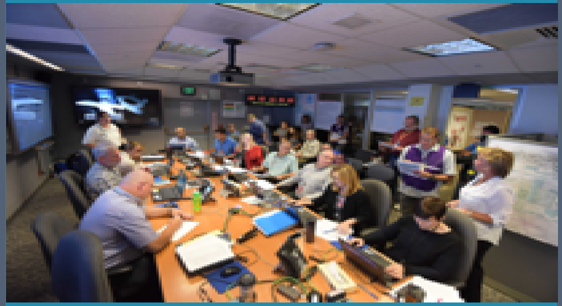
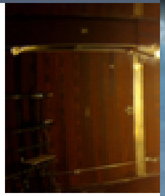
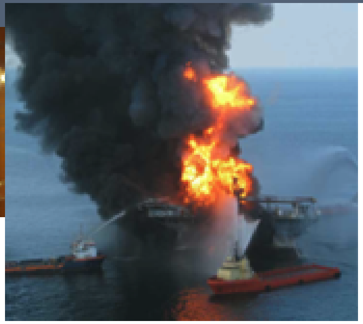
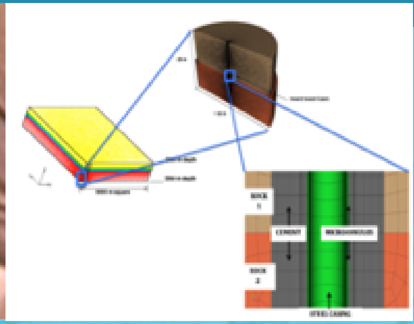
Sandia National Laboratories

SAND2021-6005C

Integrating Machine Learning into a Methodology for Early Detection of Wellbore Failure



Edward N. Matteo, Barry L. Roberts, Steven R. Sobolik, Samuel D. Gilletly, Casey Doyle, Esther John, and Stephen J. Verzi

Sandia National Laboratories, Albuquerque, NM

Interpore 2021

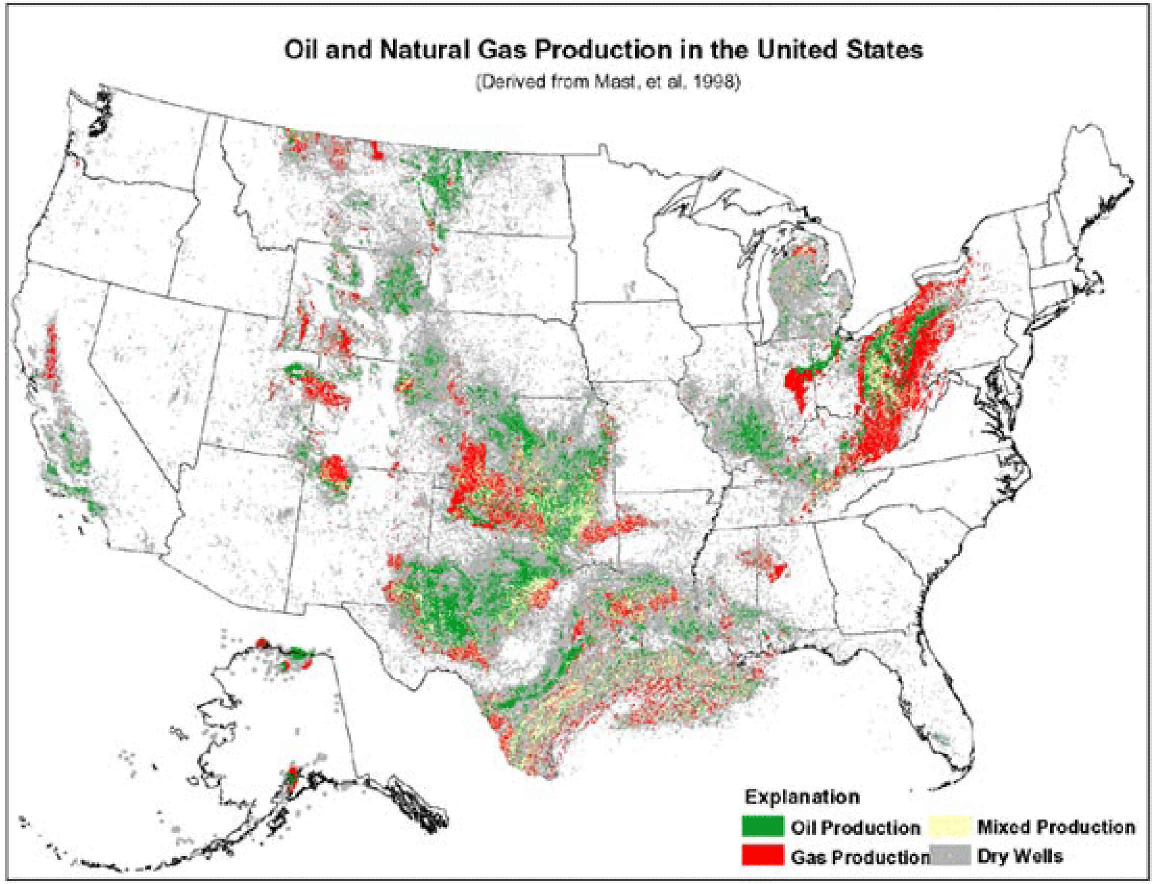
Sandia National Laboratories is a multimission laboratory managed and operated by National Technology and Engineering Solutions of Sandia LLC, a wholly owned subsidiary of Honeywell International Inc. for the U.S. Department of Energy's National Nuclear Security Administration under contract DE-NA0003525.

