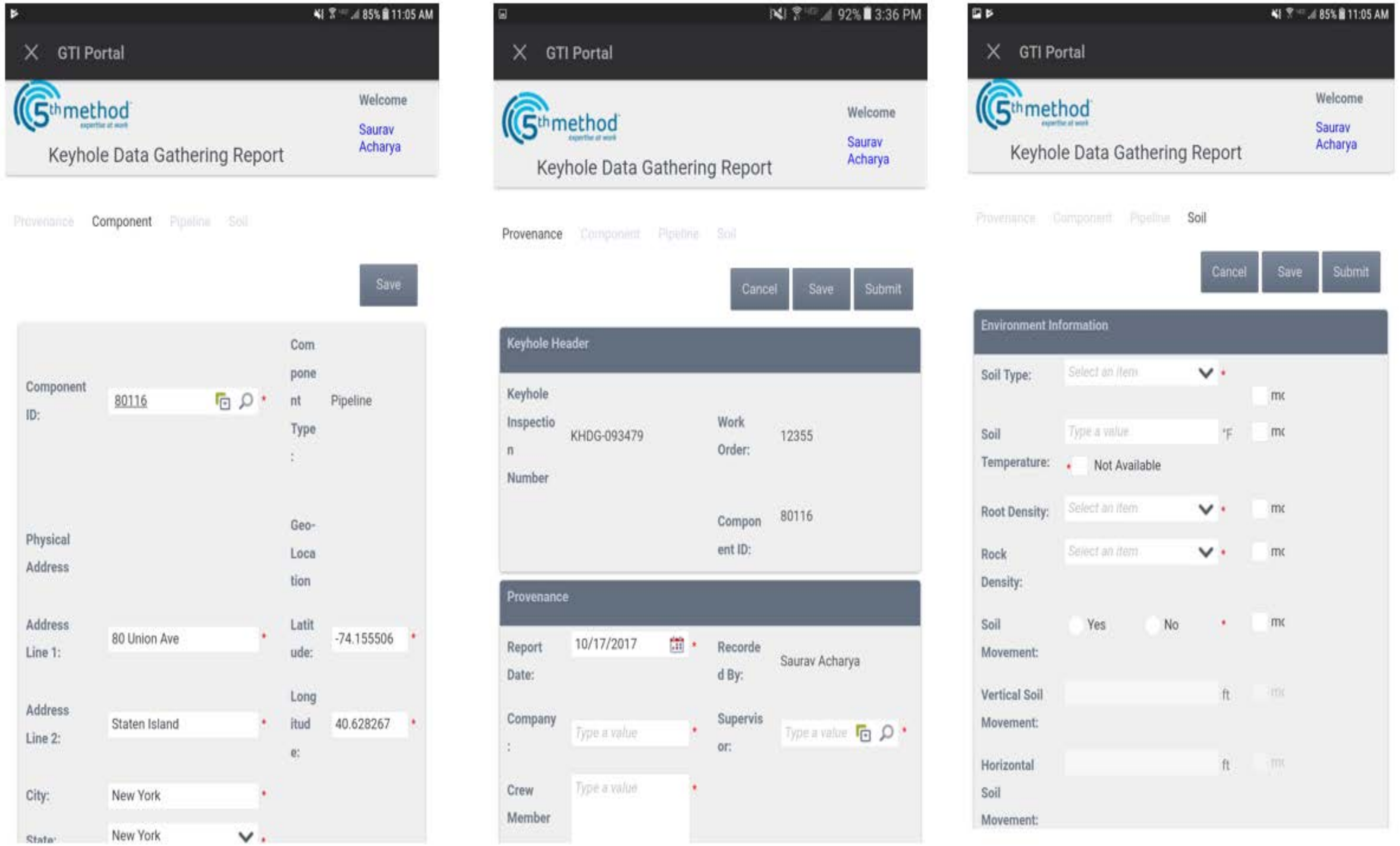


ID surface features
- Surface Oxidation
- Surface Crystals
- Boundary Crystals
- Dimple
- Rod
- Oxidation induction

Years in service
- Years after repair
- Squeeze-off

- SME knowledge, physics based models, and historic data are integrated into the Bayesian network
- Effects from different perspectives are merged using an equivalent stress intensification factor (SIF)
- Output from the Bayesian network is a probability distribution of life expectancy

