Predictive maintenance of physical assets

DETAILS

SECTOR | Water, Transport, Energy

STAGE | Strategy and Planning, Operations and Maintenance, Renewal and Disposal

TECHNOLOGIES | AI Augmentation, Data & Analytics, Sensors / IoT

SUMMARY

Predictive maintenance utilises monitoring and advanced machine learning methods to develop predictive models about failure of physical and mechanical assets such as pipes, pumps, and motors. These aim to prevent failure and optimise maintenance of critical infrastructure by providing early warning and predictive actions to issues before they occur. Key components include sensors that are installed in the machines, a communication system that allows data to be transmitted in real-time between sensors and a centralized data platform, and machine-learning predictive analytics to identify patterns and generate actionable insights. Predictive maintenance tools enable asset management workforces to automatically diagnose problems of industrial assets' breakdowns and inefficiencies and optimise maintenance scheduling ahead of asset failure as well as extend the life of the asset.

Traditional asset maintenance activities are beset by limited visibility of asset condition, infrequent monitoring, labour-intensive periodic maintenance, and manual data analysis processes. This leads to a slow response to asset deterioration, driving productivity losses, and unoptimised infrastructure capital and operational expenditure. Development of more sensitive and intelligent monitoring and modelling technologies have created opportunities to minimise labour needs and plan investments better.

Mechanical asset owners face inherent challenges with aging infrastructure and assets reaching their end of life. For example, a 2018 survey showed that USD 472.6 billion will be required over the next 20 years, to maintain and improve drinking water infrastructure in the USA. The majority of this (USD $312.6 billion) is for the replacement or refurbishment of ageing or deteriorating distribution assets[1]. The increasing need for water asset maintenance and renewal optimisation is evident in the USD $90 billion increase in 20-year investments required to repair, replace and renew existing infrastructure while there is a $30 billion decrease in investment requirements for new infrastructure [2].

Knowing which asset to maintain, renew or refurbish will potentially defer substantial amounts of capital expenditure. Increased usage of predictive failure models will be an essential planning tool to shift towards more proactive maintenance and optimise maintenance budgets. Proactive programs will prevent catastrophic failure of water distribution networks, pipe bursts and leaks causing damage to property and public infrastructure. This

[1] Drinking water investment needs. Global Water Intelligence: Water Data. Accessed 29 April 2020

[2] Global water market: breakdown by OPEX and CAPEX Global Water Intelligence: Water Data. Accessed 29 April 2020

will assist water utilities to maintain critical water services to communities, eliminate unplanned downtime, reduce maintenance costs, improve asset reliability, and enhance operational efficiency.

As more water utilities start to embrace digitalization and generate large amounts of data, the technology can access better quality and quantity of data from various inputs to train the models and improve the precision of failures detected. This technology can also be further developed and applied to other sectors and scenarios such as with critical physical infrastructure such as energy generation, transport, and manufacturing. As infrastructure continues to age and renewal investment needs continue to grow, demand for more accurate and robust failure prediction models will grow and be more widely used in all industries. Predictive models from different industries can be combined to optimise maintenance of assets in close proximity i.e. pipes, electricity, communications, gas, roads, etc.

VALUE CREATED

Improving efficiency and reducing costs:

- Optimizes capital investment through deferment of current premature rehabilitation and replacement tasks, rerouting the resources to the assets that are most likely to fail.
- Reduces operational expenditure and overhead cost investment by keeping assets at optimal conditions reducing power waste, reducing downtime and maintenance costs.

Enhancing economic, social and environmental value:

- Minimizes the break rates of pipes that can cause water damage to surrounding infrastructure.
- Decreases traffic disruption and water service interruption by minimising unnecessary maintenance activities
- Extending useful life of assets and reducing material wastage.
- Minimizes the health and safety risks of operators in carrying out rehabilitation work as well as reducing risks during operation and inspection with the remote visibility of the state of assets in real-time.