SAND2021-xxxx (slides)
SAND2021-xxxx (audio)

Background

- ~93% of US total energy supply is dependent on wellbores in some form
- Industry will drill more wells in next ten years than in last 100 years

King, 2014



- Global well population is ~ 1.8 Million of which ~ 35% has some signs of leakage (i.e. sustained casing pressure)
- ~5% of offshore oil and gas wells "fail" early, more with age and most with maturity
- 8.9% of "shale gas" wells in the Marcellus play have experienced failure (120 out of 1,346 wells drilled in 2012)

Ingraffea et al. 2014

50,000 Miles of wellbores are drilled every year in the US

Slide courtesy of Giorgia Bettin

What is a Wellbore Failure?

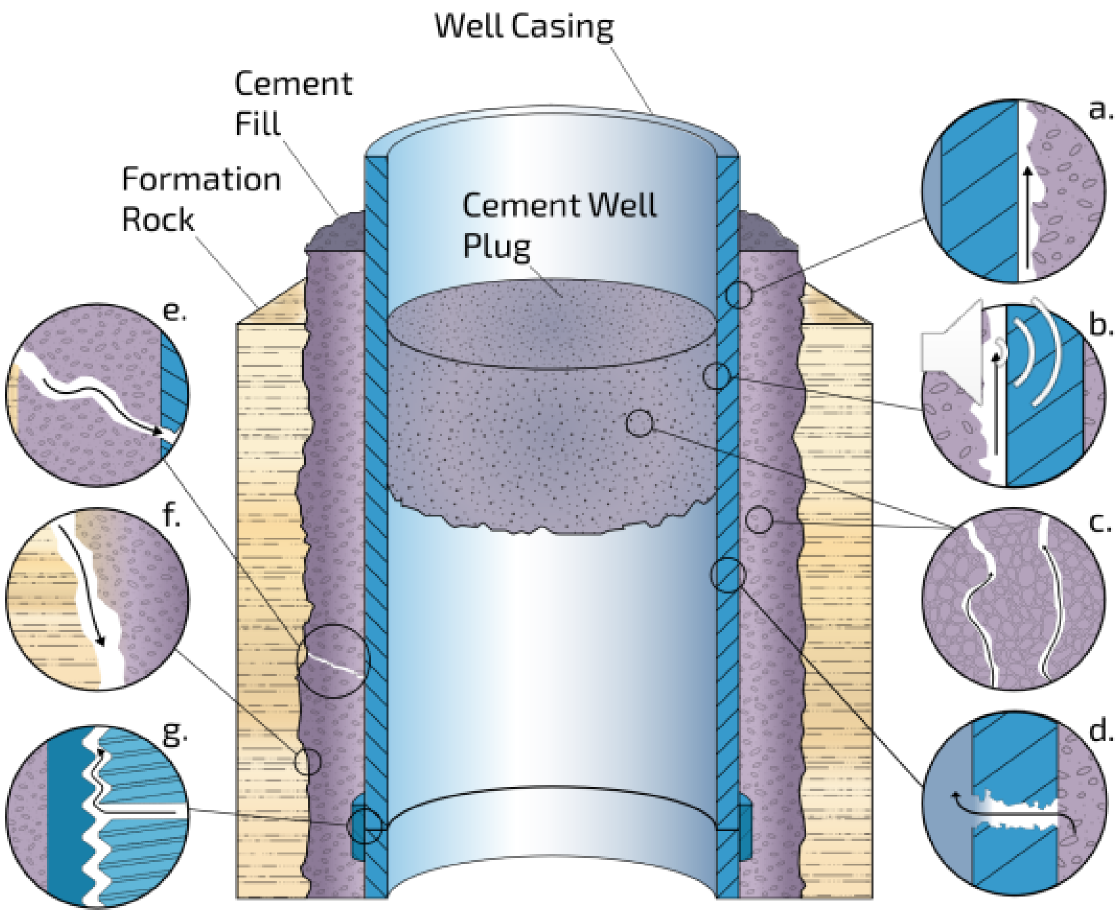


FIG. 1
Diagrammatic representation of possible leakage pathways through an abandoned well. a) Between casing and cement; b) between cement plug and casing; c) flow through cement pore space due to cement degradation; d) through casing as a result of corrosion or fracture; e) through fractures in cement; f) between cement and rock; and g) between coupling thread at pipe joint.

