

Machine Learning and Pipeline Replacement Prioritization

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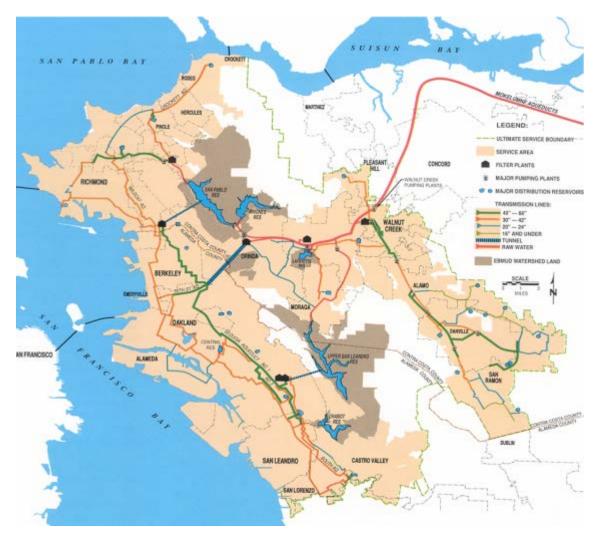
EBMUD Water System





EBMUD System & Service Area





Customers

1,400,000 customers

Raw Water System

- 2 upcountry reservoirs
- 5 local reservoirs

Treatment System

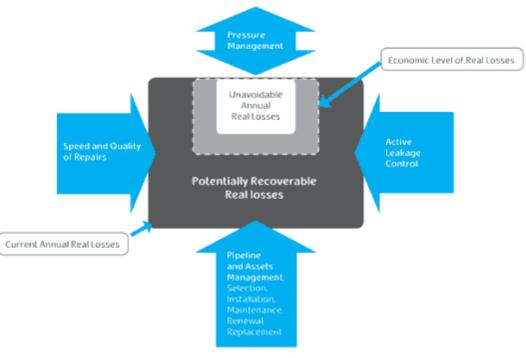
6 water treatment plants

Distribution System

- 4,200 miles of pipeline
- 122 pressure zones
- 164 reservoirs
- 135 pumping plants
- 100 regulators/RCS

