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PREDICTIVE MAINTENANCE BASED ON SMART MONITORING AND DATA ANALYTICS

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SUMMARY: This paper discusses recent world progresses in smart monitoring and data analytics that have enabled predictive maintenance (PdM) of infrastructures; however currently the industry is slow in employing new smart monitoring sensors, information technologies, and data analytics for achieving PdM. PdM is data-driven and relies on smart monitoring and data analytics insights for maintenance, protection and repairs ahead of disruptions in operation. PdM is considered to be a new industry trend and has progressed rapidly in the industrial world since the 1990s; however our recent survey of the industry has shown that its application in infrastructure maintenance is very limited. This paper also discusses briefly recent progresses in PdM enabling technologies including corrosion monitoring probes, information technology platforms, data analytics and internet-of-things.

Keywords: Predictive maintenance, corrosion monitoring, data analytics, corrosion prediction, pipeline, infrastructure, asset management.

1. INTRODUCTION

Metallic and plastic materials are widely used in major fuel infrastructure assets such as underground oil and gas pipelines and storage tanks that are the result of an enormous investment over the past 100+ years. These assets are aging and are under serious threat of corrosion and environmental degradation [1-7], which is evident by widely reported catastrophic infrastructure failures [1] and an enormous amount of unreported infrastructure incidents [4]. In order to ensure the safe and economical operation, life extension or re-purposing of aging fuel infrastructural networks for the future fuel industry, there must be new measures to enhance the integrity management and the protection of these aging assets. A practical approach to achieving this is through predictive maintenance (PdM) by means of advanced technologies for smart monitoring, data analytics and asset condition prediction.

PdM primarily involves foreseeing structural breakdown of assets and forecasting proactive maintenance needs. In simple terms, it is considered to be the asset management practice of repairing an asset or piece of equipment before it fails based on data received about it. It is the third phase in asset management: (i) Corrective maintenance: repairs made after a problem or failure occurs; (ii) Preventative maintenance: scheduled repairs made based on experience; and (iii) Predictive maintenance: repairs made because data for an asset indicates that a failure is imminent. It appears 'predictive maintenance' is also different from 'pro-active maintenance' because of it is heavily based on two critical enabling elements: 'data' and 'prediction. PdM is achieved by detecting early signs of failure, by analysing data to identify patterns and predict issues before they happen. PdM has been adopted by various sectors in manufacturing and service industries in order to improve reliability, safety, availability, efficiency and quality as well as to protect the environment [8], and has quickly emerged as a leading Industry 4.0 use case for manufacturers and asset managers [8-10]. PdM techniques are closely associated with sensor technologies and data analytics. Various sensors technologies have been implemented to monitor asset health and gaining real-time alerts to operational risks, allowing asset owners to lower service costs, maximise reliability and safety [8-10]. Sensors facilitate the easy real-time monitoring of conditions, cloud storage systems and data bases enable the long-time archiving and analysis of data for diagnostic and maintenance [10]. Recent advances in sensor, information, communication and computer technologies, such as corrosion sensors and Internet of Things (IoT), have been enabling PdM applications to be more efficient, applicable, affordable, and consequently more common and available for all sorts of industries. In particular, researches on remote maintenance and e-maintenance have been supporting PdM activities especially in unsafe working environments and scattered locations, which are common for fuel infrastructure assets [8].

The two most common approaches to PdM are condition monitoring based and machine learning-based. Condition monitoring based PdM relies on sensors to continuously collect data about assets, and sends alerts according to predefined rules, including when a specified threshold has been reached [10]. For example, if corrosion rates are above certain predefined levels, the system will send an alert to a maintenance engineer to address the issue ahead of failure. The condition monitoring data can be integrated with insight from machine learning to provide a visually understandable map of asset conditions in real-time. Artificial intelligence (AI) has also been considered to be suited to PdM because it offers a host of techniques to analyse the huge amounts of data collected from the condition monitoring, and deliver actionable insights to reach and sustain proactive maintenance and protection. These techniques are referred to as Machine Learning algorithms. As a brief summary, for PdM to be carried out on an industrial asset, the following base components are required [10]:

1. Sensors – data-collecting sensors installed on an infrastructure. Due to the 'invisible' nature of many infrastructural assets such as underground fuel pipelines, asset integrity issues are often due to 'hidden' localised corrosion and unexpected degradation of buried metal components. It is recognised internationally that the lack of corrosion and materials degradation data is a major issue that significantly impedes the timely maintenance of structural health [1,5]. Some aspects of this issue has been addressed over recent years through the development of new sensors and probes.
2. Data communication – the communication system that allows data to securely flow between the monitored asset and the central data store.
3. Central data store (industrial IoT platform)– the central data hub in which asset data and business data (from IT systems) are stored, processed and analysed.
4. Predictive analytics – industrial data integration and predictive analytics algorithms applied to the aggregated data to recognize patterns and generate insights in the form of dashboards and alerts.
5. Root cause analysis – data analysis tools used by maintenance and process engineers to investigate the insights and determine the corrective action to be performed.

Although PdM is considered to be the leading edge type of maintenance and its principles are currently broadly used to maintain industrial assets, PdM is as yet not embraced by the pipeline industry [9]. This paper discusses issues and gaps through industry survey and literature review, with particular focus on finding main weaknesses and limitations in asset integrity management tools currently used in the fuel networks, and identifying opportunities in new IT and data management technologies, online information management platform and analytics, as well as asset condition prediction models that could facilitate future PdM application in the fuel infrastructural network management.

2. SURVEY AND LITERATURE STUDY ON STRUCTUREAL HEALTH MONITORING TOOLS

In order to understand current status, issues and weaknesses in present asset management technologies and potential future technological solutions, survey of selected Organisations major players in the fuel infrastructure industry has been conducted through industry interviews and survey. A general finding is that although major effort has been made in the energy pipeline industry to improve the safety and economic operation of fuel infrastructures and help ensure the safe operation and the extension of asset life, there are significant gaps to be filled for future PdM application in these industries. This is consistent with the comment that PdM has not yet been embraced by the pipeline industry [9].

The first barrier for achieving PdM in the fuel infrastructure industry is the unavailability of in-situ and site-specific data. Structural health monitoring using various sensors (or probes) is a practical approach to acquiring data from underground pipelines. Over the past decades, many specialised sensors or probes, such as fibre optic sensors, piezoelectric actuators, vibration sensors, leakage detecting sensors, pressure, flow, and seismic sensors and corrosion detection sensors/probes have been tested in many infrastructural systems for monitoring various structural and environmental parameters such as stress, displacement, acceleration, rainfall, temperature, corrosion etc.. In the case of buried pipelines, for instance, major concerns are often soil load, temperature, geometric configuration, earth movement, strain, leaking, corrosion etc., therefore sensors selected to be installed on pipelines can be temperature, strain, gas leakage and corrosion sensors. In the case of underground and submerged oil and gas pipelines, corrosion is usually among the major structural integrity concerns because of the corrosive environmental condition and the relatively poor corrosion resistance of steel pipelines. Corrosion sensors or probes are therefore needed for providing visibility of corrosion and material degradation processes occurring on these 'invisible' and 'hidden' infrastructural assets.