After Gasda et al. 2004

What are the current methods for deciding which wellbores need attention?

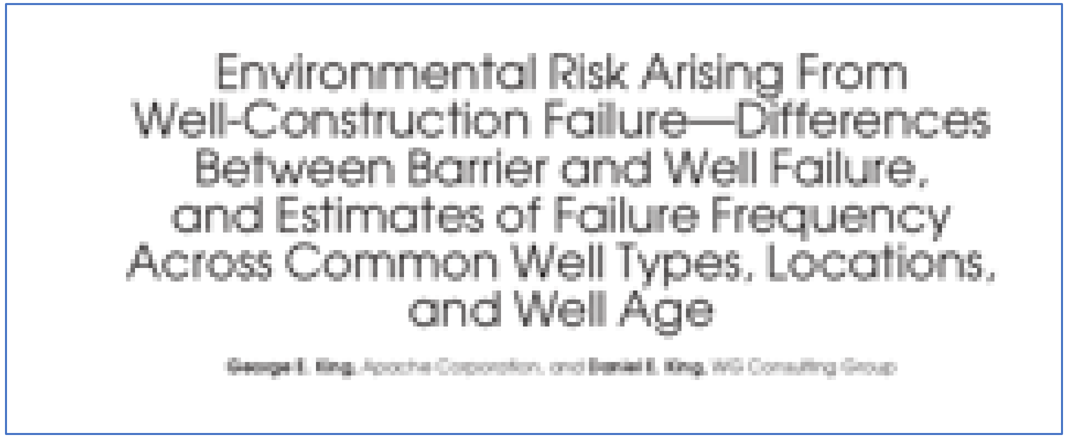
- Current approaches to evaluating wellbore risk analysis methodology focus on grading systems based on specific metrics (e.g. 1-5 for pressure rating, casing deformation, etc.)
- Physics-based models, using site-specific data, can also be used (but can't be used as a coarse sorting/prioritization tool)


HSE

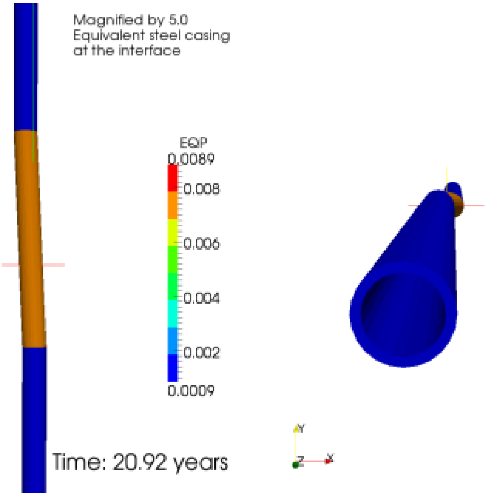
Failure rates for underground gas storage

Significance for land use planning assessments

Prepared by the **Health and Safety Laboratory** for the Health and Safety Executive 2008


Environmental Risk Arising From Well-Construction Failure—Differences Between Barrier and Well Failure, and Estimates of Failure Frequency Across Common Well Types, Locations, and Well Age