POLICY TOOLS AND LEVERS

Legislation and regulation: Governments can develop strategies to drive operators to invest in more efficient and sustainable operations of critical assets. Regulatory driven asset management plans can be implemented to maintain the efficiency of water infrastructure.

Funding and financing: Greater focus on committing funding to optimise and extend the life of existing assets rather than building new infrastructure is needed.

Transition of workforce capabilities: Training and upskilling workforce to have the skills to effectively interpret and action the insights from AI technologies.

IMPLEMENTATION

Ease of Implementation

The majority of solutions in this use case are easy to implement, however the models require sensors to be monitoring mechanical assets (such as pumps) and provide this data back to the machine learning (AI).

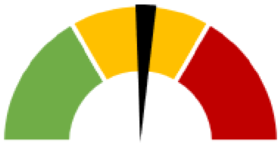
Cost

Costs per unit are relatively low but when there are a large number of assets, purchasing monitoring systems (sensors and analytics platforms) can start to add up. The costs however are often outweighed by the potential capital deferment that can be realised by using predictive data to extend the life of the assets.

Country Readiness

Very adaptable to use wherever there are mechanical assets and data communications. The countries with well-developed infrastructure can utilise predictive solutions. Collaborative investment from both government and industry may be needed to develop digital communication networks and infrastructure allowing information to be quickly accessed onsite and in remote locations.

Technological Maturity



Technologies in this use case range from established to early commercial. Updates to the technology offering have been common in recent years as machine learning algorithms improve their accuracy and tools become more user friendly.

RISKS AND MITIGATIONS

Implementation risk

Risk: Machine learning can only operate using good quality input data. There is a risk where incorrect data or lack of data can limit functionality or lead to incorrect actions, which can increase project costs and lead to poor infrastructure planning and investment.

Mitigation: Investing in sensors and monitoring solutions before investing in machine learning software.

Social risk

Risk: The shift from scheduled and reactive maintenance to predictive and proactive maintenance can create the need for re-training of workers to interpret and appropriately action results from predictive models.

Mitigation: Industry can assist through training and up-skilling programs to help mitigate these issues.

Safety and (Cyber)security risk

Risk: Control systems, especially in those located in the cloud, are at risk of cyber-attacks. Sensitive information about location and condition of critical infrastructure and potential attacks can have high risks on public health.

Mitigation: Organisations need to ensure a strong level of cyber security in their networks and data storage, for both local servers and cloud services. Focus should be on having strict data ownership models and the appropriate level of data security as needed by the application. Any implementation of data transfer and storage should be undertaken by suitable qualified and experienced professionals.

EXAMPLES

Example	Implementation	Cost	Timeframe
Data61	Sydney Water and Data61 are collaboratively researching advanced analytics approaches to solving water industry challenges, including water pipe failure prediction, predicting sewer chokes and prioritising active leakage detection areas[3].	Sydney Water found the potential to reduce maintenance and renewal costs by several million dollars over a four-year period and minimise inconvenience to customers from pipe breaks.	Projects are undertaken on case-by-case basis and can be completed within a few months.
Voda	Voda AI software have assessed more than 1200 pipes for a Florida water utility, prioritising pipe monitoring, maintenance, and replacements[4].	Voda predicted 18 avoidable breaks saving the water utility more than $100,000 in reactive maintenance and preventing negative coverage of bursts.	Projects are undertaken on case-by-case basis and can be completed within a 12 months.
Movus	The University of Queensland have installed the FitMachine on 22 chiller units, delivering 24/7 air-conditioning, on campus since March 2016 to detect the early warnings of failures, using machine-learning algorithms[4].	The University of Queensland realised 135% return on their FitMachine investment. They saved up to $100,000 in repair costs by discovering and preventing machine failure ahead of time	Movus solution was implemented in a short time frame (within 6 months).

[3] Vitanage, D. et al. *Success in Data Analytics – Sydney Water and Data61 Collaboration*. Water e-Journal 3 (1) 2018.
[4] Information for this example was gathered via communications with commercial technology stakeholders.