Smart Form for Intelligent Data Collection



Multiple Use Cases

- Leak Inspection
- Leak Survey
- Leak Repair
- Leak Monitoring
- First Respond
- Keyhole Data Collection

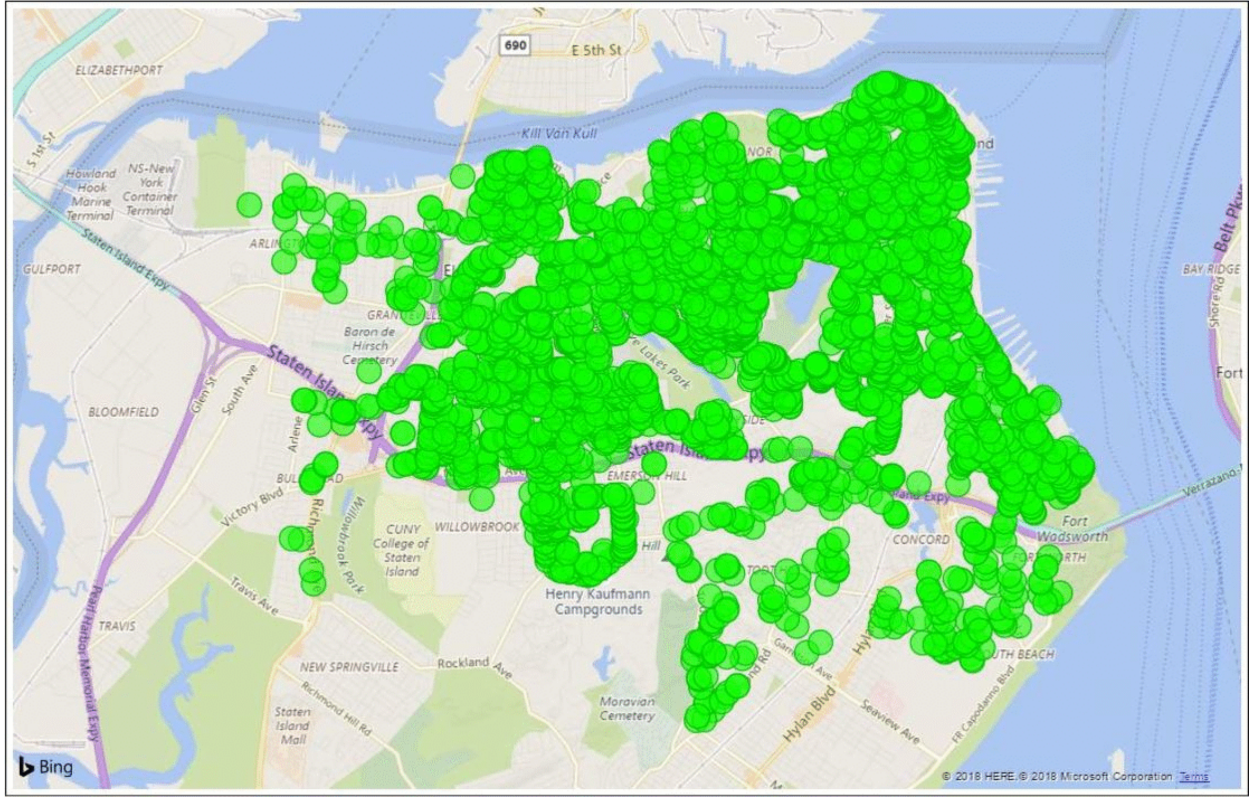
Risk Analysis

- Collect Model Input
- Bayesian Network
- Show Risk Output

Data Visualization

- Update Database
- PowerBI for Visualization

Risk Model Demonstration



Fitness for Service - Pipe Segment

Pipe Segment ID	Average of Risk_Level	Area	Pipe Length (m)	Mean Expected Life (yrs)	Replacement_Cost
1	4.00	1	1.27	6.00	$286.78
2	4.00	1	13.83	1.75	$3,111.91
3	4.00	1	85.39	18.58	$19,212.38
4	4.00	1	0.53	2.94	$118.67
5	4.00	1	1.60	4.21	$360.83
6	3.00	1	5.53	3.94	$1,244.85
7	4.00	1	35.51	1.60	$7,989.41
Total	**3.41**	**7706**	**278,951.38**	**15.97**	**$62,764,059.68**