George E. King, Apache Corporation, and **Daniel E. King**, WG Consulting Group



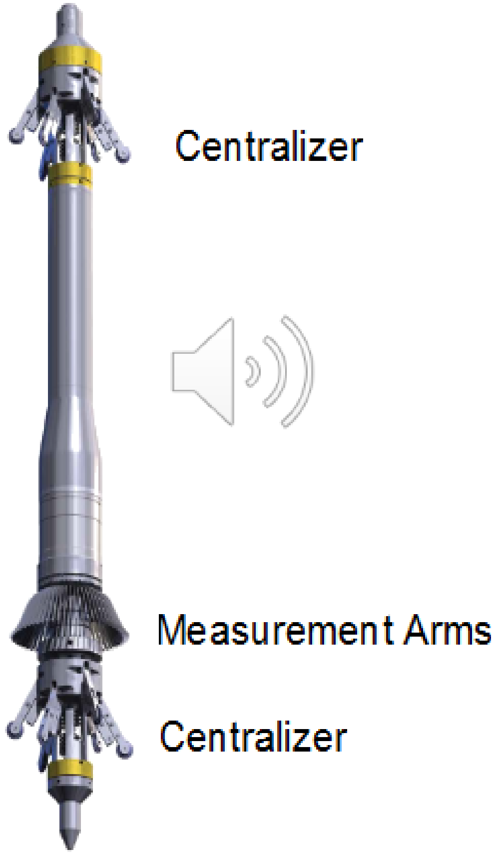
Multi-arm Caliper Well Logging Tool

As the tool is raised through the well casing 56 to 80 radial arms make direct measurement of the casing geometry. Measurements recorded with depth – 0.1 to 0.001 feet frequency.

This provides measurement of casing deformation as an indicator of potential casing failure.

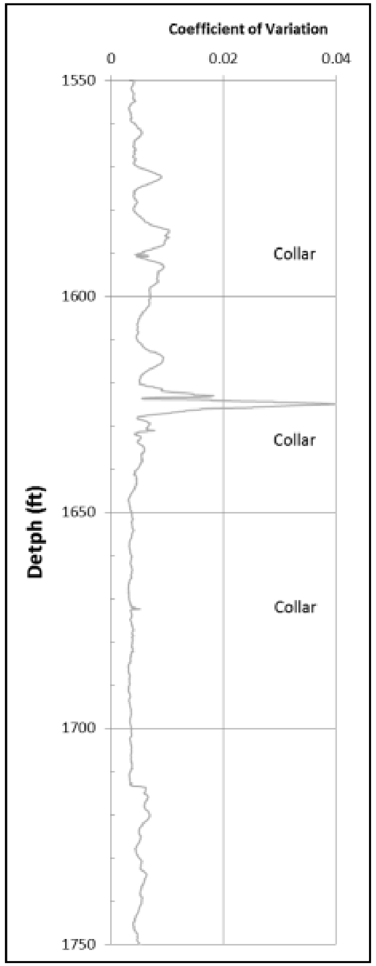
The data from this tool can then be summarized into a single parameter indicating casing deformation as a function of depth.

We have found the most useful parameter to be the coefficient of variation of the radial arm measurements

