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ORIGINAL ARTICLE

Cloud-enhanced 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 makes decisions upon this prediction. The main aim of the present research is to achieve an improvement in predictive condition-based maintenance decision making through a cloud-based approach with usage of wide information content. For the improvement, it is crucial to identify and track not only condition related data but also context data. Context data allows better utilisation of condition monitoring data as well as analysis based on a machine population. The objective of this paper is to outline the first steps of a framework and methodology to handle and process maintenance, production, and factory related data from the first lifecycle phase to the operation and maintenance phase. Initial case study aims to validate the work in the context of real industrial applications.

Keywords Predictive maintenance · Condition-based maintenance · Context awareness · Cloud manufacturing

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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 lifecycle cost [1].

Maintenance approaches in industrial history have evolved over time [2], and they are still the challenging research topics. At earlier stages, the Corrective Maintenance also known as reactive maintenance or run-to-failure was used. Later, an approach called preventive maintenance (PM) was focused on taking actions before a failure occurs. This approach has evolved to Condition-Based Maintenance (CBM), where the decisions are made based on the machine condition indicators obtained in most cases 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 health state and make decisions upon this prediction.

Three key steps [3] of CBM 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 [4] defines PdM as CBM 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 shown in Fig. 1.

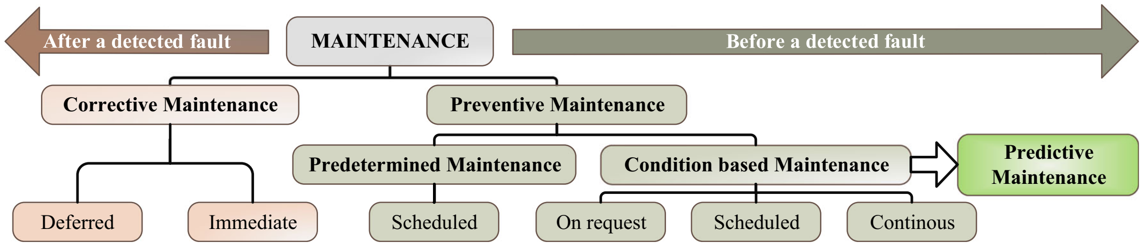


Fig. 1 Maintenance strategies—based on EN 13306 [4]

According to the ISO 13381-1 [5] 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 into account the effect of any maintenance actions.

Predictive maintenance of machinery gives the ability to ensure product quality, perform just-in-time maintenance, minimise equipment downtime, and avoid catastrophic failure [6].

1.1 Maintenance issues

The problems related to maintenance can be divided 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 [7], 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. On the other hand, there is 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 economical aspect.

One of the problems in the current implementation of maintenance is the lack of holistic view over the asset and so-called islands of knowledge. Within a company, the data about asset are gathered by different functional units such as maintenance, production, quality assurance, etc. The same machines/subsystems types can be distributed through different lines, units, and factories, causing that spread data are gathered and analysed independently. Therefore, lessons learned in one place are not used in another place.

Moreover, data are gathered, produced, and processed by different ICT (Information and Communication Technologies) systems [8] e.g. CMMS (Computerized Maintenance Management System) and CM (Condition Monitoring) for maintenance functions; SCADA (Supervisory Control and Data Acquisition) for monitoring process and controlling the asset; ERP (Enterprise Resource Planning) for business functions; and SIS (Safety Instrumented Systems) for safety-related functions.

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, the issue is lack of knowledge about the importance of the 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 materials for manufactured product. It also applies when process parameters are being optimised from the production perspective.

Emerging technologies like Cloud-based approaches offer new opportunities. Targeting this vibrant field, the present research proposes a new approach for predictive maintenance. Its novelty includes: (1) variety of utilised data; (2) context modelling; and (3) application using a Cloud-based approach.

The rest of the paper is organised as follows. Section 2 reviews methods and research areas related to the present work; Section 3 introduces our research interests; Section 4 outlines the research framework; Section 5 presents a case study; and, finally, Section 6 concludes the paper and highlights our future work.

2 Related research

In this section, research efforts related to the key aspects of the proposed approach are described.

2.1 Cloud-based approaches

2.1.1 Cloud computing

Cloud computing can be considered as evolution of grid computing with orientation to business [9]. The idea of the cloud computing is to provide on-demand services through the Internet that can be categorised in three groups: Infrastructure as a Service (IaaS), Platform as a Service (PaaS), and Software as a Service (SaaS). In recent years, there has been a noticed trend to apply the cloud computing model in the manufacturing industry [10].

During the past years, the cloud approach for CM has found several implementations; several companies are providing commercial services. Still, not many if any provide the PdM. Recently, Lee et al. [11] presented the methodology for adapting Prediction and Health Management (PHM) systems in 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 also been 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.

2.1.2 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 [12]. The term has been initially used by Kevin Ashton in 1999. In [13], he describes the IoT as follows:

'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.'