Unfortunately the lack of corrosion and materials degradation data from 'invisible' underground structures such as pipelines is still considered to be a major issue that significantly impedes the timely maintenance of the health of fuel infrastructure [1,5]. Traditionally the most common approach to collecting corrosion and degradation data from buried pipelines is through field excavation of selected sites and visual inspection (historical excavations) to provide compressive snapshots of the corrosion occurred after a long period of exposure. The selection of field excavation sites is usually assisted by various field inspection techniques such as Direct Current Voltage Gradient (DCVG) survey and inline inspection '*pigging*' [11]. Currently the most widely used tools for assessing and inspecting the condition of a pipeline and cathodic protection (CP) conditions [11-13] include the detection of metal loss using in-line inspection tools (intelligent pigs); the Close Interval Potential Surveys (CIPS) or IR Coupons; the detection of coating defects by DCVG surveys. Steel coupons (IR Coupons) buried next to the pipe and electrically connected to it are also used to assess the operation of the CP system. They can be easily disconnected from the CP, interposing a current interrupter, and the remnant IR drop can be eliminated placing a reference electrode next to the coupon. However, these coupons simulate the bare metal exposed to the bulk soil at a coating holiday, giving no information on localised corrosion such as corrosion under disbonded coatings, and they are too slow to detect corrosion due to dynamic events such as stray currents. It would not provide critical information such as the initiation of localised corrosion, localised coating damage or disbondment. The DCVG method is an effective tool to locate coating defects, however no general relationship between the potentials measured and the defect size could be established. The IR drop measured at each area is affected by many other factors beside the defect size. Other important limitation of these surveys is that they cannot distinguish disbonded coatings which are shielding CP current from intact coatings. They are also not applicable to HDD pipelines that are buried deep underground. In-line inspection tools (intelligent pigs) are cylindrical Non Destructive Testing (NDT) tools that are inserted in the pipe and inspect it while being carried by the fluid or gas flow. Many different NDT technologies are used for different particular cases. Unfortunately, some pipelines are not conventionally piggable. An issue is that field inspection occurs relatively infrequently (e.g. pigging of a pipeline is typically done every 5-15 years in Australia), and therefore historical inspection data often do not have high spatial and temporal resolution required for accurately predicting the failure of infrastructure at locations where metals are under dynamic localized corrosion attack [11-13]. Over the past decades, corrosion monitoring based on the electrochemical nature of metal corrosion has been developed to acquiring in-situ and site-specific corrosion data with high spatial and temporal resolutions [3,11-13]. Unfortunately, in principle, conventional electrochemical methods developed based on the most fundamental electrochemical relationships such as Faraday's law, Nernst equation and Bulter-Volmer formulation are applicable only to uniform electrode surfaces, and have fundamental limitations in measuring localised corrosion - the key process triggering failure of buried infrastructures [13]. Details of these survey methods and procedures can be found elsewhere [11-13]. For reasons including these listed above, the development of accurate and robust probes and sensors for acquiring corrosion data has been listed as a critical national need for infrastructure transformational research and a grand challenge for corrosion research in the United States [5].

The latest development in obtaining data for fuel infrastructural management is probably the Pipeline Corrosion Monitoring (PCM) system that was developed over the past several years by the Energy Pipelines CRC Deakin research team for performing in-situ, site-specific and sensitive corrosion monitoring of buried pipelines [15-17]. The PCM system has enabled corrosion monitoring for obtaining in-situ and site-specific corrosion data from buried pipelines. The PCM system was the result of extensive research on the refinement of the corrosion probe designs, the integration of variously designed corrosion probes, careful consideration on probe installation and application methods, the development of a data logging and analysis, computer visualisation software and IT platform [16]. This PCM system has been successfully tested in the laboratory and the field using a full scale prototype built for practical applications. These have included real life field tests on four pipeline sites in Melbourne and Geelong regions. Remote monitoring and data transmission via a mobile and satellite networks have been successfully achieved for the PCM system. A data storage and analysis software, as well as a basic web-based IT platform, has been developed to perform data storage, visualisation, and corrosion analysis functions. The features of the PCM and associated IT platform include, (i) Remotely detecting, analysing and visualising data from selected pipeline locations on an interactive map; (ii) Displaying basic 'warning' of high risk pipeline locations based on local corrosion rates; (iii) A mobile IT platform has been initiated to provide information to engineers; (iv) Efforts for the practical application, marketing and commercialisation of the PCM system has been initiated and are active. It should be noted that the PM system also has its weaknesses and technical gaps: (i) The number of sensors/probes deployed on an infrastructure such as a pipeline is limited. Therefore it provide data with excellent temporal resolution, but relatively low spatial resolution. It is believed that the full potential of the PCM would be realised if corrosion monitoring data are connected and integrated with other forms of data. (ii) Monitoring probes/sensors are usually designed to simulate and detect the worst-case scenario types of localised corrosion, and may not detect all types of corrosion or failure. More details of this research can be found in the final report of the research projects *(17,18)*, and (iii) Currently PCM data are used only for knowing asset integrity issues, not as a feedback information for automated asset protection such as CP. Another latest development in obtaining data from fuel pipelines installed using HDD technology is a new HDD probe that has been designed and tested for detecting coating damages on HDD pipelines. This tool was also developed over the past several years by the Energy Pipelines CRC Deakin research team. More details on this development can be found in reference [15-17].