Addressing Real Water Loss



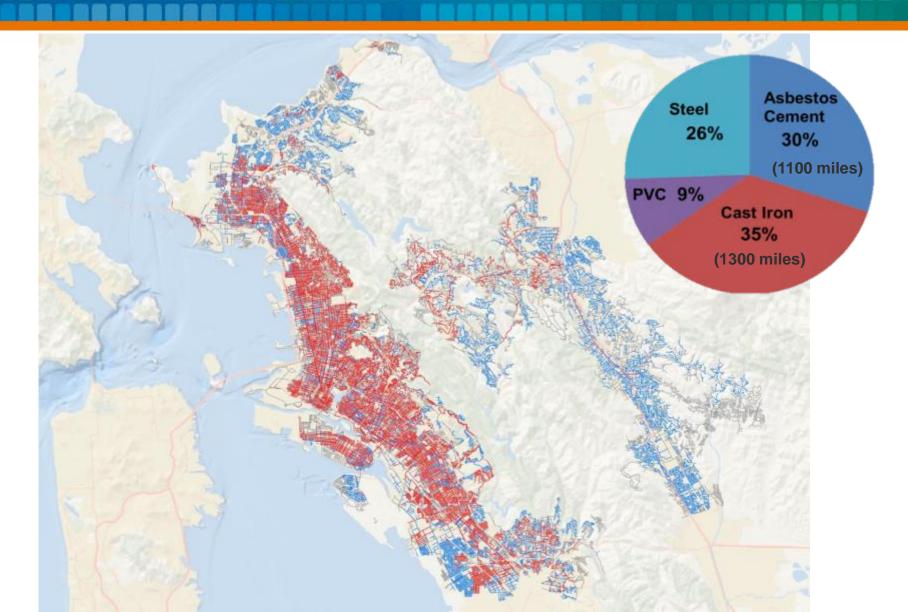


 Active leakage control

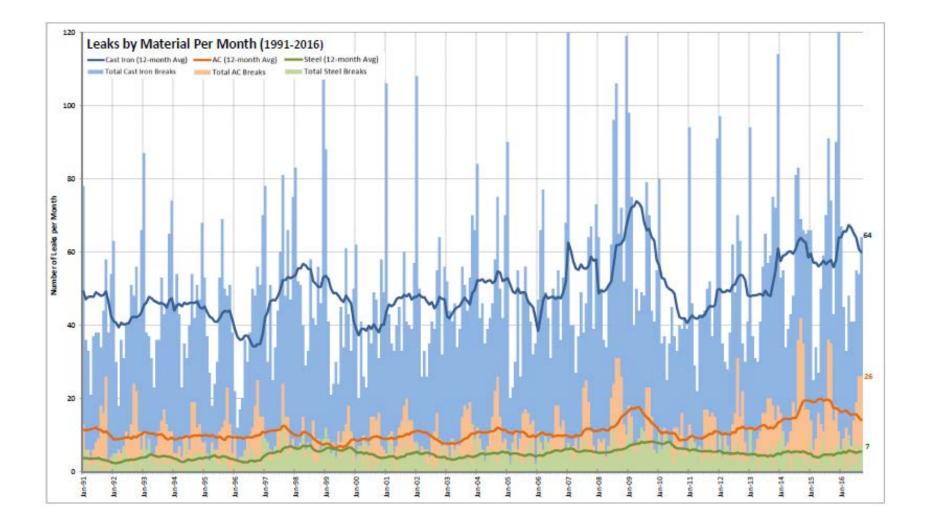
- Pressure management
- Speed and quality of repairs
- Infrastructure management

