NEXT GENERATION CONDITION BASED PREDICTIVE MAINTENANCE

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Abstract: Maintenance of assembly and manufacturing equipment is crucial to ensure productivity, product quality, on-time delivery, and a safe working environment. Predictive Maintenance is an approach that utilises the condition monitoring data to predict the future machine conditions and make decisions upon this prediction. The main aim of the presented research is to achieve an improvement in condition based Predictive Maintenance through the Cloud-based approach with usage of the largest information content possible. The objective of this paper is to outline the first steps of a framework to handle and process maintenance, production and factory related data from the first life-cycle phase to the operation and maintenance phase.

Keywords: predictive maintenance, prognosis, cloud-based maintenance

1. INTRODUCTION

Maintenance of assembly and manufacturing equipment is crucial to ensure productivity, product quality, on-time delivery, and a safe working environment. Implementation of effective prognosis for maintenance can bring variety of benefits including increased system safety, improved operational reliability, increased maintenance effectiveness, reduced maintenance, inspection and repair-induced failure, and reduced life-cycle cost (Bo *et al*., 2012).

Maintenance approaches during industrial history evolve (Alsyouf, 2007) and it is an on-going process. At earlier stages the Corrective Maintenance known also as reactive maintenance or run-to-failure was used. Later approach called Preventive Maintenance (PM) is focused on taking actions before the failure occurs. This approach evolved to Condition Based Maintenance (CBM), where the decisions are made based on the machine conditions obtained through measurement systems. Predictive Maintenance (PdM) and Prognostics and Health Management (PHM) are approaches that utilise the condition monitoring data to predict the future machine conditions and make decisions upon this prediction.

Three key steps (Jardine *et al*., 2006) of Condition Based Maintenance program are: (1) data acquisition, (2) data processing, and (3) maintenance decision making. In this model the diagnosis and prognosis are included in the last step as a part of the decision making process.

Standard EN 13306(CEN, 2001) defines Predictive Maintenance as condition based maintenance carried out following a forecast derived from the analysis and evaluation of significant parameters of the degradation of the item. According to the standard the approaches to maintenance can be categorised as presented in Fig. 1.
According to the ISO 13381-1 (ISO, 2004) standard predictive process consists of the following steps:

- Pre-processing to diagnose all existing failure modes, determine potential future failure modes,
- Prognosis of current failure modes to assess the severity of all measured failure modes,
- Prognosis of future failure modes to assess the future failure modes,

- Post-action prognosis to identify actions that will halt or eliminate current failure modes and prevent the initiation of future failure modes, perform prognosis process taking in to account the effect of any maintenance actions.

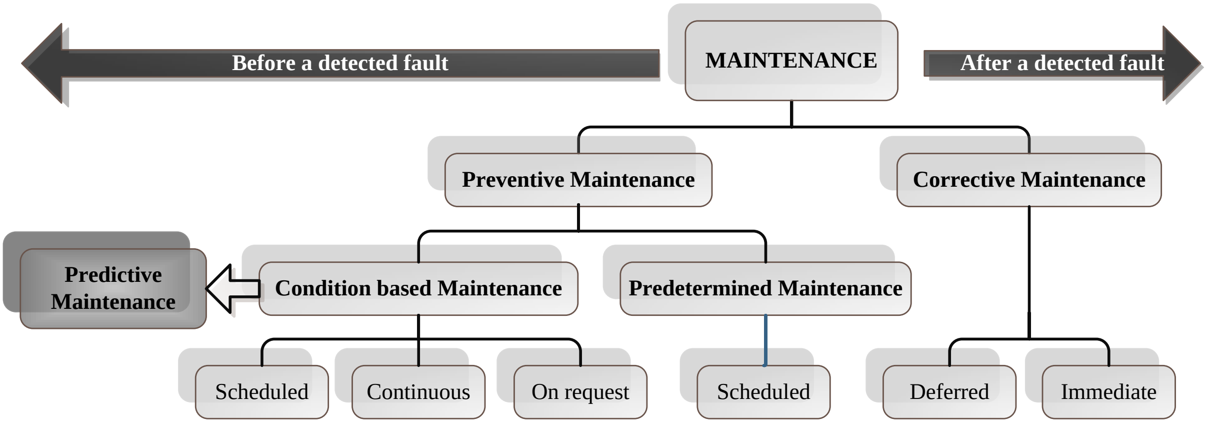

Fig 1. Maintenance strategies - based on EN 13306 (CEN, 2001).

