MONITORING PUMPING STATION PERFORMANCE FOR MAINTENANCE OPTIMISATION

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ABSTRACT This paper describes the Environment Agency's ambition to develop and trial a condition-based monitoring system for its mechanical and electrical flood risk management assets. The aims, objective and research methods for this project are described. The challenge of developing any predictive capability for flood risk management assets which, typically have a low frequency of operation and therefore a paucity of data, is discussed. Some practical suggestions to overcome this specific challenge are presented. The paper calls for researchers interested in this challenge, to partner the Environment Agency to develop solutions.

1. Introduction

This short paper describes the Environment Agency's ambition to develop a new condition-based monitoring system (CBMS) for their Mechanical, Electrical, Instrumented and Automatic (MEICA) flood defence assets. A new Research and Development (R&D) project has been initiated to develop a proof-of-concept CBMS system using existing and novel sensing instruments allied with predictive analytical techniques.

The proof-of-concept system will move through in to a stage of trial application, where it will be deployed on an Environment Agency owned pumping station as a pilot. The Beddingham pumping station on the river Ouse in East Sussex has been identified for this project as a site representative of the Environment Agency's pumping station portfolio. See Figure 1.

Figure 1: Location of Beddingham Pumping Station.
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The aims and objective of this R&D project are introduced. Whilst it is too early in the project to present results, this paper aims to highlight some of the important research challenges this work will be tackling. In particular the project is anticipating the need to develop practical strategies and novel methods for sensor array design and robust predictive analytics that can operate in an environment that is data poor with low equipment utilisation.

The paper calls for researchers interested in this challenge to engage with the Environment Agency to seek solutions to these challenges.

2. Background

2.1 Strategic context

The Environment Agency has set out its ambition to modernise its approach to Flood and Coastal Risk Management (FCRM) asset management and to be an industry leading Asset Management (AM) organisation in its asset management strategy (Environment Agency, 2017). The AM Strategy sets out further strategic objectives and outcomes for the period 2017-2022. Among them is are objectives to improve efficiency in maintenance delivery by 10%, and to create better quality data and information. Allied to this is the target to reduce operational carbon by a further 45%.

In England there are over £35bn of flood risk management assets protecting people, property and infrastructure from flooding. The Environment Agency owns and maintains a significant proportion of these assets with an approximate value of £20bn and has a strategic oversight for the remaining £15bn (Environment Agency, 2017). A significant proportion of the value of this infrastructure is attributable to (MEICA) systems.

The Environment Agency spend around £12m annually on the maintenance of MEICA systems. From analysis of their computerised maintenance management system (CMMS) it can be seen that on average per year the Environment Agency currently experiences approximately 1200 breakdowns of MEICA assets rendering them redundant until repair. Associated with each of these equipment failures are costs of mobilising repair engineers (often out of hours) and cost of replacement components. There are of course, also, reputational risks and the risk that homes, business and lives could be disrupted if failure of equipment leads to flooding.

The Environment Agency is therefore exploring the opportunity with new sensing technology and predictive analytics to help ensure maintenance budgets are spent efficiently and costly failures are avoided. With the ultimate aim increasing the overall reliability of the MEICA asset portfolio, so the risk of flooding to people and their property is lower.

2.2 Current maintenance philosophies

Maintenance of electro-mechanical assets, such as the pumps in a pumping station, has traditionally taken place over set time periods per the maintenance models set out by Barlow and Hunter (1960). This planned preventative maintenance philosophy (PPM) seeks to replace or repair components at set time intervals before a failure occurs. This maintenance regime has been adopted to ensure a high degree of 'on demand reliability' (ODR). In lower risk locations, a PPM philosophy cannot be economically justified, in such cases, equipment is simply replaced when it starts to show signs of imminent failure or has failed.

It has been demonstrated that neither of these maintenance philosophies deliver an optimum balance between risk of failure and cost of maintenance during the asset operating life (e.g. Liu, Makis and Jardine, 1995; Nguyen and Murthy, 1981) PPM can result in costly maintenance programmes and equipment could be replaced with considerable operating life remaining or when relative simple repairs could usefully extend operating time. Conversely, replacing equipment as the tell-tale signs of failure become visible can mean that the deterioration processes have reached the 'point of no return'. Routine maintenance and repair becomes ineffective and the only option for the asset is complete refurbishment or replacement.

