The need for Big Data collection and analyses to support the development of an advanced maintenance strategy

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***Abstract*— Data mining applications are becoming increasingly important for the wide range of manufacturing processes. During daily manufacturing operations large amounts of data is generated. The abundance of data however, often impedes the ability to extract useful knowledge. In addition, the large amount of data stored in often unconnected databases makes it impractical to manually analyse for valuable decision-making information. New intelligent Data Mining tools and techniques are required which can intelligently analyse data and produce useful knowledge for manufacturing. This is an important issue with regard to the development of an advanced maintenance strategy. Maintenance optimization is critical for enhancing the productivity of assets within an organisation. Maintenance effectiveness depends on the quality, timeliness, accuracy and completeness of the information related to asset optimization based on which decisions are made. Recently developed Condition Monitoring Systems (CMS) generate and collect large amount of data during daily operations. These systems contain hundreds of attributes, which need to be simultaneously considered in order to accurately model the system's behaviour and provide operators and senior management with the necessary data required to ensure production levels are met.**

This paper will present an overview of the big data tools and techniques required to collect and analyse a range of data to support the development of an advanced maintenance strategy. The challenges of big data in maintenance including capturing, accessing, and processing information will be analysed. To achieve e-maintenance, how to integrate information and communication technologies into maintenance and the corresponding requirements and constraints will be identified.

I. Introduction

Effective use of leading edge Information and Communication Technologies (ICT) is seen as important, and possibly critical, to the future competitiveness of European Industry. In particular, manufacturing organisations are frequently characterised by high staff turnover, lack of knowledge and training, and a lack of appropriate asset management strategies. This has resulted in poor manufacturing efficiency and large amounts of waste. The implementation of structured maintenance methods has made possible the development of ICT including software and hardware systems.

The production and process industry are passing through a continuous transformation and improvement for the last couple of decades, due to the global competition coupled with advances in ICT. Manufacturing organisations are focusing more on big data collection and analyses to support e-business intelligence. The data should also be used to support other functions within the organisation which could impact asset management such as marketing and customer relations. The aim is to remain competitive and efficient by improving equipment performance and reliability by introducing an asset management strategy based upon accurate data collection and analyses tools and techniques.

Maintenance effectiveness depends on the quality, timeliness, accuracy and completeness of information related to machine degradation state, based on which decisions are made. This translates into two key requirements: (i) preventing data overload, ability to differentiate and prioritize data (during collection as well as reporting) and (ii) to prevent, as far as possible, the occurrence of information islands. With the emergence of intelligent sensors to measure and monitor the state of health of the component and gradual implementation of ICT in organizations, conceptualization and implementation of e-maintenance is turning into a reality [1]. While e-maintenance has a number of benefits seamless integration of ICT into the industrial environment remains a challenge. A variety of techniques are available to enable the above goals. Different data mining techniques serve different purposes, each offering its own advantages and disadvantages. The most commonly used techniques can be categorized in the following groups: Statistical methods, Artificial Neural Networks, Decision Trees, Rule Induction, Case-Based Reasoning, Bayesian Belief Networks, and Genetic Algorithms and Evolutionary Programming. It is very critical to understand and address the requirements and constraints from the maintenance as well as the ICT standpoints in parallel in order to identify and understand which information is required and when.

II. Big Data Benefits and Challenges for Maintenance

Big data is a revolutionary advanced methodology where big data sets which are collected at an unprecedented scale, are often complicated and difficult to process using traditional data processing tools such as relational and object-relational database management systems. Big data refers to the datasets that could not be perceived, acquired, managed, and

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processed by traditional Information Technology (IT) and software/hardware tools within a tolerable time [6].

Regarding the adoption of Big Data technologies by industrial sectors, following a pattern typical in technology transference between sectors, there are important differences. For example, in sectors not very fragmented where most of the information is already structured and comes from the same source, the use of big data analytics is nowadays a standard (e.g. bank sector or pharmaceutical sector). For these sectors, there is also a great number of SW tools and IT services that cover most of the end user needs.