Predictive Maintenance of machinery gives the ability to ensure product quality, perform just-in-time maintenance, minimize equipment downtime and avoid catastrophic failure (Lee *et al.*, 2013).

Emerging technologies like Cloud-based approaches give new opportunities. Targeting this vibrant field presented research proposes a new approach for Next Generation Predictive Maintenance. Its novelty includes: (1) variety of utilised data; and (2) application within Cloud-based approach.

The rest of the paper is organised as follows. Section 2 describes problems related to maintenance implementation in industry; Section 3 introduces the research interests; Section 4 outlines the framework; Section 5 depicts researches and research areas related to presented work; and finally, Section 6 concludes the paper and highlights our further steps.

2. MAINTENANCE ISSUES

The problems related to maintenance can be distinguished into two complementary aspects: economical and technical.

The first is related to the economic justification of maintenance related actions. It considers cost/benefits/investment related aspects. Traditional approach treats maintenance as only cost related (Salonen and Deleryd, 2011), however considering maintenance activity in broader scope with relation to production and quality can point out that it could be treated as an investment and analysed from this point of view. This aspect is related to questions of what should be done and why – economical justifications.

However there is another – technical aspect related to questions of what can be done, and how it can be done. Research presented in this paper is focused on technical aspect, but with consideration of certain economic aspect.

One of the problems in maintenance is the lack of holistic overview over the asset and so called island of knowledge. Within the company data about asset are gathered by different functional units as maintenance, production, quality, etc. The same machines/subsystems types can be distributed through different lines, units, factories, this causes the data are gathered and analysed independently. Lessons learned in one place are not used in another place.

There are some existing data that could be used, however it is analysed only in special cases, or not at all. Example of this kind of data is data in machine tool controller systems; it includes different events and parameters. Often issue is the lack of knowledge about importance of data. This resulted in the situation that the data important to diagnosis and prognosis are not collected although all the technical resources exist.

Another problem is related to the inability to predict future performance while introducing new working conditions, e.g. new manufactured component, new material.

3.RESEARCH

Presented research is toward improvement in maintenance activities by applying cloud-based predictive maintenance approach. The main aspects of the reseach can be summarised by following four research questions.

RQ1. In what ways can Predictive Maintenance activities for one entity be improved by utilising information from multiple similar entities? This research question aims to study possible improvements for Predictive Maintenance. The hypothesis for this question can be expressed by the following mathematical formula (1).

$$I\ in\ KA_k < \sum_i I\ in\ KA_i < \sum_i I\ in \bigcup_i KA_i \qquad (1)$$

where*: I in KA$_x$* is the information that can be obtained from xth knowledge area, $\sum$ is a fusion operator for information, U is a fusion operator for knowledge areas.

Knowledge area can be interpreted as knowledge about each separate entity or group of entities. It can also be interpreted as knowledge from specific perspective e.g. maintenance, production, quality. Very often data from this perspective are analysed independently. Jay Lee (2013) provides an example where overall equipment effectiveness (OEE) only provides the status of production efficiency without relationship between performance and the cost involved in sustaining a certain OEE level. Furthermore, machine condition data is not correlated with controller and inspection data to distinguish between process and machine degradation.
Fusion of multiple pieces of information obtained separately from different knowledge areas should provide lower information uncertainty than single information. Moreover fusion of information obtained from fused multiple knowledge area should provide even more improvement.

RQ2. How Predictive Maintenance activities for one entity can be improved by utilising information from multiple similar entities? This question can be further break down into following two questions:

RQ2a) What data and information are required?

RQ2b) How the data and information from different sources and of different kinds can be integrated in a useful way for the predictive maintenance purpose?

Traditionally, condition based maintenance of entity focuses and limits to condition monitoring data related to monitored entity. This research question addresses the issues of improving maintenance activities by considering information and data from other similar activities. This could provide solutions already found for similar problems. This research questions is focused on methods that can be applied to utilise data from multiple entities in useful way for PdM.

