The Digital Revolution for Water Asset Management

by Contributing Author

Bringing AI and Machine Learning to Underground Pipe Infrastructure

By Greg Baird

Water asset management in the United States has advanced through various stages of education and the practical application of best practices. The U.S. EPA has concluded that nearly 60 percent of the value of water infrastructure remains hidden underground delivering drinking water through more than 1.2 million miles of pipes. The American Water Works Association (AWWA) attests that this lifeline network requires renewal and replacement to a tune of $1 trillion over the next couple of decades, and recent findings from research companies project that advanced asset management in all of its shapes is poised to drive $41 billion in savings over the next decade. At the heart of these funding gaps, cost savings and replacement estimates, the United States and Canada are experiencing a significant increase in water main breaks.

Water Main Break Data

Water main breaks reflect the physical condition of a distribution system's health. In fact, a U.S. Conference of Mayors survey concluded that 86.2 percent of cities use the number of water main breaks per unit length to evaluate drinking water pipe performance. Additional literature reviews indicate that between 250,000 and 300,000 breaks occur every year in the United States, which corresponds to a rate of 25 to 30 breaks per 100 miles per year with the average pipe break rate (regardless of cause) for water utilities between 21 to 27 breaks per 100 miles of pipeline per year. When construction, third party damage and maintenance errors are eliminated, the number of water main breaks based on pipe material drops below 15 breaks per 100 miles. This is the data set used for predictive analysis. Pipe material condition and performance are key cost drivers to both the O&M and capital budgets, and financial sense dictates an effective utility to determine how it compares to the new 2018 national metrics of water main pipe breaks by material type.

Most utilities maintain the pipe data and pipe attributes in the ArcGIS system supporting linear assets. This pipe data is used by GIS-centric computerized maintenance management systems (CMMS), such as Cityworks, to perform asset management's risk-based criticality analysis. This determines the likelihood or probability of failure and the consequence of failure to arrive at a business risk exposure score in order to conduct additional risk mitigation and location-based spacial analysis. Correlating a pipe's condition decline to increasing maintenance costs can provide the best budget defense approach for the water department.

J.D. Edwards reports that water customer satisfaction is down, water quality issues are on the rise and utilities support these findings while stating that prediction is more complicated as water main pipes are not failing in sequential order based on age – newer pipes are now failing at a higher rate. While condition assessment is at the core of asset management enabling a utility to move from reactive to preventative asset maintenance and management strategies, accurate predictive analysis requires an enhanced digital analysis approach called machine learning or artificial intelligence (AI).

Machine Learning Applied to Underground Pipe Infrastructure

Asset management practices combined with machine learning for underground water pipes provides a new solution of aligning both maintenance, repair and replacement strategies to better allocate resources. Machine learning provides another asset management tool to help address the water industry's most pressing concerns of producing an accurate prediction of water main Likelihood of Failure. Fracta Inc., for example, is one company in the water sector working on this. Fracta produces an accurate five-year model using machine learning to direct leak detection efforts, focus preventative maintenance crews, validate capital plans and align master planning efforts.

Machine learning algorithms need a large amount of historical and geospatial data. Water main condition assessment data contains all the necessary components for machine learning in water utilities with years of historical data. Analyzing this data consistently can uncover trends, gain insight on pipeline health, and offer data-driven assessments.

Data acquisition, assessment and cleaning for any machine learning process is roughly 60 to 80 percent of the work — also known as pre-processing or data wrangling — with the remaining percentage being the machine learning itself. Once the data is assessed, cleaned and imputed where needed, it is ready to be fed into a machine learning algorithm where it is subsequently 'trained' to learn the patterns that predict breakage events.

The more data a model contains, the more robust the model. As utilities are, over time, constantly collecting data such as new breaks and installed pipes, that data can continually be fed into a machine learning model.

New pipe data strengthens the predictive power of a machine learning algorithm. Machine learning can also benefit utilities with limited asset or breakage data by "filling in the gaps." Machine learning can utilize many streams of data in order to perform certain predictions and begins to learn patterns that can inform situations where many of the usual data points may not be available creating a new digital revolution in advanced asset management practices.

Greg Baird is president of the Water Finance Research Foundation. He specializes in long-term utility planning, infrastructure asset management and capital funding strategies for municipal utilities in the United States. A frequent contributor to *Water Finance & Management,* he has served as a municipal finance officer in California and as the CFO of Colorado's third-largest utility.