However, these examples are only the exception, since massive business, susceptible to incorporate the Big Data concept, have not adopted Big Data yet, either for the lack of specific tools or the excessive cost to involve all the required stakeholders. One of these sectors is maintenance of assets. Within this field, big data has become a new specialization for monitoring, maintaining, and optimizing assets for better quality and performance. Kurtz [2] states that big data helps to solve complex technical and operational issues in maintenance, such as:

- Lack of visibility into asset health;
- Unexpected costs for unscheduled maintenance and unexpected failure;
- Not capable to accurately predict asset downtime and maintenance costs;
- Lack of analytical insights and tools for maintenance optimization.

Therefore potential benefits of Big Data technologies in the field of maintenance will require predictive algorithms using heterogeneous data sources, scalable data structures, real-time communications and visualizations techniques. These technologies and methodologies applied to such a challenging industry relevant sector will provide the expected system component degradation prediction modelling, maintenance cost prediction modelling, and asset condition monitoring. This should lead to boost the efficiency and maintenance cost reduction.

As an advanced predictive analytics methodology, big data is tailored to meet the needs of optimizing maintenance tasks in order to reduce operational expense and increase equipment reliability. For example, big data can be used to improve the production line continuity: A sensor network can be applied to collect the real-time production line data. The data is then used to analyse the asset health and predict failure or the mean time to failure (MTTF) and suggest possible solutions to minimize disruptive and unscheduled downtime. Big data is a multi-stage process, including data acquisition, information extraction, data modelling and analysis, decision making. Big Data can also be used to influence the next generation of products by identifying the issues that cause unnecessary and unplanned downtime. An analysis of the data could provide an insight to known and unknown issues and by feeding the results back into the design process the aim is to improve the manufacturing process and product quality based upon accurate data.

According to authors including [3] and [4], big data intelligent mining techniques should be applied within manufacturing organisations to support a number of processes including (1) Manufacturing knowledge acquisition by examining relevant and accurate data, which implicitly contains most of the required expert knowledge (2) adaptive or intelligent manufacturing system which are capable of learning from previous situations (3) quality control systems which with monitor standard operating procedures and identify deviation from the norm. New intelligent data mining tools and techniques are required which can intelligently analyse data and produce useful knowledge for manufacturing. This is an important issue with regard to maintenance strategy development.

The following section will explain the process of big data in maintenance and discuss the specific challenges to each step.

A. Data Collection, Storage and Integration

Acquiring and storing such large and rapidly increasing volumes of data has often been challenging. With the deployments of mobile networking, cloud computing has become the best solution for big data in data collection, storage, integration, and distribution. However, a widely accepted solution for data management in cloud computing still has not been designed [5]. Cloud computing still encounters unsolved problems related to e.g. data heterogeneity, data redundancy, assessing the value of data (to decide which data should be discarded and which stored), and data confidentiality [6].

Also moving big data to and from the cloud has presented a challenge because the capacity of the network bandwidth has proven to be a bottleneck [7]. Traditional wide area network (WAN) based data transfer methods use a fraction of available bandwidth for transmission; they cannot move such large amounts of data at a suitable speed, which may introduce unacceptable delays in data collection. IBM Aspera [8] had created an innovative data transport technology to solve this issue: Without using traditional transmission control protocol (TCP), IBM Aspera [8] designed FASP (Fast, Adaptive, and Secure Protocol) for transferring files over public and private internet protocol (IP) networks which is independent of network delay and packet loss [8].

Data integration can be seen as a process including data extraction, transformation and loading. It aims for uniform data despite the numerous data sources used [6]. Comprehensive solutions for integrating big data do not exist at the moment, and this poses a challenge for developing advanced data-based maintenance strategies.