A new need for future fuel infrastructure is the detection of hydrogen related asset integrity and safety issues when hydrogen is introduced to future fuel mixtures. The introduction of hydrogen as a consumer fuel has caused heightened concern over its safety with a corresponding increased interest in hydrogen sensors and leak detection. A solution to this issue is the use of hydrogen sensors [18,19]. Hydrogen detection has been extensively discussed in the literature, however relatively little interest has been on the detection of hydrogen in underground pipeline conditions. In a relevant report [19], the experience with the United State has been presented. The United States currently has >1000 km of dedicated steel hydrogen trans hydrogen pipeline infrastructure. The chief technical concern is hydrogen embrittlement of metallic pipelines and welds. In the simplest sense, hydrogen embrittlement describes the decrease in ductility or toughness of materials as a result of interaction with atomic hydrogen. It is also recognised that the application of hydrogen sensors to current and future gas-filled (or liquid filled) pipe around lines is a major area requiring development. Multiple microsensors that can be "wrapped" in improving the safety. It has identified 'desirable/ideal' characteristics of sensors for leak detection has been identified as [18]*:*

- be inexpensive, so that it could be used prolifically wherever the potential for a flammable mixture of hydrogen exists;
- Positive indication of both the absence of hydrogen, as well as the presence of hydrogen;
- be simple, reliable, easily incorporated into the system it is monitoring, and not require an external power source;
- be hydrogen specific and sensitive enough to detect concentrations well below the lower flammability limit;
- have a rapid response time as well as provide historical information of leaks; and
- have a long useful life operating over a wide range of conditions and environments.

Generally speaking, future development to enhance the reliability of sensors is necessary. Take localised corrosion sensors as an example, it is a highly challenging task to design reliable sensors. Firstly it is essential to ensure the sensors are able to effectively simulate corrosion behaviour in actual service environments and reliably evaluate the effects of various factors on corrosion processes, rates and mechanisms. It is well appreciated that corrosion sensors needs to simulate the actual service exposure environment; however relatively less considerations have been given to the effects of environmental parameters on corrosion patterns and mechanisms. It is not uncommon to receive misleading test results due to inappropriate selection of testing parameters and measuring techniques. This challenge is more acute when corrosion is affected by many inter-related variables such as non-uniform temperature and pressure, heterogeneous metallurgy, inhomogeneous soil or solution chemistry and thermo-mechanical conditions, local mechanical stress, coating defects, and cathodic cathodic potential and excursions. These effects may have not yet fully quantified and need to be better understood and used in corrosion sensor design and application. In order to fully realise the advantage of corrosion sensors for providing site-specific and in-situ warning of unexpected structure failures, corrosion sensors may need to be placed at strategic and 'worst-case scenario' high risk locations of a structure. For a buried pipeline, for instance, typical high risk structure sites could be those with high stray current activities, low soil resistivity, high underground water level, high concentration of corrosive species, and those highly corrosion rate areas identified by pigging, field survey and historical excavations. Sensors embedded at these strategic sites can be used to collect real-time and site specific data that would contain critical 'predictor features' and parameters needed for modelling and predicting localised corrosion, coating disbondment and degradation.