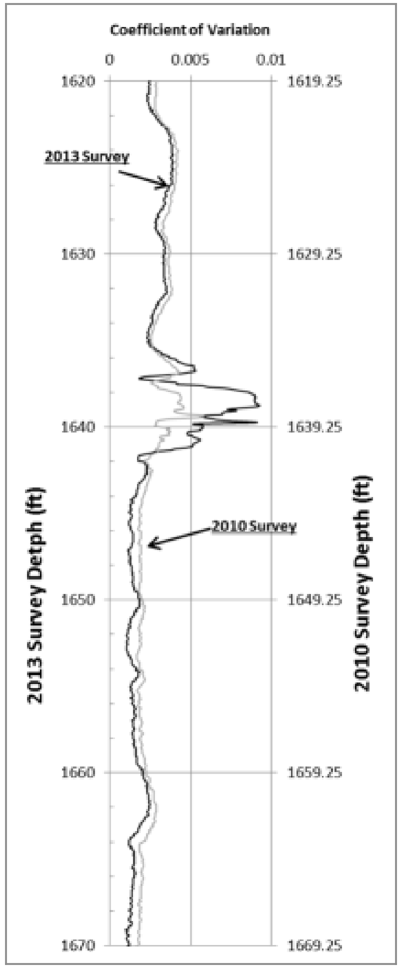



Measurement Arm Detail

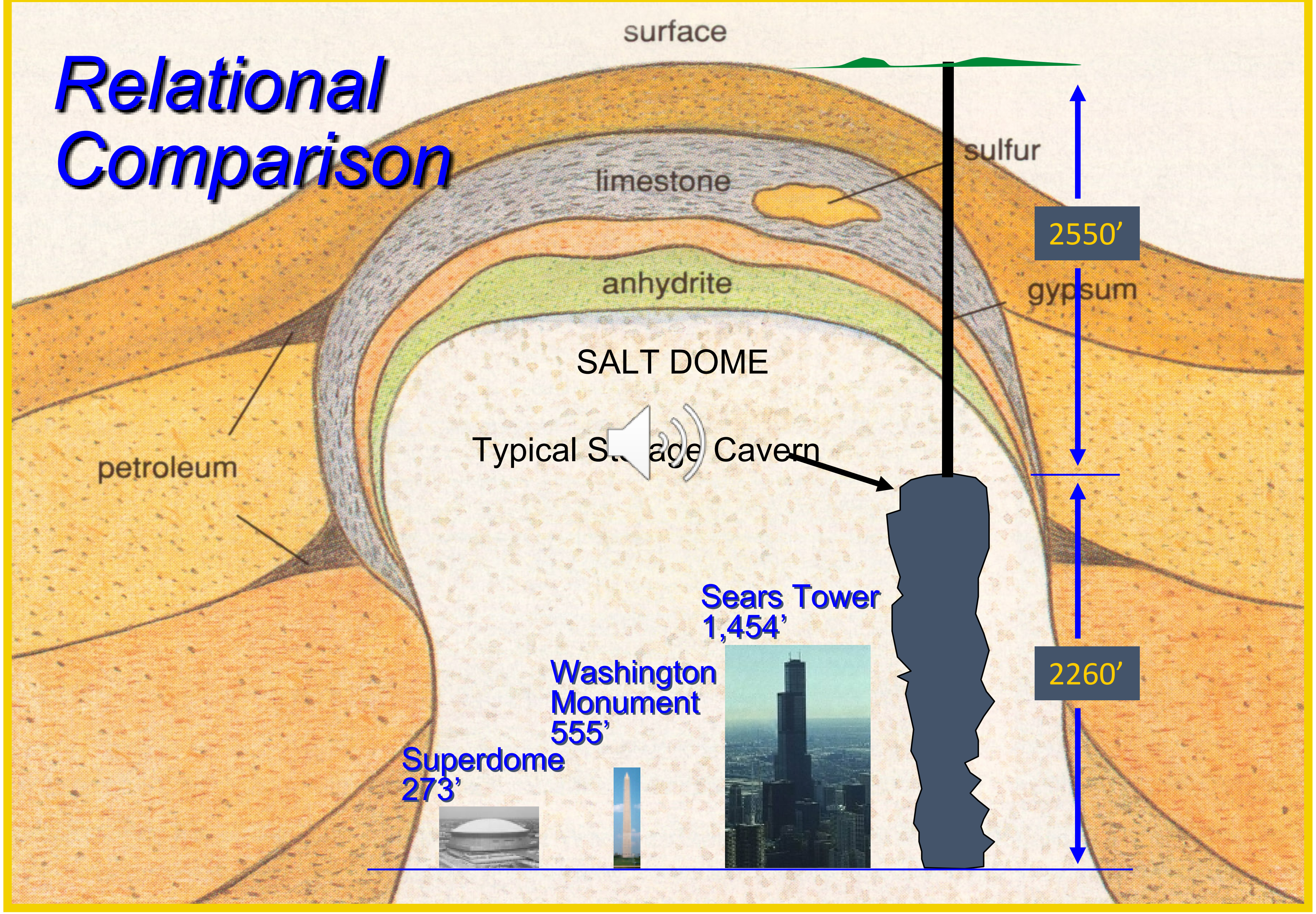
Identification of Deformation



Increasing Deformation



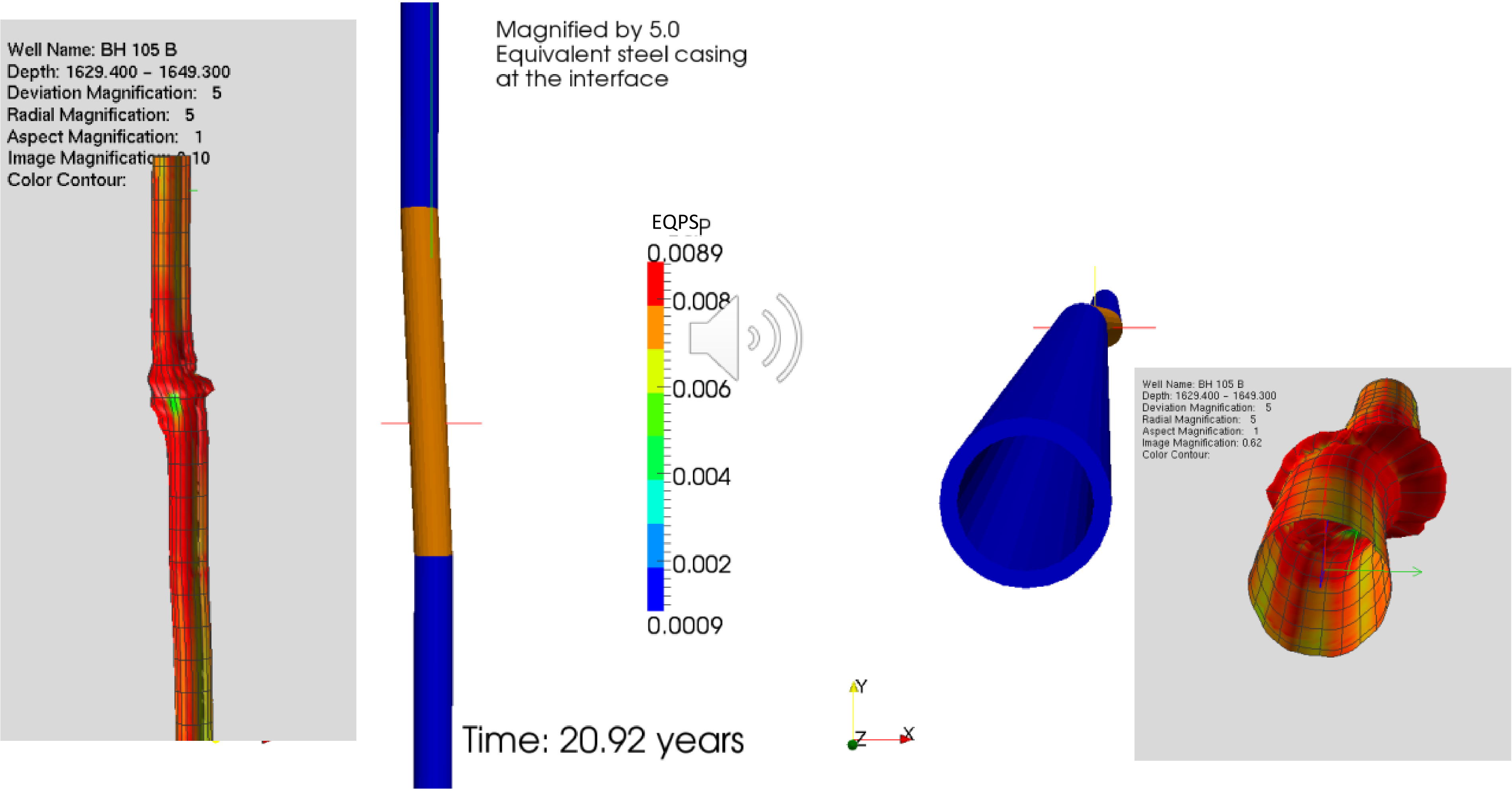
Relational Comparison



Sandia salt dome geomechanical models

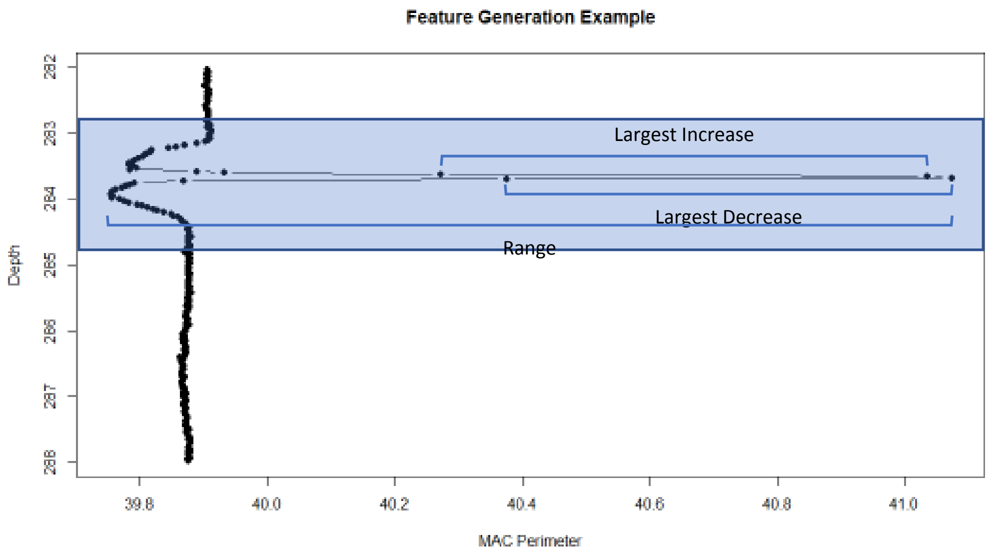
- Sandia has mature geomechanical models for several sites for underground storage of oil in salt domes:
  - Use of SNL Sierra/Adagio solid mechanics code
  - Finite element meshes fit to cavern, dome geometries
  - Implementation of full Munson-Dawson creep model (used for salt creep at WIPP)
  - Use of historical wellhead pressures
  - Historical understanding of site behavior
- Goals of geomechanical models:
  - Evaluate effects of salt creep on cavern closure, cavern integrity
  - <u>Evaluate effects of cavern closure on well integrity (specifically, steel casings and cement liners)</u>
  - Use results to provide operators with technical advice on wellbore monitoring, remediation

