Chapter 15

Geospatial AI for pipeline failure risk

Geospatial AI (artificial intelligence) leverages the power of machine learning and automated pattern recognition to deliver sophisticated geospatial data analytics for a host of industries, including the water, agriculture, infrastructure and forestry sectors.

For the water industry, Geospatial AI is a cutting-edge technology to identify the conditions under which network failures occur. It combines local environmental data such as soil, weather and topography, regular insights derived from Earth-observing satellites, with data on pipeline attributes, such as material, age, depth and diameter. Together, these data are integrated into a sophisticated risk model that considers both pipeline characteristics and relevant aspects of the environment in which the pipeline resides.

These data are then calibrated against historic failure event data in the model, which help train and validate machine-learning algorithms to produce a risk analysis. With all this information in hand, machine-learning techniques are applied to current data to recognise patterns and produce insights. The resulting analytics quantifies the likelihood of failure across a network.

Geospatial AI does not provide information on the precise location of water losses or leakages in a water network. Instead, it provides an innovative method for proactive pipeline risk management and strategic investment planning by offering crucial information on how to optimise the deployment of resources, repair and maintenance, and capital expenditure based on the likelihood of failure at the whole network level or DMA level. Furthermore, by regularly updating contemporary data, risk hotspots can be tracked temporally to allow rapid identification of high-risk sections.

The information Geospatial AI provides has significant real-world impact. Taking just two years of historic data to train Geospatial AI algorithms, areas of the network more likely to be at risk from failure can be prioritized for investigation to enable efficient asset management. As an example by using a Geospatial AI approach, typically it can highlight the 30% of the network where a water company can expect 70% of leaks to occur. The degree of optimization achieved can be higher and depends upon the quality of the data supplied by the customer (Figure 15.1).

There are many benefits of geospatial AI for network operators, each described in the following sections.

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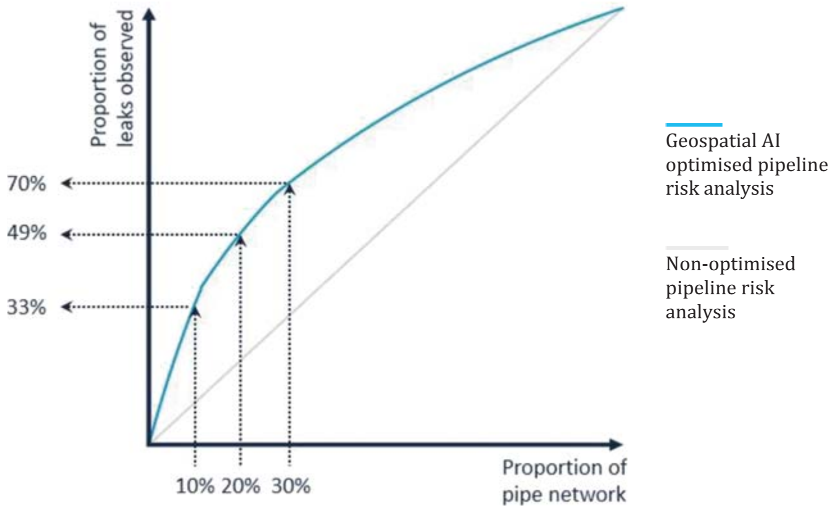

Figure 15.1 Prioritization and optimization of resources to manage pipeline network assessment. (Source: Rezatec)

15.1 LOGGER DEPLOYMENT

Geospatial AI is an efficient and fast way of figuring out the best disposition of sensors for optimal coverage of a given water network, identifying high-risk assets so that remote loggers can be installed selectively. Moreover, these decisions can be based on granular data about pipe material, size and consequence of failure. Not only does this maximise the effectiveness of logger deployment, placing them in spots with the highest risk of failure, but it also allows operators to invest in fewer loggers, thereby minimising not just capital expenditure but also operational expenditure, e.g. ongoing logger maintenance and access to data.

15.2 SURVEY PRIORITISATION

Another application of geospatial AI is survey prioritisation. Data analytics can produce failure risk maps and priority risk zones that are regularly updated and show the probability of failure of all network assets. Operators can use these insights to trace leakages, plan inspections or prioritise maintenance, optimising in-field surveys in terms of both time and cost, and ultimately allowing early interventions that reduce leakages and water loss.

15.3 CONSEQUENCE ANALYSIS

Analysis can be further improved by incorporating additional geospatial datasets and earth-observation satellite data in order to identify the specific conditions under which network failures occur, mitigate high consequence risks, and digitise general knowledge and understanding of the network. This information can be used by key stakeholders to help alleviate environmental impact, prioritise pipeline repair and maintenance around other utility works, and assess and manage risk to vulnerable buildings and other infrastructure assets. Additionally, water utilities can better manage costs associated with standard service measures such as interruption of supply, disruption to traffic and internal flooding.

15.4 CONCLUSIONS

Geospatial AI combines remote sensing and data science to identify the conditions under which network failures occur and to quantify the likelihood of failure across networks. By identifying which sections of a network have a higher likelihood of failure, network operators can concentrate their ground survey teams and IoT sensors on those high-risk areas and optimise their repair and monitoring work, thereby both preventing leaks and reducing the cost and time to find established leaks. Additional geospatial datasets and earth-observation satellite data can also be incorporated into the analysis to further mitigate high-consequence risks and to digitise general knowledge and understanding of the network.