2.3 Sensing and predictive analytics

Sensing instruments now exist that have been designed to collect data from the pumps across a range of key performance variables such as vibration (Bindu and Thomas, 2014; Wang *et al.*, 2018; Xu *et al.*, 2018); temperature (Antunes *et al.*, 2012) and many other variables that include but are not limited to:

- current (amps)
- noise
- flow
- pressure
- level

Data gathered from sensors arrays, together with analytical tools can provide complex views of network asset performance (Dadashi *et al.*, 2014). Data analysis, can provide valuable insight in to the development of anomalies that indicate the onset of failure. Similarly, gradual deviations away from mean operating values revealed by sensing instruments, and subsequent signal processing, can indicate the degradation of parts. Analysing this sort of data can improve decisions by, predicting when routine maintenance is required; preventing unexpected and expensive equipment failure; and, helping to optimise operations as well as maintenance, refurbishment and replacement activities. Kajko-Mattsson *et al.* (2010) describe the ideal management situation as, not just an awareness of where an asset has failed, but a clear picture of future states of degradation. The aspiration is to achieve predictive maintenance scheduling, with the twin benefits of identifying asset degradation before actual failure, and to allow planning of maintenance and renewals to be responsive to the actual state of the asset, rather than driven by a fixed schedule (McDonnell *et al.*, 2018).

2.4 The rationale for a pro-active approach to maintenance

It has been estimated that by adopting a pro-active approach via a condition-based monitoring approach to MEICA maintenance could unlock a significant operational maintenance efficiency. This is the real motivator to ensure we overcome the challenges associated with the adoption of a predictive maintenance philosophy. Of the £12m average MEICA maintenance allocation 80% of £9.6m is spent on motor driven assets.

The case for change becomes more compelling when the potential for carbon savings are considered. The 340 pumping stations the Environment Agency operates contribute to over 30% of the total of the Environment Agency's operational carbon emissions. Small efficiencies across all pumping stations operations stand to yield large carbon savings when viewed at an organisational level. When the pumping stations that are operated by the other risk management authorities (RMAs) such as the Internal Drainage Boards are considered too, then there is the real opportunity to ensure greater carbon efficiency across flood and water level management as a whole. This this work could make a significant contribution to our organisation's e-mission targets to reduce our carbon footprint.

3. Objective and research methods

The aim of this research project is therefore enable uptake of new sensing technologies and predictive analytical techniques by the RMAs so proactive maintenance strategies can be developed.

The objectives for this project can be divided in to four stages:

1. Review and proof-of-concept of CBMS.
2. Proto-type design and specification of CBMS.
3. Deployment and pilot testing of proto-type.
4. Development of deployment strategy.

Figure 2 outline the expected programme and tasks within these stages.

Figure 2 Stages of programme and key tasks

The methodology for the development of the proof-of-concept CBMS system (stage 1) are expanded further below.

3.1 Methods to develop proof-of-concept

Work on the project start will start during March 2019. The first task will to review the suitability of sensing instruments which are either already established or are emerging on to the market place. The review will require the engagement of research organisations, original equipment manufacturers and sensor instrument suppliers to understand maturity, future potential and value. The exercise will also review installation implications to ensure that all proposed solutions are suitable to retrofit to the pilot site.

To guide the design and specification of the CBMS a full Failure Mode Effect and Criticality Analysis (FMECA) will be carried out in the first stage. The historical failure data will be used to understand how the components in the pumping station have failed and how frequently. Using the FMECA process, each plant item will be assessed against various failures modes (for example pump electrical failure). Each failure is then assigned a risk score on the frequency of the failure event, the likelihood of detecting and reacting to the failure and the consequences of that failure. See Figure 3.