RQ3. How the Cloud-based models of Predictive Maintenance could be designed? The aim of this research question is to define benefits, opportunities and threats of using the Cloud concepts in application to proposed approach with consideration of current and future problems. How the Predictive Maintenance can be implemented within Cloud-based concept. Example of opportunity given by the cloud concept is to share data between Machine Tool Builder (MTB) and machine users.

RQ4. How the presented approach could be implemented? In focus of this research question is the framework and methodology for proposed Cloud-based Predictive Maintenance approach.

4. FRAMEWORK

In presented framework data from various sources and of different types are considered. They include (1) condition monitoring data such as: vibration from accelerometers, temperature, ball-bar measurements, etc.; (2) event data about fault, failure, maintenance actions; (3) context data related to manufactured product specification, production environment, and geometrical setup.

Aquiring and analysing context data will benefits in various way. It allows us to compare monitoring data from population of entities, e.g. by finding items that work in similar conditions. When applying new working conditions to particular item, prediction can be improved by analysing data from other items that have already been working with those or similar conditions. For prediction purpose monitoring data could be analysed in the context of past, present and future working conditions.

Event data are important from different aspect of prognosis. One is identification which and when component failed and/or have been replaced. Connecting event data with condition monitoring data allows mapping performed maintenance actions and occurred events to changes in performance. To achieve this, there is need to fuse information of different type. i.e. structured and unstructured data.

Considered Cloud–based concept is not only limited to the Cloud Computing where IT resources such as infrastracture, platform and applications are delivered as a services, but broader concept with adoption of the Internet of Things (IoT) and Cloud Manufacturing ideologies is considered.

By combining together the CBM/PdM and the Cloud concept we could gain in multiple areas and solve some existing and future problems. However, this process should not be only one directional, when existing applications are being brought in to the cloud and provided as services. Probably methodologies and techniques used in CBM/PdM should be adapted to benefit more from the fact that are realised with the Cloud concept. This step further will bring new opportunities as well as new threats to overcome.

Having shop floor machines in the Cloud allows us to include in steps of prediction, not only data from items under investigation but also from whole population of identical or similar item. Data can be gathered and processed without or with minimal intervention of the human operator. Moreover, it will allow of direct feedback to the machine, e.g. to modify controller parameters to maintain performacne according to current situation and machine health status. Farther, having all equipment interconected allows acquisition of better context information. Within this concept, connected equipment can deliver Data-as-a-Service to the Clouad-based Predictive Maintenance. From the other side equipment can subscribed Prognosis-as-a-Service or in more general case Maintenance-as-a-Service. Overview of the approach is presented in Fig. 2.

Within the Cloud data, knowledge and resources could be exchanged. Example of one potentially fruitful data and information link is between Machine Tool Builder and machine user.

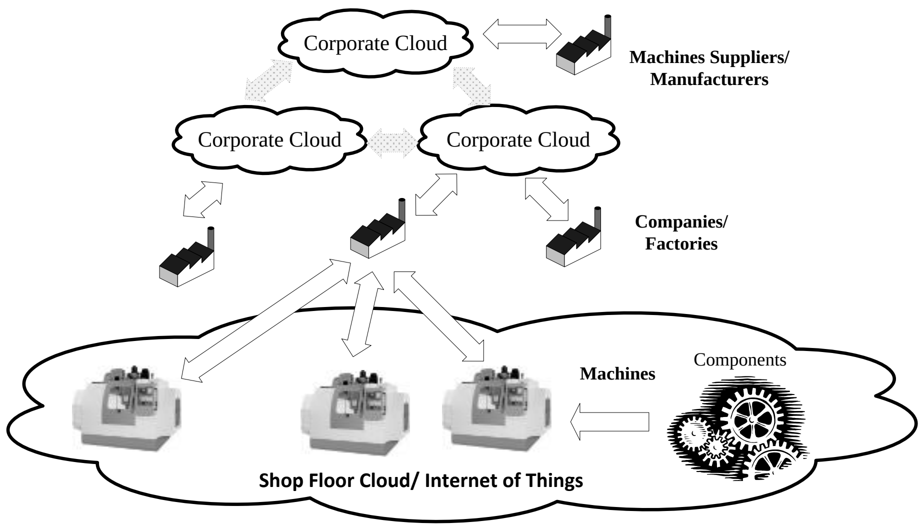

Fig. 2. Cloud approach for data collecting and sharing.