Computational analysis of borehole deformation, comparison to measured behavior



Machine Learning for Wells

- **<u>Goal:</u>** Use ML to identify prior deformations and predict new ones
  - Helper ML algorithms to identify known well anomalies (ie collars)
- **<u>Data:</u>** Utilizes data from 122 wells, from 4 cavern locations, with an average of 2 date files per well and more in some caverns
  - 244 data files total
  - Data can by split by segment, further increasing data by a factor of ~50
- **<u>Methods:</u>** Two main methods of prediction
  - DNN and Random Forest
  - Timeseries predictions and existing categorization of deformations



Features			Label
Largest Increase	Largest Decrease	Range	Response (Binary)
0.763	-0.69865	1.319	1

Random Forest Model Performance

- Hyper-parameters: 2ft sliding window .5ft step, 1000 trees
- Model trained on 80% of the available data and tested on 20% with a random split

Confusion Matrix

		Predicted	
		TRUE	FALSE
Labeled	TRUE	5634	527
	FALSE	366	113622

- contains many more non-collar data points than collar data points
- is slightly more likely to miss a collar than label something that isn't a collar

Performance Metrics

Correct Prediction	0.99257
Sensitivity	0.91452

- 99.26% overall correct classification
- 91.45% of collars are identified by the model

The nature of the sliding window means that these values may slightly underrepresent the true performance

Feature Importance

Variable	Feature	Importance
Perimeter	Max_Change	0.17064519
DiaMax	Max_Change	0.13540578
XSectionalArea	Min_Change	0.12447533
Perimeter	Range	0.11132529
DiaMax	Range	0.08909376
XSectionalArea	Range	0.07256046
Max ID Delta	Max_Change	0.05560978
Rel Wall Thck Shift	Max_Change	0.04040498
Perimeter	Min_Change	0.03490684
XSectionalArea	Max_Change	0.02962785
Max ID Delta	Range	0.02812874
Rel Wall Thck Shift	Range	0.01924062
DiaMax	Min_Change	0.0173233
Isoparametric_q	Range	0.01441069
Random	***Unif(0,1)***	0.01358489
Isoparametric_q	Min_Change	0.01191637
Isoparametric_q	Max_Change	0.01087293
Max ID Delta	Min_Change	0.01046707
Rel Wall Thck Shift	Min_Change	0.01000014