Pipeline Inventory



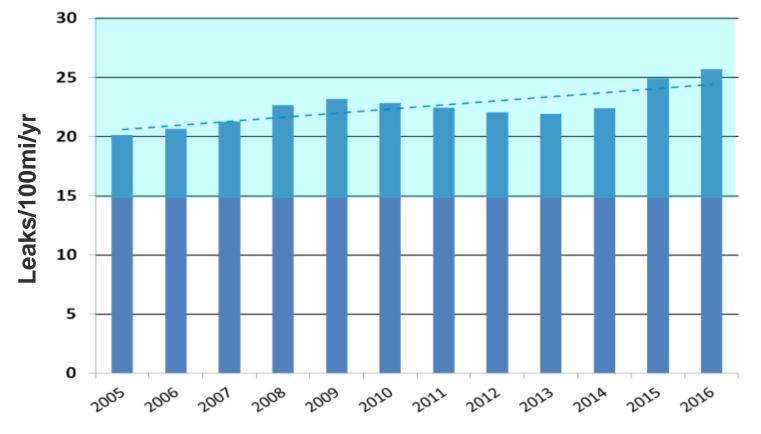






Infrastructure Renewal Program --Ramping Up Replacements

Industry Benchmarks for a well maintained system = < 15-30 leaks/100 miles/year

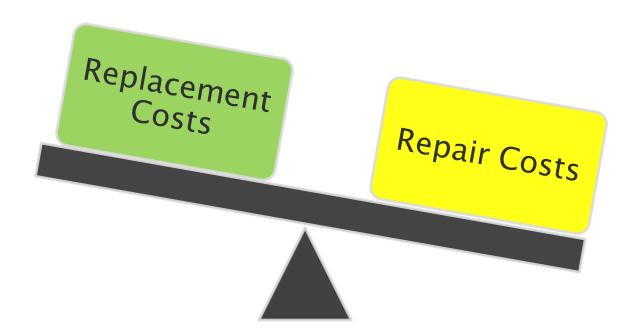


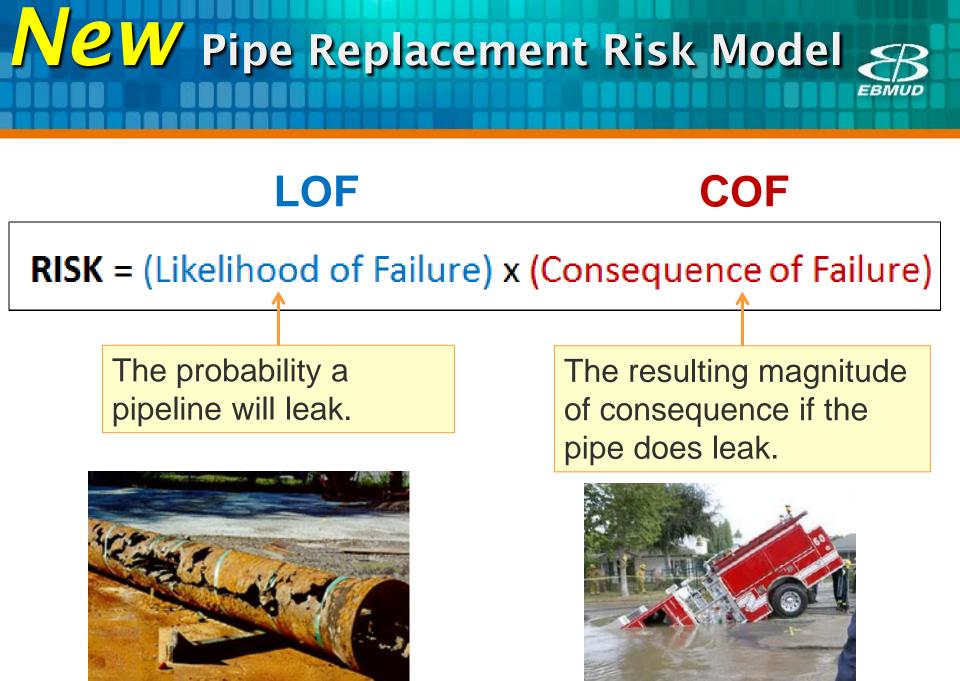
How do we make sure we are replacing the right pipe?





> 1.0 , more beneficial to replace pipe





Pipe Replacement Risk Model

Consequence of Failure

Very High





- Creek crossing
- Diameter
- Consumption
- Access
- Slope
- Backbone/Critical
- Highway crossing
- Railroad crossing

- Likelihood of Failure Very Low Very High Medium High Low **Very Low** Low Medium High
- Pipe Leak History
- Pipe Age

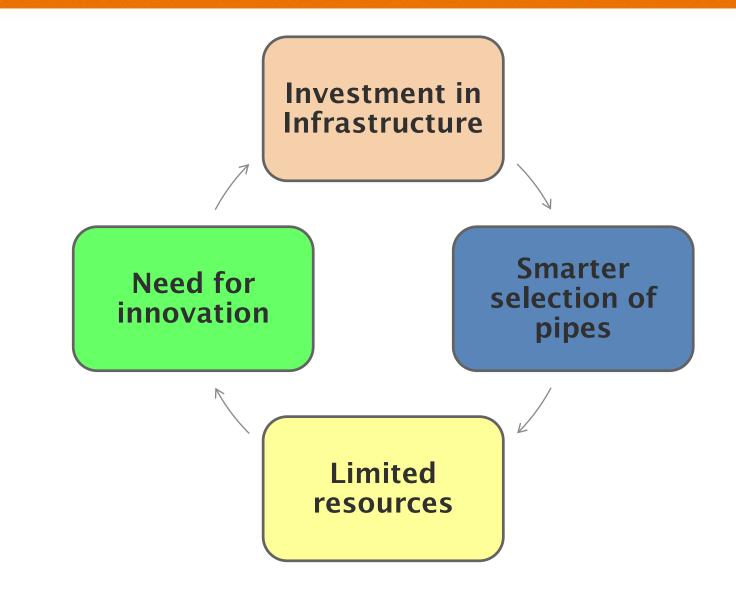
How we choose projects using the Risk Model