Figure 3: Process for Failure Mode, Effect and Criticality Analysis

The results of the FMECA will then be used to prioritise the design of the concept CBMS. This will ensure that the most critical components are instrumented with sensors and the right performance variables relating to failure modes are being measured.

Once a concept CBMS has been developed, factory testing will be undertaken. The FMECA will again be used to help specify the range of testing to be carried out. It is anticipated that a hybrid approach when both synthetic and physical stimuli will be used to demonstrate the system's ability to gather and retrieve data via remote connectivity. Similarly both physical and simulated data will be used to develop and demonstrate the predictive analytics. At this point in the project we anticipate that the analytics will be developed using proxy failure mode signals. These proxies will be developed based on the limited historical failure data supplemented with expert judgement so realistic failure signals are created. Models can then be trained against these failure signals, so they can observe and predict them in the live data from the sensor array.

Signal processes techniques such as those described by Tavner, (2008) will then be applied to the data from the sensor array to boost the indicators of imminent failure. The analytics will also look for the subtler signs of degradation. Methods will need to be developed to smooth signals, by normalising for changes in operational state over time. Minor inflections in the signals are likely to be indicative of emerging inefficiencies and signs of equipment wearing out.

Prior to deployment to site, the CBMS will need to go through a rigorous security penetration test. Once this is complete the

system will be installed and will undergo a 3-month commissioning phase. If successful we will then commence with the full 12-month field trial.

4. The challenge of low utilisation

The deployment sensing systems allied with predictive data analytical techniques is now becoming increasingly routine in many settings such as infrastructure asset management (Thaduri, *et al.*, 2015) manufacturing (Lee *et al.*, 2016) mineral extraction (Gupta *et al.*, 2016) With the advent of Internet-of-Things (IoT) and smart, predictive analytics technologies, companies have been building a networked data-rich environment. Rapid sampling during continuous operational periods can quickly yield large amounts of data about the performance of critical components. Hence, frequently the term 'Big data' is often associated with predictive analytics (e.g. Gandomi and Haider, 2015; Waller and Fawcett, 2013)

The key challenge for the effective asset management of a lot water-level and flood risk infrastructure, is the lack of data! Floods by definition are rare events. Therefore, flood risk management infrastructure is used relatively infrequently and only for relatively short periods. This paucity of data associated with the use of plant and equipment under load, makes it difficult to predict anything about future performance. The collection of detailed and dense data during real operations is critical if we are to realise our ambition of a pro-active a maintenance strategy.

There are some measures that can be taken to generate more data. These include exercising components such as pumps and their motors and soft starts (i.e. starting motor but not engaging the drive to the pump impellers). However there are also practical challenges and limitations with such strategies. For instance, the exercising pumps is often kept to a minimum as it can stir up sediments in the watercourse. This in-turn can lead to low-levels of dissolved oxygen and potential fish kills. Soft starting a motor only provides an indication of its performance as the motor does not experience any loading.

Another strategy to enrich the data might be to collect historical performance data from similar asset types across the asset portfolio. Again this comes with the difficult on correcting for the difference in operational regimes and other variables.

Novel sensors and techniques may offer a solution. For example techniques more often used in the field of structural health monitoring could offer some insight in to possible performance of important components. For example, Mba, (2006) reviews the potential of Acoustic Emission Technology to the condition monitoring of rotating machinery.

If this work is to be successful it is likely that all of these strategies will have to be employed. Data will have to be mined from unstructured sources and integrated with those collected from the sensing instruments. Pragmatic solutions will have to be found to increase utilisation without having negative impacts on the environment, CO₂ emissions and energy consumption.

5. Conclusions

The Environment Agency is undertaking innovative research to develop a CBMS system for its MEICA asset portfolio. Whilst other infrastructure owning organisations have been highly active in the area and have relatively mature operational systems, the specific challenge of low utilisation of equipment has to date hampered flood and water-level managers from adopting similar approaches.

This research project aims to face this challenge head on. The research team will seek to use both pragmatic changes to operational rules to generate performance data allied with new advance in predictive analytical techniques and sensors. We keen to work closely with the research community to tackle these challenges and encourage interested individuals and organisations to get in to contact.

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