Fitness for Service - System

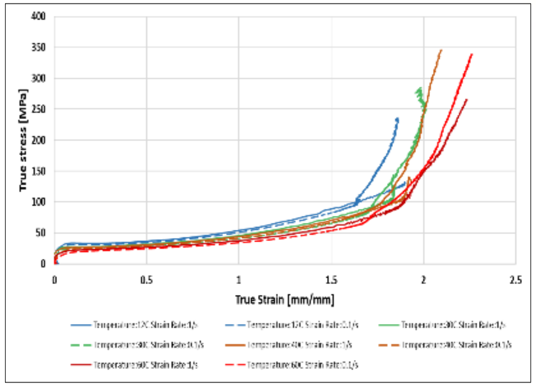
Area	Risk Level	Risk	Pipe Length (m)	# Segments	Mean Expected Life (yrs)	Replacement_Cost
1	3.42	0.6	26,174.17	616	16.26	$5,889,188.02
2	3.45	0.6	74,003.72	1940	16.16	$16,650,837.49
3	3.62	0.7	125,166.17	3475	14.79	$28,162,388.89
4	2.95	0.5	45,330.67	1505	18.46	$10,199,401.14
5	2.38	0.4	8,276.64	170	15.01	$1,862,244.15
Total	**3.41**	**0.6**	**278,951.38**	**7706**	**15.97**	**$62,764,059.68**

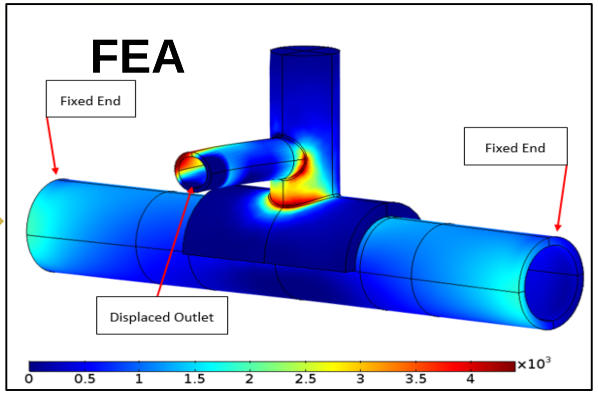
PowerBI Dashboard-Risk evolution over 0-30 years

Fitness for Service after 30 years

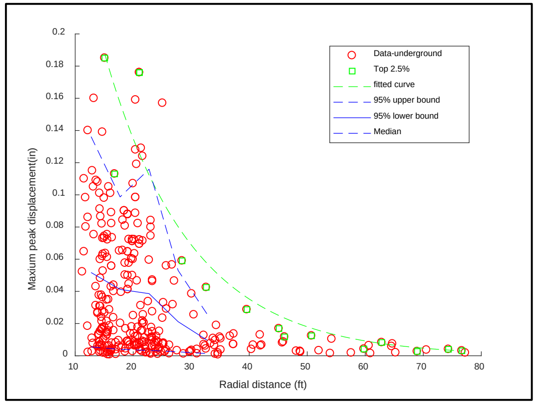
Risk Analysis: Blasting Adjacent to HDPE Distribution System