Another important aspect of prognosis is uncertainty. It is an effect of sensor measurement errors, missing data and/or knowledge as well as errors introduced by the methods. Predictions are also affected by uncertain future conditions. Recently this aspect of prediction has attracted more interest. To schedule the maintenance action not only value of Remaining Useful Life (RUL) prediction is needed but also uncertainty associated with this value. To handle and process uncertainty probability theory, Evidence theory, Fuzzy Set or Rough set theory could be applied.

Presented research is on the junction of several areas. Overview of core theories and their relation to the presented project are shown in Figure 3.

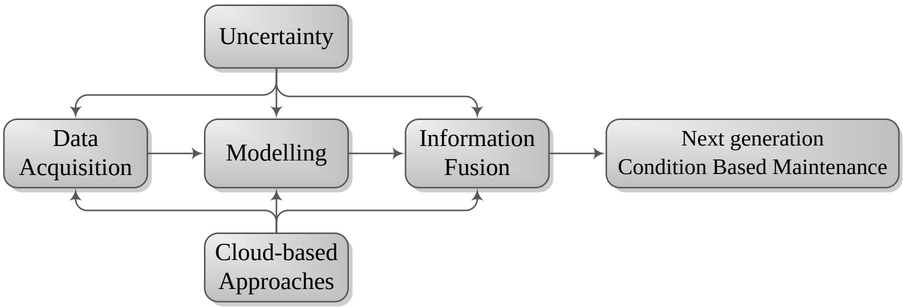

Fig. 3. Theories considered in the project and their dependencies.

5. RELATED RESEARCH

In this chapter in following subsections researches related to the key aspects of presented approach are described.

5.1 Information Fusion

In Predictive Maintenance there is a need to handle different data from different sources. These are the inputs to the process as well as intermediate results. Foo and Ng (2013) provided an overview on High Level Information Fusion. Data and Information Fusion has been explained as a technique that involves a process of combining data from multiple inputs with the aim to obtain information that is better than that would be derived from each of the sources individually. Data fusion is used in Predictive Maintenance in various ways. Recently a review on multisensory data fusion state of the art can be found in (Khaleghi *et al.*, 2013). Information Fusion (IF) research has an origin in military area, however it could and is applied in other areas. Work has been done (De Vin *et al.*, 2006) that presents the application of IF in manufacturing for simulation based decision support.

The IF and CBM processes have many in common. Therefore, knowledge from IF research could be used for improvements in CBM. Figure 4. presents an overview of the IF and CBM processes, while Table 1 reveals the correspondence between steps in those two processes. For proper maintenance decision making the processes included in high level IF should be with high importance.