3. LITERATURE STUDY ON IT PLATFORM AND DATA ANALYTICS

Although sensors can provide useful in-situ data from selected locations of an asset, there is a need to integrate data from limited monitoring sites into the whole database by suitable models in order to provide fuller coverage of a huge structure (e.g. a 1000km underground pipeline). More specifically, huge data of various forms have been generated using asset management tools, however the analysis, storage and application of these data are often less sufficient and remain challenging, and therefor the potential of these data is often not fully realised. Currently individual pieces of monitoring/inspection data from structural health monitoring tools are generally not integrated to generate a complete picture of the condition and health issues of the asset. This could be a major underuse of valuable monitoring and inspection data and limit the accuracy of failure prediction and asset maintenance and protection decisions - another barrier for achieving PdM in the fuel infrastructure industry. On the other hand, currently these data are mainly used for assessing asset integrity issues, not use sufficiently as a feedback information for automated asset protection such as CP. For instance unfortunately, current CP systems use static setting that might lead to temporal and local over or under protection levels in the presence of stray currents or due to dynamic changes in soil resistivity. These are major gaps in current knowledge that limit technologies available for the integrity management of future and existing energy and fuel infrastructures networks.

A development trend is a suitable IT platform and data analytics for corrosion data management and analysis, where sensors form part of the data sources to help overcome weaknesses in asset management models. An information platform would enable the integration of various data inputs and allow industry to cost effectively gather information on the in-service integrity of assets/infrastructure, gain high levels of confidence in the condition of the asset, timely maintenance, safety and continuous availability/operation of the asset. A web-based information platform that can linkup multiple industries and multi-disciplinary areas of research would be extremely useful for infrastructure health monitoring, failure prediction and life extension. However such a web based information platform is complex to develop because it requires expertise from several disciplines. These needs of future developments in terms of instrumentation, data acquisition, communication systems and data mining and presentation procedures for diagnosis of infrastructural 'health' have also been discussed in references [20-22]. Some progresses and needs have been identified including,

1. The GPS has provided new possibilities for direct measurement of infrastructure and should be used in structural health monitoring.
2. Data collection, storage and communications: Wireless or land links are a necessity for remote unmanned installations; dialup modems or permanently connected leased lines may be used. Robust low-cost wireless systems play an increasing communications role but due to present limited data capacity, data compression or pre-processing will be necessary unless data are slowly sampled static signals. Successful structural health monitoring procedures should incorporate the means to compensate for or filter out the environmental and noise effects or at least establish confidence levels for anomaly detection against noise [21].
3. Data mining and information presentation: One of the most significant issues with structural health monitoring is converting data to information, an issue addressed in detail elsewhere in this set of papers. Not to be overlooked is the charting or presentation of information to operators who are very unlikely to be familiar with the sophisticated underlying numerical procedures [21].

These needs are actively discussed in commercial literature associated with PdM [23-27].

In the oil & gas industry, PdM is considered to be very suitable because,

- Engineers often lack visibility into their infrastructure condition, especially in remote buried pipelines, offshore and deep-water locations.
- This could be changed if more data become available by means of monitoring and inspection: Availability of large amounts of data gathered through instrumented and connected assets; Availability of data gathered through the IoT… For instance, IoT data such as weather-related information can strengthen predictive maintenance.
- Data analytics based on 'big data' could provide insight and prediction to infrastructure failures in order to achieve the optimal lifetime of the system and components. This is facilitated by advances in analytics to gain insights from data. Artificial intelligence (AI) technologies such as machine learning — the ability for a system to learn from data on its own without programming.
- Considerable work has been done in the area of health monitoring and fault diagnosis. This has also made it possible to achieve 'Convergence of IT with operational technology', such as automated cathodic protection control.