B. Data Modelling and Analysis

The use of big data, to support maintenance task selection, could be described as (i) the use of data to detect and predict product failures and (ii) to increase equipment effectiveness i.e. increase quality, reduce costs and improve up-time. Generating user-friendly predictive models and conducting cause analysis are therefore very important actions which need to be supported by the use of big data. To fully realize the potential benefits of big data, there are two technical challenges that need to be addressed:

a) Data uncertainty and inconsistency: Besides volumes of data, the inconsistency, uncertainty, and incompleteness of data makes modelling and analysis more challenging. Different from small samples, big data is always noisy, dynamic, diverse, inter-correlated, and sometime inaccurate. In fact, with generating suitable statistics, one can use approximate analysis to expose some reliable knowledge hidden in the data [9].

b) Analysis timeliness: As data grow rapidly in volume and it is not economical to store all raw data, real-time analysis techniques are needed to perform data processing. Some examples of general platforms designed for real-time analysis are EMC Greenplum and SAP HANA [6]. Regarding maintenance, one possible solution is to find elements that meet a specified maintenance criterion. And in this case, index structures to support various criteria need to be designed.

There are already a number of commercial and open source software systems available for mining and analysing big data [6]. However, according to Begoli and Horey [10] specialized data management systems are needed to support the range of analysis methods and environments. The software architecture should not extensively limit the tools available for the user because the data needs are very different depending on the decision-making situation in question. It can also be stated that the currently applied analysis methods are based on data mining from the 1980s and statistical methods from the 1970s [11]. Currently there are no ground breaking modern approaches available for analysing big data.

C. Decision Making and Actions Recommendation

Ultimately, provided with the result of analysis, decision will be made and maintenance actions will be recommended. As reported in [12], there exist many challenges during this process, including getting functional managers to make decisions rather than based on intuition, putting analysis of big data in a presentable form for making decisions, determining actions with the insights created from big data, etc. These challenges hold the manufacturing and maintenance managers back from seizing the benefits offered by big data. It is important to address this. Chen and Zhang [7] state that the weaknesses of the existing visualisation tools for big data focus on response time, functionalities, and scalability. In addition to visualisation, also mobile interfaces and human-computer interaction have been identified as major topics for future research [11].

III. E-MAINTENANCE EXPECTATIONS AND INTEGRATION

Condition based maintenance (CBM) is the first step toward e-Maintenance practice. It is important to note that e-maintenance is more than a collection of tools and techniques joined to enhance maintenance, it must be seen as a complete system which must be dynamic and flexible and able to interact with CBM technologies. Companies are moving from traditional corrective and preventive maintenance program to CBM to reduce the maintenance cost and unnecessary maintenance schedules. A CBM program consists of three key steps [13]:

1. Data acquisition, to obtain data relevant to the system health
2. Signal processing, to handle the data or signals collected in step 1 for better understanding and interpretation of the data,
3. Maintenance decision making, to recommend efficient maintenance policies based on diagnosis and prognosis extracted from the data.

A CBM programme essentially forms part of the e-maintenance system, as the assessment of machine's performance information requires an integration of different components health status and the performance requirements. For achieving near zero down time, near zero defects, instantaneous response, decision-making and world-class OEE performance prognostics and diagnostics are used through embedded sensors and device to business tool. All these needs have led to e-health card for equipment's degradation assessment, which forms part of e-maintenance.

For an integrated e-maintenance improvement programme, the information logistic as described below needs to be streamlined [1]

- Right information (in right quantity and quality),
- In right formats and form, as per stakeholders requirement,
- To right person,
- In right time,
- At right place

The plant and or equipment health management system (HMS) could consist of condition monitoring (CM) diagnostics and prognostics, and condition based operation and support, to improve the dependability and safety of the technical systems, besides decreasing life cycle cost of operation and support [14, 15, 16]. This system delivers data and information, which indicates the health condition of the system. The stakeholders of the system are the receivers of the data and information [17, 18, and 19]. The problem today in a health management system is the existing information islands, i.e., the different specialized systems, within an organization speaking different data and information languages. In order to destroy these information barriers some objectives have to be accomplished.

A stakeholders requirements based health management system (HMS) framework is given at Fig. 1[1]. With increasing use of condition monitoring, data collection, and internet in management of maintenance process, the information logistic is required to be streamlined. Condition monitoring uses various intelligent health monitoring techniques to monitor and control the health status of plant and machineries by analysing the data after it has been collected. The identification of effective and efficient strategies for the maintenance of a plant and machineries is of a major importance from global competition, safety and financial point of view. Today, most of the organizations are trying to follow the condition based preventive maintenance, based on the state of component degradation. However, in reality, the relevant parameters behind the degradation process are very complex, and needs to be undertaken analytically.