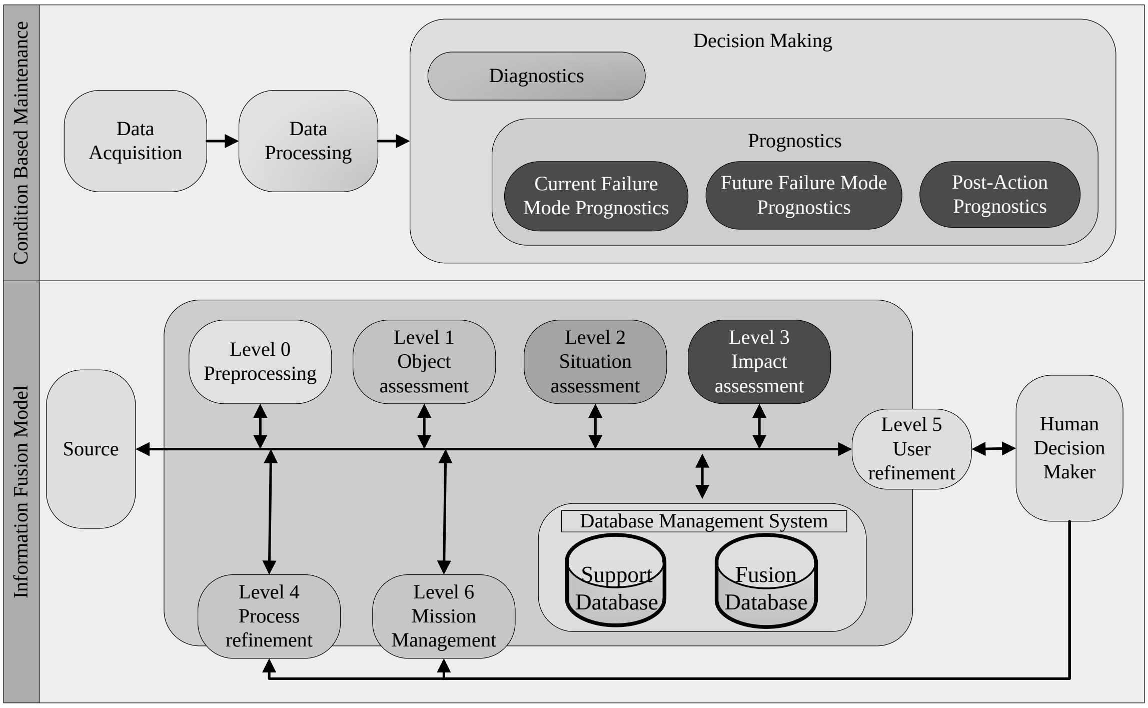

Fig 4. Modes for Information Fusion and Predictive Maintenance.

Table 1. Correspondence between IF and PdM.

Level	**IF JDL definition (**Foo and Ng, 2013**)**	**PdM correspondence**
0: Data Assessment	Estimation and prediction of observable states of signals or features.	Signal processing, feature extraction.
1:Object Assessment	Estimation and prediction of entity states based on data association, as well as continuous and discrete state estimation.	Diagnostics - health condition of machine. Faults and failures can be treated as entities.
2: Situation Assessment	Estimation and prediction of relationships among entities.	Root cause analysis. Future failure mode prognosis.
3: Impact Assessment	Estimation and prediction of effects of entities' actions on goals/missions.	Impact of faults and failures on production, quality, etc. Post-action prognosis.
4: Process Refinement	An element of Resource Management that encompasses adaptivity in the data collection and fusion processes to support mission objectives.	Sensor management, adaptive sampling.
5: User Refinement	An element of Knowledge Management that encompasses adaptivity in the determination of user query and access to information, as well as adaptivity in the retrieval and display of data, to support cognitive decision making and actions.	Representation of the maintenance data for decision makers on different levels: maintenance technicians, maintenance manager, plant manager, etc.
6: Mission Management	An element of Platform Management that encompasses adaptivity in the determination of spatial-temporal asset control, as well as route planning and goal determination to support team decision making and actions.	High level goals and vision of the company that are supported by proper maintenance actions.

5.2 Cloud-based approaches

Cloud Computing. Cloud Computing can be considered as evolution of grid computing with orientation to business (Foster *et al.*, 2008). The idea of the Cloud Computing is to provide on-demand services through the Internet that can be categorised in three groups: Software as a Service (SaaS), Platform as a Service (PaaS), and Infrastructure as a Service (IaaS). In recent years there has been a noticed trend to apply the cloud computing model in manufacturing industry (Xu, 2012).

During the past years the Cloud approach for CM has found several implementations, several companies provide commercial services. Still, not many if any provide the PdM. Recently Lee *et al*. (2013) presented the methodology for adapting Prediction and Health Management (PHM) systems in to a cloud environment, exemplified by IMS Watchdog Agent® Toolbox. . In the presented example, the system has been adopted to run on virtual machines in Cloud with enhanced configurability enabled by modularisation of its functionality. It has been also mentioned that Cloud Computing allows recording of data and status of machine throughout its whole life span. Therefore degradation process can be tracked by both the machine builder and the user.