The followings are two typical examples of successful PdM application in oil & gas related industries:

1. <u>GE Digital Case study [23]:</u> GE Digital has developed a Platform namely, <u>Predix</u>, which the company claims can help oil and gas businesses create automated analytics models that could help in the predictive maintenance of its industrial equipment using machine learning. It is claimed that the application's machine learning algorithms are able to process data that sensors collect, such as equipment or parts performance, environmental data, and weather conditions, among others. The algorithms then compare these against the ideal performance data contained in the database. If the algorithms find discrepancies between the current and ideal state, the application is triggered to send an alert to technicians. who in turn conduct predictive maintenance or part replacement. Please note that the GE Platform has not shown any cases of using for buried infrastructures, although the Predix's human-machine interface and supervisory control and data acquisition (HMI-SCADA) application called iFIX has been implemented in 'five distribution plants' [23]. Employees at each location learned to use the system to input critical data. With the centralized system, the user was reportedly able to track field data, such as gas and liquid flow rates, composition analyzers, and tank levels and volumes. The system also enabled the company to monitor the performance rates of equipment, daily throughputs from process units, and weather conditions. This data was automatically processed, formatted to a spreadsheet, and uploaded to the government's website. With this data, the user was able to calculate and project the efficiency of its furnaces using this data. The data was recorded in the server to enable the team to study trends related to the furnace's performance. According to GE Digital, implementing Predix allowed the user to cut the time spent on routine processes by 60% and save 20% more fuel. Management also reportedly stopped asking employees for manual reports. GE Digital also lists Exelon, Gerdau, Spomlek, Lek Pharmaceuticals, and the City of San Luis Obispo as some of its clients [23].

2. Baker Hughes case study [24]: Baker Hughes has developed predictive maintenance software for gas and oil extraction equipment using data analytics and machine learning. It is claimed that the predictive maintenance system reduced pump equipment costs and downtime. Use MATLAB to analyze nearly one terabyte of data (Multiple types of data easily accessed) and create a neural network that can predict machine failures before they occur. To monitor the pumps for potentially catastrophic wear and predict failures before they occur, Baker Hughes analyzes pump sensor data with MATLAB® and applies MATLAB machine learning algorithms. Baker Hughes engineers used MATLAB to develop pump health monitoring software that uses data analytics for predictive maintenance. They imported data gathered in the field from temperature, pressure, vibration, and other sensors into MATLAB. The team worked with a MathWorks support engineer to develop a custom script for reading and parsing sensor data stored in binary files in a proprietary format. Working in MATLAB, the Baker Hughes team analyzed the imported data to determine which signals in the data had the strongest influence on equipment wear and tear. This step included performing Fourier transforms and spectral analysis as well as filtering out large movements of the truck, pump, and fluid to better detect the smaller vibrations of the valves and valve seats. To automate the processing of almost one terabyte of collected data, the team wrote MATLAB scripts that they executed overnight. The engineers discovered that data captured from pressure, vibration, and timing sensors was the most relevant for predicting machine failures. Working with the MathWorks support engineer, the team evaluated several machine learning techniques using Statistics and Machine Learning Toolbox™ and Deep Learning Toolbox™. This initial evaluation showed that neural networks produced the most accurate results. The group created and trained a neural network to use sensor data to predict pump failures. They validated this model using additional data from the field that was not used to build the model. Field tests confirmed the pump health monitoring system's ability to predict pump failures. Baker Hughes' predictive maintenance alarm system, based on MATLAB. It is claimed that "MATLAB gave us the ability to convert previously unreadable data into a usable format; automate filtering, spectral analysis, and transform steps for multiple trucks and regions; and ultimately, apply machine learning techniques in real time to predict the ideal time to perform maintenance." (Gulshan Singh, Baker Hughes). "MATLAB enabled us to automate the processing of large data sets… the wide variety of technologies that MATLAB provides for working with data, including basic statistical analysis, spectral analysis, filtering, and predictive modeling using artificial neural networks."