2.1.3 Cloud manufacturing

Cloud manufacturing (CMfg) paradigm is a result of combination of cloud computing, the IoT, service-oriented technologies, and high performance computing [14]. It transforms manufacturing resources and capabilities into manufacturing services. It is not the simple deployment of manufacturing software tools in the computing cloud. The physical resources integrated in the manufacturing cloud are able to offer adaptive, secure, and on-demand manufacturing services over the Internet of Thinks [15]. One of the services included in CMfg concept is Maintenance-as-a-Service [16].

2.2 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 [8, 17]. XML language is presented as a tool that can be used for data integration. However, there is no research reported on how this data can be used to improve the prediction. In [18], the architecture and the basic concept of an integration platform for maintenance have been presented.

2.3 Fleet-wide approach

Research described in [19, 20] presented an 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 (remaining useful life) estimation as presented in [21]. 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. Offline stage is used to determine the aggregation function, which allows conversion of multidimensional time series of faulty and nominal signals into mono-dimensional 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 the referenced work through a case study for diesel engines. In online 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.

2.4 Massive machine maintenance data analysis

In [22], 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 a 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 used 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 will occur. 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.

2.5 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 [23] 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 was reported in [24]. Information fusion (IF) research has an origin in military area; however, it was also applied in other areas. As an example, the work done in [25] presented 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 applied for improvements in CBM. Figure 2 presents an overview of the IF and CBM processes. For proper maintenance decision making, the processes included in high-level IF should be with high importance.

2.6 Challenges in predictive maintenance

In analysing surveys and state-of-the-art papers in the field of predictive maintenance, several challenges are found.

2.6.1 Context data utilisation

Beside condition monitoring data, there is a need to collect and utilise in predictions effect of external environmental variables such as operational condition data, as well as effects of minor maintenance actions [26]. Moreover, better correlation of machine condition with process and inspection data are required to provide context needed to differentiate between process and machine degradation [6]. The appropriate means to synthesise data in this way remains an open research question [27].

2.6.2 Knowledge management

Knowledge extracted during process should be managed in the way that it can be reused in later cases. Incorporate subjective information from the area experts in RUL estimation and effect on it for prediction reliability.

2.6.3 Uncertainty management

It is important to develop robust algorithms that can accurately perform the prognosis in the presence of uncertainty as well as methods to quantify the confidence in the results of prognosis [28].

2.6.4 Systematic approach

There is a lack of systematic way in predictive maintenance system design and implementation [29]. It should also include an economical justification of a selected approach [1]. To be able to compare and select proper approach, there is a need of an evaluation framework for predictive methods.

3 Problem definitions

This research aims at improving maintenance activities by applying cloud-based predictive maintenance approach with utilisation of variety of data types and sources. The main aspects of the research can be summarised by the 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).

$$I\ in\ KA_k < \sum_i I\ in\ KA_i < \sum_i I\ in \bigcup_i KA_i \tag{1}$$

where I in KA_x is the information that can be obtained from xth knowledge area, $\sum$ is a fusion operator for information, and 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, and quality. Very often, data from those perspectives are analysed independently. Lee et al. [6] provided 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

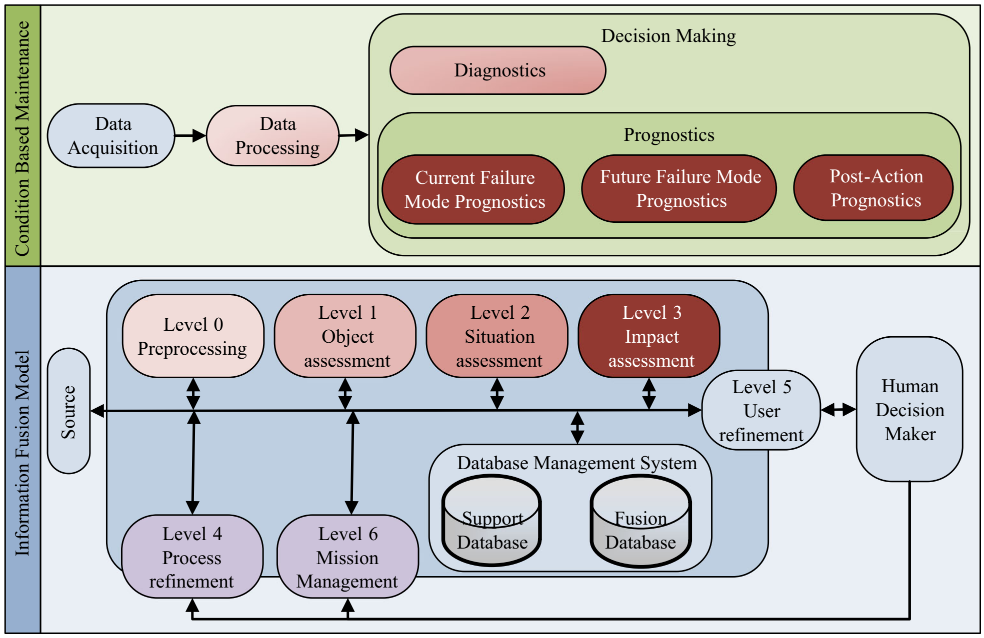


Fig. 2 Modes for information fusion and predictive maintenance

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 areas should provide even more improvement. Some examples of potential improvement are provided in Section 4 of this paper.