Deep Neural Net Performance

- Regression model with 7 layers and sigmoid activation function
- Model trained on 80% of the available data and tested on 20% with a random split
- Prediction output is a probability that a collar exists at that depth

Confusion Matrix

		Predicted	
		TRUE	FALSE
Labeled	TRUE	5706	459
	FALSE	641	113347

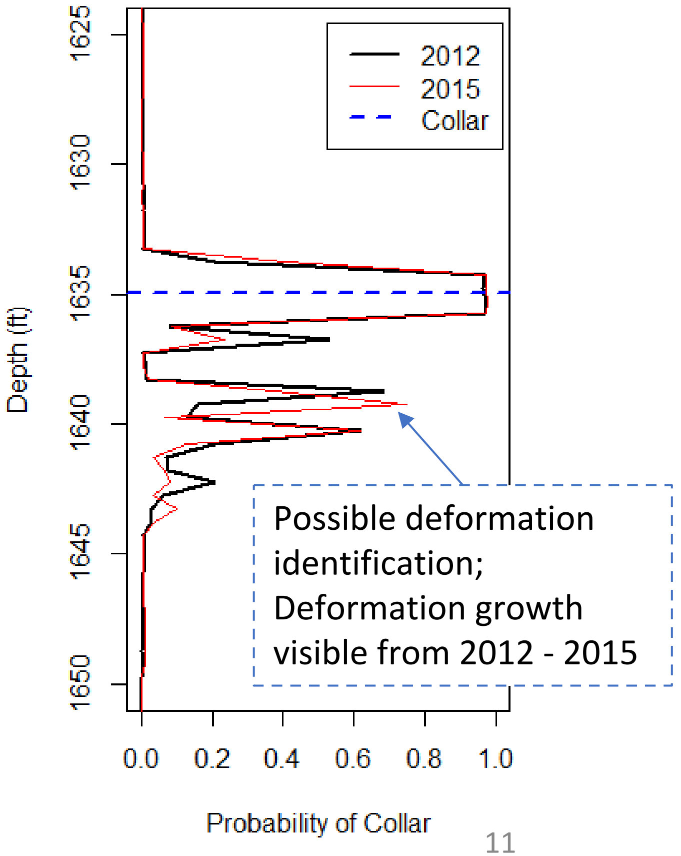
- Uses a prediction threshold of 0.5 for collar prediction
- Slightly more likely to label non-collars than to miss a collar

Performance Metrics

Correct Prediction	0.990845
Sensitivity	0.925547

- 99.1% overall correct classification
- 92.6% of collars are identified by the model

Deformation identification



Both ML algorithms are unoptimized, but performance is similar between the two on first pass

Conclusions

- Current methods for identifying wells that are at highest priority for increased monitoring and/or at highest risk for failure consists of "hand" analysis of multi-arm caliper (MAC) well logging data and geomechanical models
- ML methods are of interest to explore feasibility for increasing analysis efficiency and/or enhanced detection of precursors to failure (e.g. deformations)
- MAC datasets used to train ML algorithms and preliminary tests were run for "predicting" casing collar locations and performed above 90% in classification and identifying of casing collar locations

Next Steps

- Improve ML algorithms and reframe for deformations
  - Include sequential considerations in collar prediction
  - Test current performance of deformation detection from collar locator
  - Optimize DNN with Ax, optimize RF with GridSearch
  - Build predictive ML algorithm for timeseries data
- Use time series data (MAC’s performed a few years apart) to train and analyze data for deformation events and/or precursors
- Explore options to integrate existing geomechanical models of wellbores with ML methods to utilize a “physics informed” approach

REFERENCES

- King, George E., and Randy L. Valencia. *Environmental Risk and Well Integrity of Plugged and Abandoned Wells*. Paper presented at the SPE Annual Technical Conference and Exhibition, Amsterdam, The Netherlands, October 2014. doi: https://doi.org/10.2118/170949-MS
- Anthony R. Ingraffea, Martin T. Wells, Renee L. Santoro, Seth B. C.Shonkoff. *Casing and cement impairment in oil and gas wells.* Proceedings of the National Academy of Sciences Jul 2014, 111 (30) 10955-10960; DOI:10.1073/pnas.1323422111
- . SE Gasda, S Bachu, MA Celia *Spatial characterization of the location of potentially leaky wells penetrating a deep saline aquifer in a mature sedimentary basin.* Environmental geology, 2004