Other aspects of enhanced maintenance effectiveness are to integrate the ICT with the strategy and objectives of the organization with that of the maintenance division. This will facilitate the management with effective decision making.

ICT is changing the way we communicate; it is not only connecting us to new people, but developing a global network for conversation and facilitating the mechanism of feedback. ICT with its communication capacity can dramatically improve the standard of information and can create a new social and economic network. ICT is global; as it creates a global network, applied to the whole range of human activities, encourages the dissemination of information and knowledge regardless of geographic boundaries, and is low cost, can therefore lead to substantial efficiency gains.

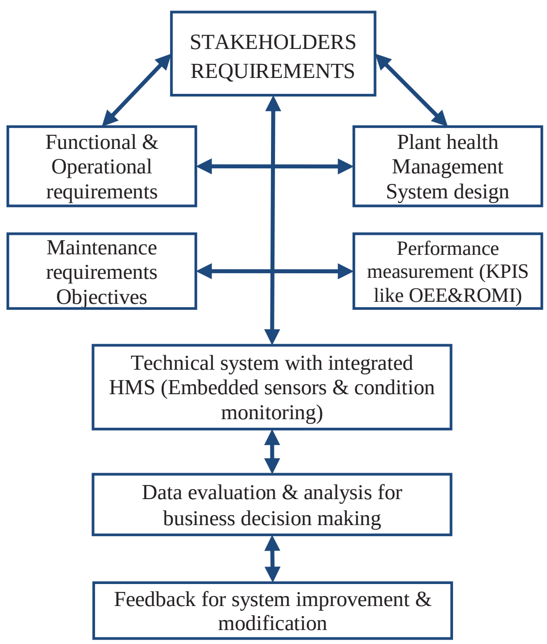

Fig. 1. A stakeholder based health management system (HMS) framework. (Adapted from Health management of Complex technical systems [20])

Integration has been addressed this far largely from the view point of representing the collected information to the end-user (operator or manager) in an effective manner, i.e. bridging the gap between information collected from plants and equipment and the enterprise resource planning (ERP) platforms. According to [21], initiatives have been developed which integrate open, industry-driven, integrated solutions using big data analyses tools for asset management. Such systems provide an information schema at the application-level and an application programming interface (API) to communicate with the underlying protocol stack (e.g., the TCPIIP suite). To our knowledge, existing communication technologies are not well-suited for reliable and timely delivery of appropriate data between distributed end-systems in industrial environments; this, in our opinion, remains a critical missing link in the seamless integration vision.

A. Integration of data sources

The main function of CBM is to monitor the operation of equipment by condition monitoring (CM), and to analyse the sensor data by comparing with normal state parameters based on historical knowledge of the equipment. If failures are detected, CBM will determine the fault location and fault type via its diagnostic function and then make maintenance implementation according to the maintenance strategy.

The modules of system architecture of CBM are presented as follows:

- Physical layer: It consists of a variety of equipment and component parts.
- Information acquisition layer: It acquires running state of equipment by setting up various sensors, filtering and amplifying the sensor data, and submitting these data to the information processing layer. It consists of various sensors, information acquisition terminals, direct numerical control and other intelligent devices.
- Information processing layer: It is to process information provided by the information acquisition layer and to support the function of application layer. The processing includes identification, transformation, classification, feature extraction, feature fusion, etc.
- Data layer: It consists of a variety of database such as maintenance database, knowledge database and equipment information database. It stores maintenance operations, maintenance plans, maintenance events, reference values, etc.
- Application layer: It consists of online monitoring module, troubleshooting module, failure prediction module and maintenance management module. Its function is to display the running state to users, perform fault diagnosis and prediction，and implement the maintenance management.
- User layer: It can be divided into three types: administrator, operator and serviceman.