Over the recent years, a range of new IT technologies have been developed that could be adopted for fuel infrastructure industry. An example is Google Cloud Platform (GCP) services [25]. It is claimed that the platform can enable a system of globally distributed networks to communicate with and monitor on-site equipment. You can monitor equipment health in real time and analyze and predict impending equipment failure. By taking advantage of cloud services, you can schedule planned maintenance instead of resorting to expensive and inefficient emergency repairs that destabilize the entire system. This is achieved through,

- Use multiple sensors to collect and aggregate data from operational components associated with production systems.
- Leverage supervisory control and data acquisition networks currently used at many sites, and add an edge gateway that allows access to cloud services. The first step to gaining insights from large-scale time-based data is to visualize the data in a meaningful way. This means putting the data into the context of the equipment. For example, rotating equipment lends itself to visualizations that plot speed of rotation, duration of rotation, vibration, heat generated, pressure generated, and so on. Static equipment, such as a valve, reports usage, position, flow, pressure, and so on. By aggregating data across plants and geographies, you can monitor the overall health of all connected systems. Over time, visualizations of these types of metrics enable you to spot patterns of change.
- Gain insights into operational health by using cloud services to analyze the collected data in combination with data from related information systems. After you visualize the data, you can compare it to optimal operating conditions. Examining performance thresholds over time gives you insight into the overall health trends of the asset. Comparing measures across the range of monitored assets helps identify the best-performing equipment. By correlating against operating parameters, you learn which conditions yield the best performance, and you develop an analytical basis for improving the lowest performing assets.
- Optimize production and maintenance by applying machine learning (ML) predictive scenarios. You can use patterns established from analysis to develop digital models that represent physical assets. To improve the fidelity of the models, you aggregate data related to general operation, maintenance, incidents, and problems. Developing these models often depends on using historical data to train ML algorithms. It is important to connect operating conditions to failure incidents so that the algorithms can identify what might have caused each incident. By drawing on a set of observed operating conditions, these trained ML models can then identify and predict when asset performance will be affected. This approach can be valuable in avoiding or reducing the impact of potential outages.

Other examples of predictive modelling and its application have been described in the literature: [26-30]

1. Big data driven smart energy management:
    - The big data platform can support the creation, development, maintenance and exploitation of smart energy services through the utilisation of cross-domain data
        - Direct data sources
            - Energy consumption data from smart meters
            - Asset management data
        - Indirect data sources
            - Weather data – for renewable energy power generation forecasting, system fault identification, user energy consumption forecasting,
            - Mobile data
            - Electrical vehicle data
            - Real estate data, etc.
    - Generate meaningful operational insights for city authorities and local administrations, energy managers and consultants, energy service companies, utilities and energy providers.
    - A web-based Decision Support System (DSS) has been developed according to the proposed architecture, exploiting multi-sourced data within a smart city context towards the creation of energy management action plans
    - Components
        - A Data Interoperability and Semantification Layer: feeding all the multiple-sourced data
        - Able to receive and handle data of different types
        - The Data Storage Cluster - provide data storage for the incoming data, the data generated from the services and the semantic information and metadata – a NoSQL cluster is suitable
        - Data Access Policy Control – isolates data from different providers and grants access to other tools based on data ownership and advanced user permissions.
        - Analytics Services - propose meaningful analytics, expose ‘‘hidden’’ knowledge
    - Outputs (prediction models) –
        1. Forecasting renewable energy production
        2. Energy consumption
        3. Indoor temperature
        4. Energy prices
    - Action plans (suggestions to energy managers)
        1. Scheduling and management of the occupancy
        2. Scheduling the set-point temperature
        3. Scheduling the ON/OFF of the heating system
        4. Management of the air side economiser, etc.
2. Machine learning and pattern recognition based system to count wildlife
    - Uses:
        - monitoring populations after bushfire, floods or drought
        - measure the impact of introduced predators, such as foxes and cats
        - replace the costly and labour intensive process of using traps for wildlife monitoring.
    - Automated sensor cameras installed in the targeted parks
    - A central database stores and compiles data
    - Machine learning and pattern recognition algorithms developed to identify if wildlife is in the photographs
    - Wireless sensor networks are to be implemented to collect data automatically within parks
3. An operational River flow prediction system - using Artificial Neural Networks (ANN)
    - Performing an operational river flow prediction of for a military site
        - Requirements: rapid response and high accuracy
        - Challenges: Uncertainties associated with the historical record

Drone data analysis examples from literature [26-30]

1. Urban traffic analysis through an UAV
    - Use Unmanned Aerial Vehicle (UAV) to evaluate the real traffic flow conditions in urban areas based on videos
    - Equipment used: Vertical Take-off and Landing micro-drone
    - Advantages:
        - low altitude operations (very high spatial resolution)
        - timeliness for data obtained
        - reduced operating costs.