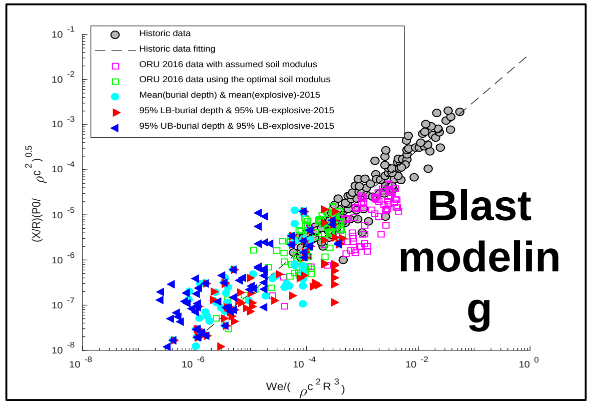
Material Testing

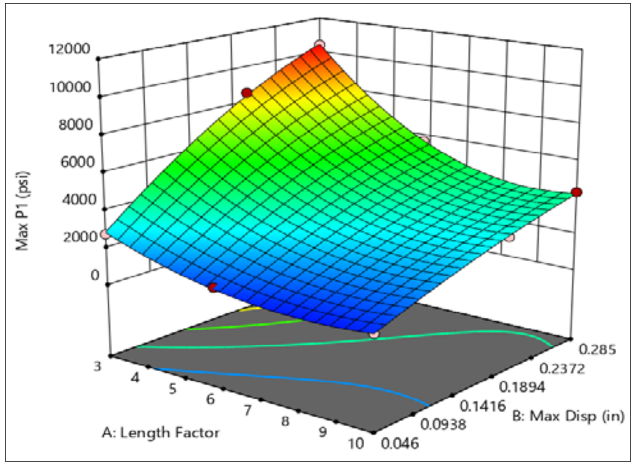




Field data collection







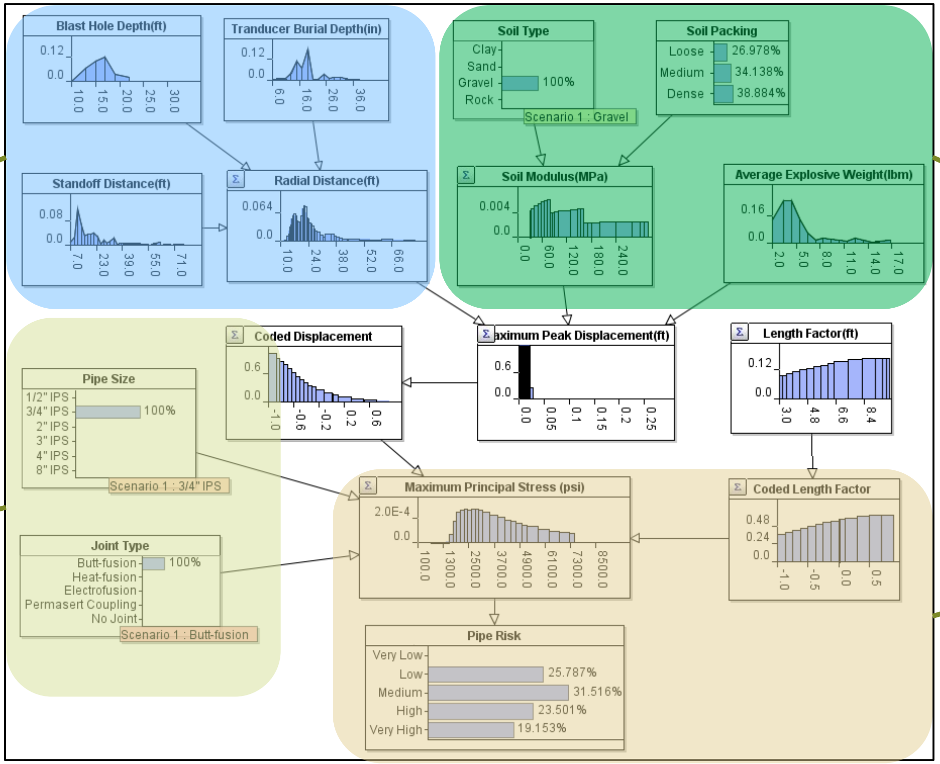
Response surface model

- The developed model fuses field data, soil movement, wave propagation, pipe deformation, FEA, and SME opinions
- It is verified by subsequent data provided by the sponsor and included in the GIS system to facilitate the implementation
- The risk on fusion joints should be carefully assessed when blast activities are performed in proximity

Bayesian Network: Blasting Adjacent to HDPE Distribution System

Interaction with blasting
- Standoff distance
- Burial depth
- Blast hole depth
- Blast information

Pipe
- Pipe geometry
- Joint type



Soil movement
- Soil movement
- Soil properties (modulus, density)