Internet of Things Internet of Things (IoT) is a paradigm where everyday objects are connected to the Internet. It allows devices communication with each other with minimum human intervention (Perera *et al.*, 2014). The term has been initially used by Kevin Ashton in 1999. In (Ashton, 2009) he describes the IoT as follow:

> *"If we had computers that knew everything there was to know about things—using data they gathered without any help from us—we would be able to track and count everything, and greatly reduce waste, loss and cost. We would know when things needed replacing, repairing or recalling, and whether they were fresh or past their best."*

Cloud Manufacturing. Cloud Manufacturing (CMfg) paradigm is a result of combination of cloud computing, the Internet of things, service-oriented technologies and high performance computing (Zhang *et al*., 2014). It transforms manufacturing resources and capabilities into manufacturing services. CMfg can provide cheap, reliable, high-quality, safe and on-demand manufacturing services for the whole life cycle of manufacturing. One of services included in CMfg concept is Maintenance-as-a-Service (Ren *et al*., 2013).

5.3 Disparate Data Source

Integration of disparate data sources that are commonly available in industry can be integrated for better maintenance decision making. The cloud approach is pointed as a feasible solution for this integration (Galar *et al.*, 2012 a,b). The XML language is presented as a tool that can be used for data integration. However there is no research presented on how this data can be used to improve the prediction. In (Bangemann *et al*., 2006) the architecture and the basic concept of an integration platform for maintenance have been presented.

5.4 Fleet-wide approach

Research described in (Voisin *et al*., 2013, Medina-Oliva *et al.*, 2012) presents the approach of Predictive Maintenance at the fleet level. By adding not only data from identical units, but also similar ones, the higher volume of data can be obtained to reduce uncertainty. Semantic model is used to determine similar cases that have been registered in the past among the fleet. Indicated context have been divided into:

- Technical context – technical features,
- Dysfunctional context – degradation modes,
- Operational context – operational conditions
- Service context – operation modes
- Application context - context indicated as needed for optimisation.

It applies a similarity-based prognosis approach for RUL estimation as presented by Wang *et al*. (2008). Multiple models are built upon data from previous run-to-failure cases and data from current case are compared with the obtained models. Prediction is done based on the models that are closest to the current situation. Off line stage is used to determine the aggregation function, which allows conversion of multidimensional time series of faulty and nominal signals into mono-dimension health time series. Relevance Vector Machine (RVC) and Sparse Bayes Learning (SBL) are used to utilise new knowledge for prognosis. The approach has been tested in referred work through a case study for diesel engines. In on-line stage the time series from the current unit are converted to health time series. Among learned time series the similar ones are found and similarity based interpolation is applied for RUL prediction.

5.5 Massive Machine Maintenance Data Analysing

In (Bahga and Madisetti, 2012) the Cloud-based case-based reasoning has been adopted for fault prediction. Case Based Reasoning (CBR) is an effective way for solving problems. Cases are created based on data fault and sensor data retrieved from maintenance database and machine sensor data respectively. When new case is created, this is updated in a local node. To maintain the case database, some cases need to be updated or removed. In this approach the local nodes are used for real-time monitoring and prognosis, while cluster computing in the cloud is using for case-base creation and its maintenance. In the local node the "target case" is created and all similar cases from the local database are retrieved. Based on the similarity the cases are ranked. Each case is associated with a fault type. This is used to predict the failure. However, this is prediction of what type of failure can occur, but not when it occurs. The presented framework is of big potential, but methods for estimation of RUL have not been mentioned. Moreover it does not fully utilise the Cloud Computing concept. It is limited to distributed and cluster computing.

6. CONCLUSIONS

This paper presents and situates framework for Cloud-based Predictive Maintenance. The main aim of the presented research is to achieve an improvement in condition-based Predictive Maintenance by using the largest information content possible – a maximum content in a factory or in between factories. However novelty is not in the amount of data but in the variety of data sources and the approach to gather, process and utilise the information within Cloud-based concept. It could be also a better solution economically compared with existing working manner based on multiple stand-alone systems and island type of data collection and decision making.

The next step covers performance of Case studies. At first attempt variety of data regarding one machine / subsystem will be analysed. Next phase will include addition of a set of similar entities to the analysis.

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