- Process:
    - HD video recording by UAV
    - video processing
    - evaluation of traffic kinematic data – using open source software “Tracker”
- limitations:
    i. Geomorphological: e.g. presence of mountains, the presence of strong electromagnetic fields, of the prevailing winds, areas of "no-fly", etc.
    ii. Technical constraints of the drones: autonomy, load capacity, weather, etc.

2. Drone remote sensing for forestry research and practices
    - Using drone remote sensing to survey and map tropical forests in Indonesia because of the high costs of high-resolution satellite remote sensing data, frequent cloud cover, and difficult/expensive ground surveys.
    - Used drone could fly for about 25 min per mission and cover a total distance of about 15 km
    - assembled the drone images to develop land use/cover maps at a spatial resolution of 5.1 cm
    - Usage:
        - used the video footage to detect human activities (e.g., burning and logging)
        - combined the photographic and video information to survey wildlife species and identify flora
        - Mapping canopy gaps - small forest gaps cannot be measured accurately with satellite remote sensing
        - Measuring forest canopy height
        - Tracking forest wildfires
3. Vegetation encroachment monitoring for transmission lines right-of-ways

4. CONCLUSIONS

It has been found that there is an obvious gap in the application of new sensor and data analytics technologies in the fuel infrastructure industry that could enable more reliable operation and life extension through ‘predictive maintenance’ (PdM). The detection, monitoring and protection of ‘high risk’ infrastructure components has also been identified again by industry as major issues and difficulties. Another finding is that progresses in smart monitoring and data analytics have provided necessary technological bases for PdM being adopted in the fuel infrastructures to achieve more reliable asset health monitoring, prediction, protection and life extension, despite the fact that currently the industry is slow in employing new smart monitoring sensors, information technologies, and data analytics.

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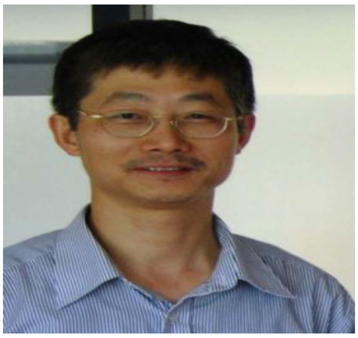
7. AUTHOR DETAILS



Mike Yongjun Tan is a Professor in Applied Electrochemistry and Corrosion Technologies at Deakin University in Australia. He is also a Research Program Leader of the Energy Pipelines Cooperative Research Centre. Dr Tan's principal teaching and research interests are in corrosion science and engineering and their applications for enhancing the reliability and durability of civil and industrial infrastructures. He contributed to electrochemical methods for corrosion testing, monitoring and prediction and corrosion inhibitor and anti-corrosion coating research. He is the author of some 200 publications and a book entitled 'Heterogeneous Electrode Processes and Localised Corrosion' (2012 John Wiley & Sons).

Ying Huo is an enthusiast in energy pipeline CP area. I finished my Ph.D thesis entitled 'A study on the effects of potential excursions and the environment on the effectiveness of cathodic protection (CP)'. I am currently working on two FFCRC projects, Gap analysis of smart monitoring and data analytics; Closed-loop CP control system for fuel networks. I hope I can contribute effort on improving future energy pipeline life expectation. My hobby is fishing, kayak, travelling and basketball.

Facundo Varela, also known as Bob, is a research fellow at the Institute for Frontier Materials at Deakin University. He has recently completed his PhD project that focused on new electrochemical methods for monitoring localized corrosion under cathodic protection. As a research fellow, he is working on an Energy Pipeline CRC sponsored project aiming to perform field trials of the sensors developed during his PhD.