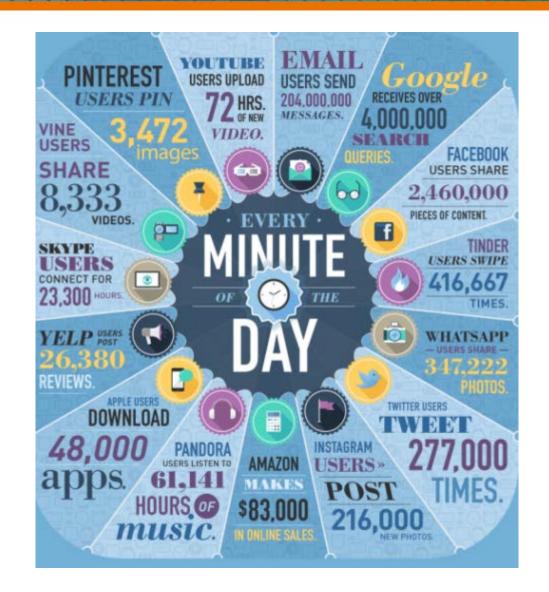
New Decision-Making Tools





Data Never Sleeps





Operational Data

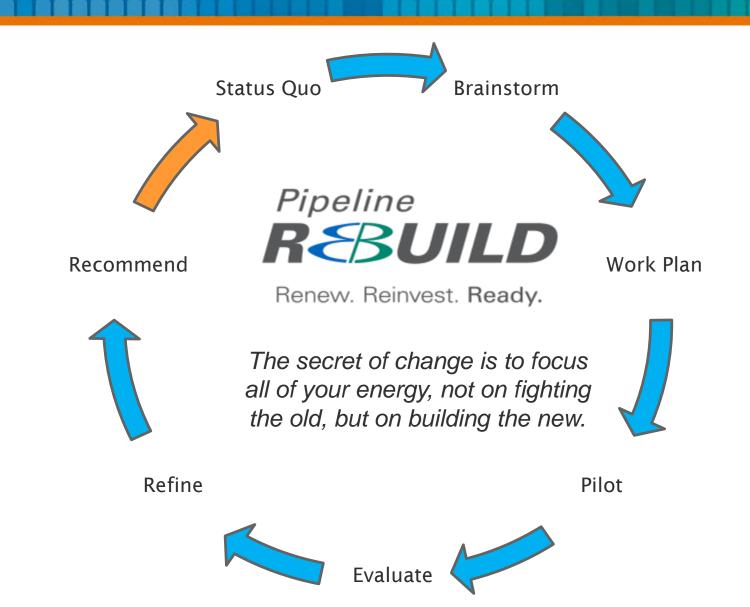


· SCADA

- Enterprise database: ~150 million readings per year
- Data historian: ~7 billion readings in the database
- What's Next
 - Pipeline data
 - Maintenance data
 - AMI data
 - Pressure and leak detection data

Pipeline Rebuild





Machine Learning How It Works?









Wrangle and import water main and geographic data Layer geodata and run machine learning algorithms Visualize vulnerabilities and apply LOF results

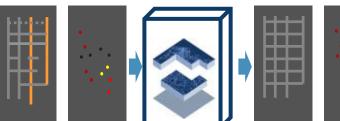






Step 1: Wrangle and Import Data





Utility Pipe Utility Data Asset Data Break History

Data Wrangling Cleaned

Cleaned Cleaned Pipe Asset Break History Data

+ Cleaning and normalizing the data

+ Correcting wrong/outlier data points and filling in missing values

+ Geocoding breaks with pipe segments

Example :

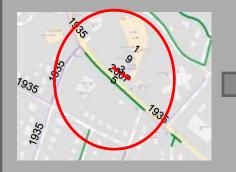
Received Pipe Data as ESRI Shapefile 23876 Pipe Segments ~15% Total Missing/Error