This modules listed above are based upon a system developed for the United States military. The framework for the next generation machinery monitoring and diagnostic systems, named Open System Architecture for Condition Based Maintenance (OSA-CBM). This comprised of 7 functions which would request data directly from any other layer as needed. The functions are: Data Acquisition, Data Manipulation, Condition Monitor, Health Assessment, Prognostics, Decision support and Presentation [22]. However, implementing the standard is often a difficult task data processing aspects, such as Fast Fourier Transform (FFT) algorithm, k-means clustering, Bayesian reasoned [23]. Therefore a more simplified system with the key functions is required.

The complete workflow of data integration in CBM is shown in Fig. 2. As shown in this figure, fault diagnostics and prognostics are two important steps. Fault diagnostics includes fault detection, classification and identification, where fault detection is a task to indicate faults, fault classification is to locate the faulty component or the parts of equipment, and finally fault identification determines the nature and causes. Fault prognostics deals with fault prediction, in order to determine whether a fault is impending and estimate how quickly and how likely a fault will occur. That is, diagnostics is posterior event analysis and a prognostic is prior event analysis. Diagnostics will be combined with prognostics to achieve an almost zero-downtime performance [24].

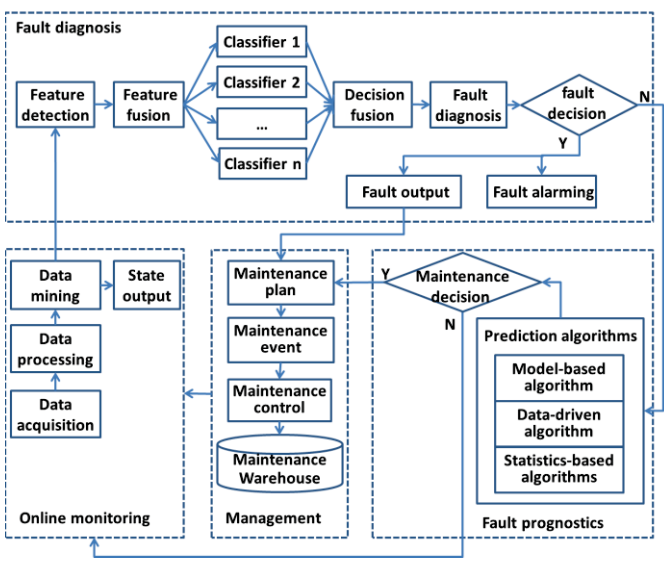

Fig. 2. A workflow of data integration in CBM.

B. Analysis and Correlation

Preventing data overload and closing the gap between information islands are the key requirements. Data overload is one of the common drawbacks noticed in most of the organization and this creates serious problem for the maintenance manager for analysis of the right information. If the data is not specified or prioritized for the decision making, it creates a tremendous work overload, missing the right information. The other issue of Information Island speaks of having individual excellence in isolation. Lack of integration of these excellences, in any organization is a waste of resources, not only from maintenance point of view, but from organizational point.

We tie these maintenance requirements in the light of ICT system constraints. We foresee the following constraints and challenges in the design, development and deployment of an e-maintenance system from an ICT perspective.

a) In an industrial environment, the ICT deployment is seen as heterogeneous – the types of plants and equipment being monitored, the types of computing devices involved the physical media of communication and the nature of access. Hence, the one size fits all paradigms is often seen (incorrectly) as inapplicable, e.g., standard commercial-off-the-shelf communication equipment (such as Bluetooth and IEEE 802.11) and standard Internet protocols (such as the TCP/IP suite) are not suitable for implementing the entire system. For seamless operation, it is important that e-maintenance platforms account for this heterogeneity and operate on standard as well as proprietary protocol stacks. Further, heterogeneity in terms of network capacity should be addressed. Wireless networks are resource-constrained (in terms of limited bandwidth, battery-powered devices with limited processing and storage capacity) as compared to the wired counterparts. Avoiding data overload becomes significant in such networks with scarce resources.