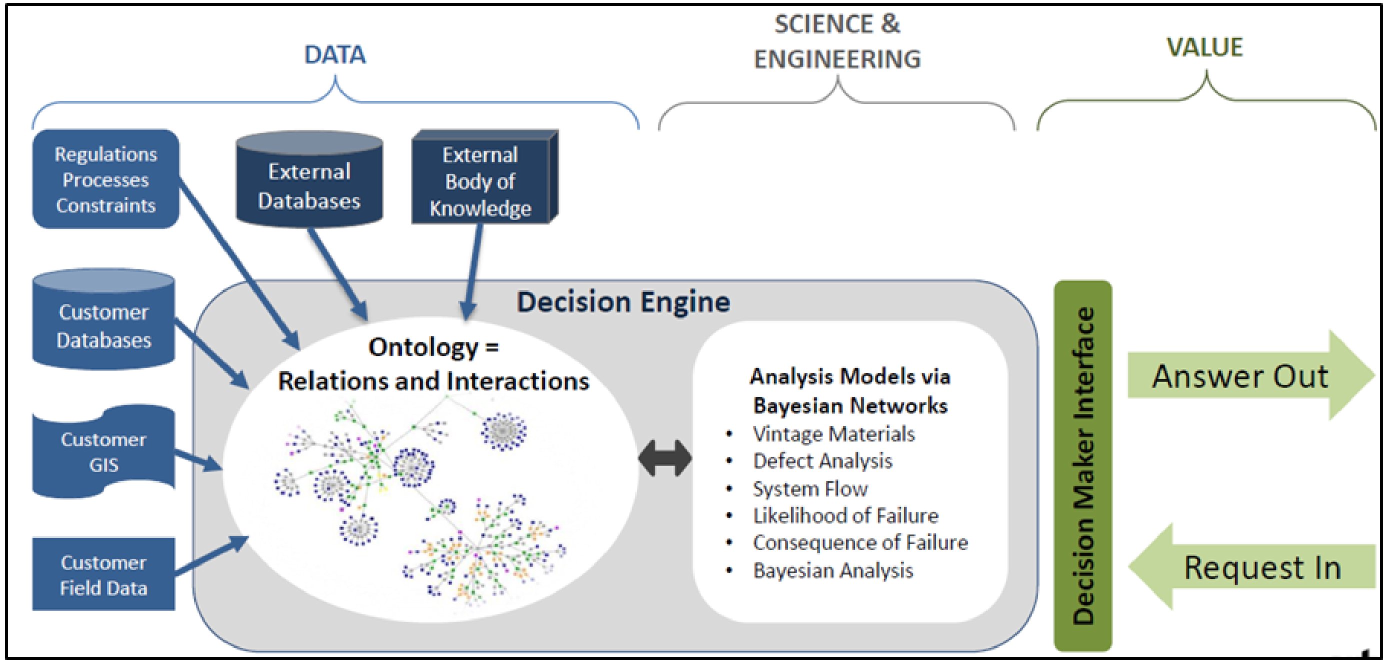
Failure probability
- Maximum principal stress
- Probability category

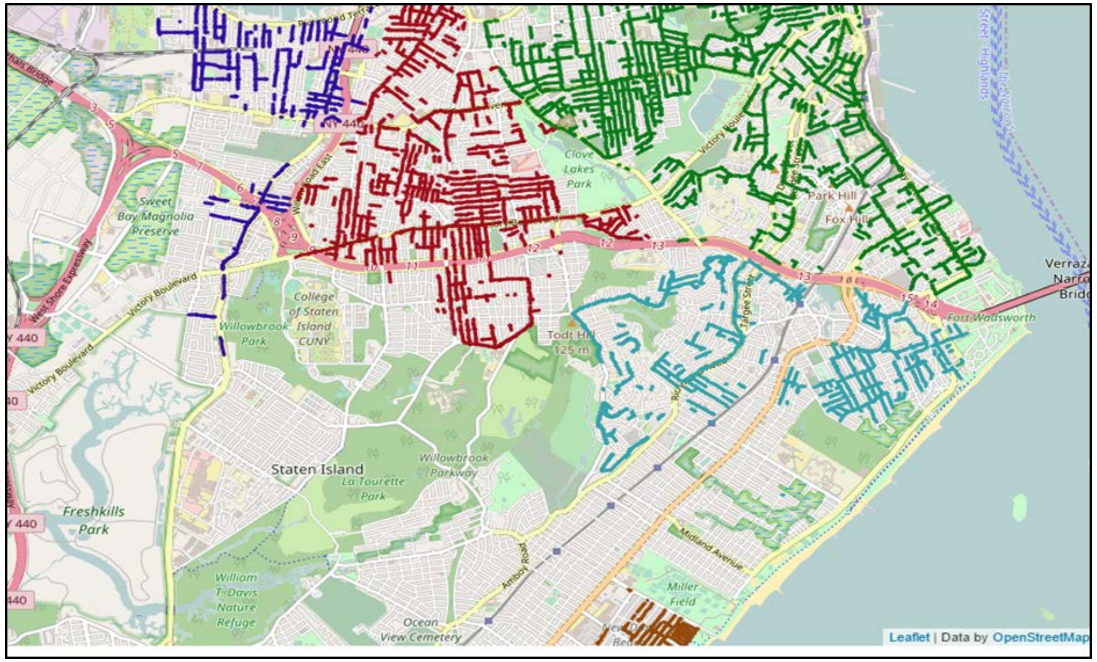
> The developed model fuses field data, soil movement, wave propagation, pipe deformation, FEA, and SME opinions