Received Break data as two Excel sheets + GIS file

Clean

Correct

Geocode and assign to pipes

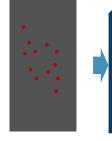


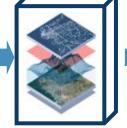


Step 2: Machine Learning Analysis











Cleaned Cleaned Pipe Asset Break History Data

Machine Learning Process

Pipe Asset with LOF Scores

<u>Utility Data</u>

- Pipe Parameters
 - Length, Material, Diameter, Install Year, Pressure etc.
- Break History
 - Break info assigned to pipe segment

Variables derived from Utility Data

- Age-Derived Variables
- Pipe and Leak Density

Geo Variables

- Environment
 - > 40+ Soil Properties from USGS
- Location
 - Slope, Elevation
 - Proximity to Transportation Features (roads, rail etc.)
 - Proximity to Water (salt water, river etc.)
- Population and Buildings
 - Population, Zoning, Buildings etc.

Variables derived from Geo Data

- Min/Max/Mean Distance
- Density of Soil Type Changes

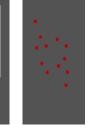


1000+ variables

Step 2: Layer Geodata and Run Machine Learn







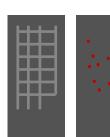


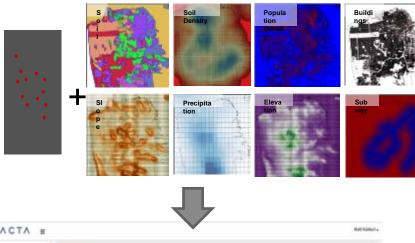


Cleaned Cleaned Pipe Asset Break History Data

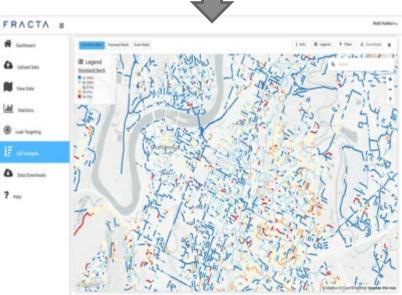
Machine Learning ry Process

Pipe Asset with LOF Scores





- Process in a repeatable and scalable manner
- Layer additional variables
- Look for correlations
- Calculate 5-year LOF probability scores



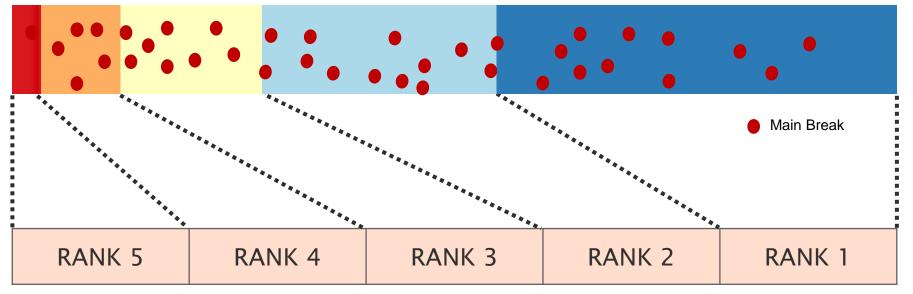




Prediction



Actual



Measuring Accuracy



Fracta LOF Focused Ranking	Rank F5	Rank F4	Rank F3	Rank F2	Rank F1
	41.6 miles (1%)	166.3 miles (4%)	415.8 miles (10%)	831.8 miles (20%)	2702.9 miles (65%)
Pipe Segments	979	2692	7151	17462	76245
5-yr forecasted breaks	397	901	1160	1251	1183
5-yr forecasted break rate (x/100mi/yr)	191.0	108.3	55.8	30.1	8.8

Used historical data, $1990 \rightarrow 2011$, to predict next 5 years LOF

Comparing to Actual Events Break Data (2012-2016)



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Actual Breaks 2012-2016	436	991	1177	1038	838
Actual Break Rate 2012-2016	209.5	119.2	56.6	25.0	6.2

Broad Correlation of Projected & Actual break rates

Demo & Questions