b) Given the challenging, hostile environment in which computation and communication will be carried out, network survivability - the robustness of a communication network in preventing failures, and in case of failure, its ability to gracefully degrade to a state where it can still operate optimally within the constraints of available resources is of primary importance. Network survivability can be viewed as comprising two complementary mechanisms: prevention methods that minimise the probability of a communication network being disrupted by failure, and mitigation methods that limit the damage when a failure occurs. Mitigation can be implemented via network design approaches based on redundancy, e.g., using route redundancy to reroute data flows in case of failure of one or more routes. Redundancy, of course, can be expensive and hence is limited in its extent. More importantly, both methods call for innovation in development of new protocols and mechanisms, both at the application level as well as underlying networking layers that are fault tolerant and provide feedback options to the e-maintenance system. The idea is to allow the e-maintenance system to recover and sustain itself with minimal human intervention, in the wake of failures.

c) In harsh industry environments, we anticipate intermittent connectivity among network devices as being the rule rather than the exception. This clearly rules out the use of traditional TCP/IP based protocols to transport and route data in these networks, since they assume connectivity between end-points of a data flow.

Given the ad hoc nature of communication, an opportunistic communication architecture is necessary - one that takes advantage of existing connectivity to optimize data transfer among network devices.

d) Cognitive radios are set to define wireless access in the future [25]. Cognitive radios are intelligent and flexible in that they can adapt their spectrum use in response to the operating environment, identify spectrum that is unusable under current conditions and enable efficient spectrum utilization. These radios have the potential to radically improve the way wireless networks operate, and are a promising choice for building future industrial ICT infrastructure. Given that sensor networking will be a crucial part of such infrastructure, one important task is to explore if the new generation of cognitive, smart radios can be integrated onto miniature sensors for facilitating robust, energy-efficient sensor networking.

e) The existence of ambience intelligence (sensors) in the environment should be used for ubiquitous, pervasive, context-aware (e.g., location of equipment and personnel, situation: normal vs. emergency, etc.) computing. To our knowledge, most existing e-maintenance platforms lack context-awareness. The need is to develop new generation of e-maintenance platforms that fully utilize context-awareness to pre-process gathered data and to disseminate proper information, in proper amount and at proper time, in tum alleviating problems such as data overload and occurrence of “information islands”.

f) Given that the data being monitored and transmitted could be of varying levels of importance (from mission critical to casual), there is a need to provide differentiated service while collecting and transferring such data. This term is called Quality of Service (QoS) which means to classify various applications into different service classes, assign different priority levels to the service classes and allocate different amount of resources to those classes. In computer networks, QoS mechanisms have been primarily used for providing performance assurances to the different types of applications. These mechanisms can be tailored to specific needs of e-maintenance; they can also be used to address the data overload problem as well as to enhance network survivability via graceful degradation when network resources become scarce.

IV. Conclusion

Competitive pressures found within manufacturing has forced organisations to examine systems, strategies, tools and techniques to increase asset efficiency and effectiveness, Management are now aware that for decades manufacturing and maintenance data had been collected yet rarely utilised due to the large amounts of data and the uncertainty of what to analyse and how to decipher the data to ensure the data is supporting new approaches to manufacturing and maintenance. However, organisations are aware that computing resources have increased in capacity and computational speed while decreasing in cost. This has allowed Big Data collection and analyses techniques to improve asset monitoring and management. Indeed big data algorithms will be directed to Data Analytics, Data Based Models and Decision making algorithms. These algorithms will aid to the asset maintenance and wearing cost assignment since current traditional methods are not able to handle all the data captured from infrastructure due to its volume, velocity and variety.

In order to adapt an approach to using big data tools and techniques to support an advanced maintenance strategy development it is important to take full advantage of recent advances in information technologies related to CBM, software and semantic information to develop an effective information and communication infrastructure. While implementing an e-maintenance system, a thorough understanding of the requirements and constraints in conjunction from maintenance and ICT perspectives is necessary.

In this paper, benefits and challenges of big data implementation have been identified in order to achieve optimized maintenance. The main benefits include detecting and predicting product failures, reducing operation expenses, and improving maintenance reliability. However, the challenge is not to collect as much data as possible but to collect, store and analyse the necessary data to make informed decisions based upon accurate and up-to-date data.

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