> It is verified by subsequent data provided by the sponsor and included in the GIS system to facilitate the implementation

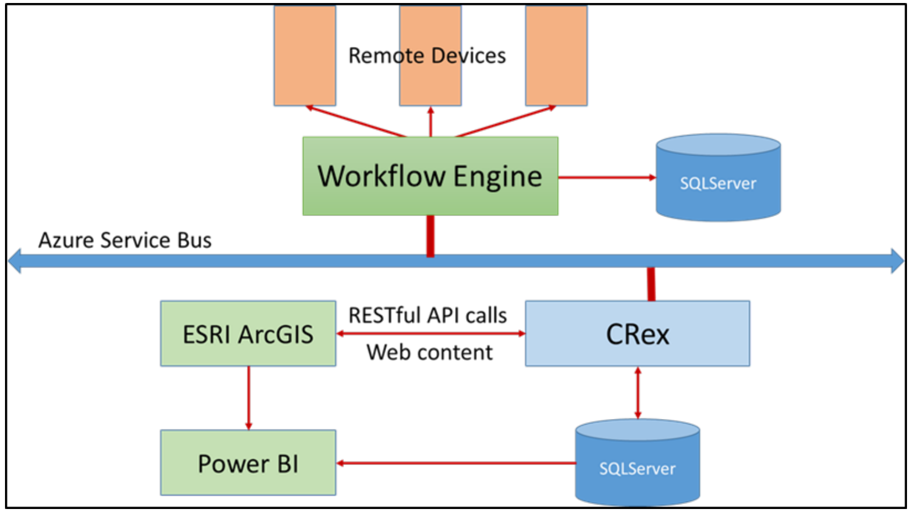
> The risk on fusion joints should be carefully assessed when blast activities are performed in proximity

Integrated Analysis Tools





Probability of Failure within 5 years	Number of Segments	Percent of Segments	Cumulative %	Average Years in Service	Linear Feet	Replacement Cost	Cumulative Replacement Cost
90%+	183	2.38%	2.38%	51.8	12,426	$2,795,756	$2,795,756
80-90%	975	12.66%	15.03%	44.1	82,997	$18,674,363	$21,470,118
70-80%	985	12.79%	27.82%	44.0	81,316	$18,296,065	$39,766,183
60-70%	993	12.89%	40.71%	44.1	88,431	$19,896,967	$59,663,150
50-60%	398	5.17%	45.88%	40.4	31,286	$7,039,312	$66,702,463
40-50%	218	2.83%	48.71%	44.1	16,707	$3,759,120	$70,461,583
30-40%	64	0.83%	49.54%	43.9	4,141	$931,670	$71,393,253
20-30%	1,162	15.09%	64.62%	45.3	121,652	$27,371,634	$98,764,887
10-20%	1,494	19.40%	84.02%	37.0	131,774	$29,649,092	$128,413,979
<10%	1,262	16.38%	100.40%	40.7	123,825	$27,860,680	$156,274,660



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What do the models currently offer

1) The probabilistic models capture expected system behavior very well
2) The material models and damage propagation models are state-of-the-art and based on sound science
3) The model outputs are calibrated to historic data
4) The probability distributions used to assign asset conditions match known aggregate system performance
5) The models offer valuable assistance in root cause analysis and the temporal progression of failures due to the various root causes
6) The Bayesian Network models are the best known solution for addressing all system interactions, including human factors and unknown factors

Questions