RQ2. How predictive maintenance activities for one entity can be improved by utilising information from multiple similar entities? This question can be further broken down into the following two questions:

RQ2 (a) What data and information are required?

RQ2 (b) 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 is focused on and limited to condition monitoring data related only to the monitored entity. This research question addresses the issue of improving maintenance activities by considering information and data from other similar activities. This could provide solutions that have already been 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 concept in application to proposed approach with consideration of current and future problems.

RQ4. How the proposed approach could be implemented? The focus of this research question is on the framework and methodology of the proposed cloud-based predictive maintenance approach.

4 Framework

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

Acquiring and analysing context data benefits in various ways. 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. An example of how estimation of remaining useful life can be improved within this framework is depicted in Fig. 3.

Simple scenario of RUL estimation is presented in Fig. 3a. The health indicator is obtained from condition monitoring signal, and degradation curve from run to failure could be recorded. With this scenario, if the degradation curve is present, it could be compared and fitted to the current state. Then, by comparing fitted degradation curve with threshold value, the RUL can be obtained. This case can be seen as related to single knowledge area. It needs to be noticed that proper RUL

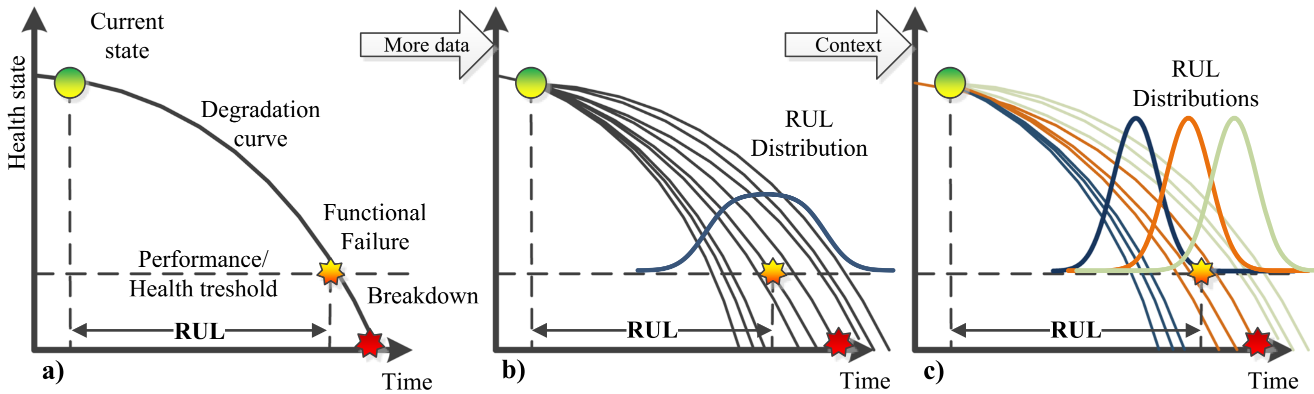


Fig. 3 **a**–**c** Possible improvements in estimation of remaining useful life (RUL)

should provide time to occurrence of functional failure. It is a moment that machine or component cannot perform its tasks fulfilling requirements e.g. machining accuracy, surface roughness, or cycle time.

Next scenario presented in Fig. 3b corresponds to usage of more data by means of more degradation curves from a population of machines. Fitting those curves gives a set of possible RUL values that allow us approximating the RUL distribution. It is additional information that can be used in the decision process. This is an example how much information can be obtained by fusing information from a set of knowledge areas. In this case, each knowledge area represents knowledge regarding each separate machine from the same perspective related to its health state monitoring.

Figure 3c shows the third scenario which accounts the context data beside the condition monitoring data. In this scenario, degradation curves from similar working conditions represented by context data are grouped together. It is marked with different line styles for degradation curves. When estimating the RUL, planned future working conditions could be accounted that leads to more accurate predictions as the only set of the most relevant data is taken for the estimation. In this case, information regarding each separated machine has been obtained from fused knowledge areas, when one knowledge area is the area mentioned in the previous two scenarios, and the other areas are related to context knowledge.

One of the means of context modelling is ontology. According to [30], an ontology-based context modelling allows:

- Knowledge sharing between computational entities by having a common set of concepts about the concept;
- Logic inference by exploiting various existing logic reasoning mechanisms to deduce high-level, conceptual context from low-level, raw context;
- Knowledge reuse by reusing well-defined Web ontologies of different domains, e.g. a large-scale context ontology can be composed without starting from scratch.

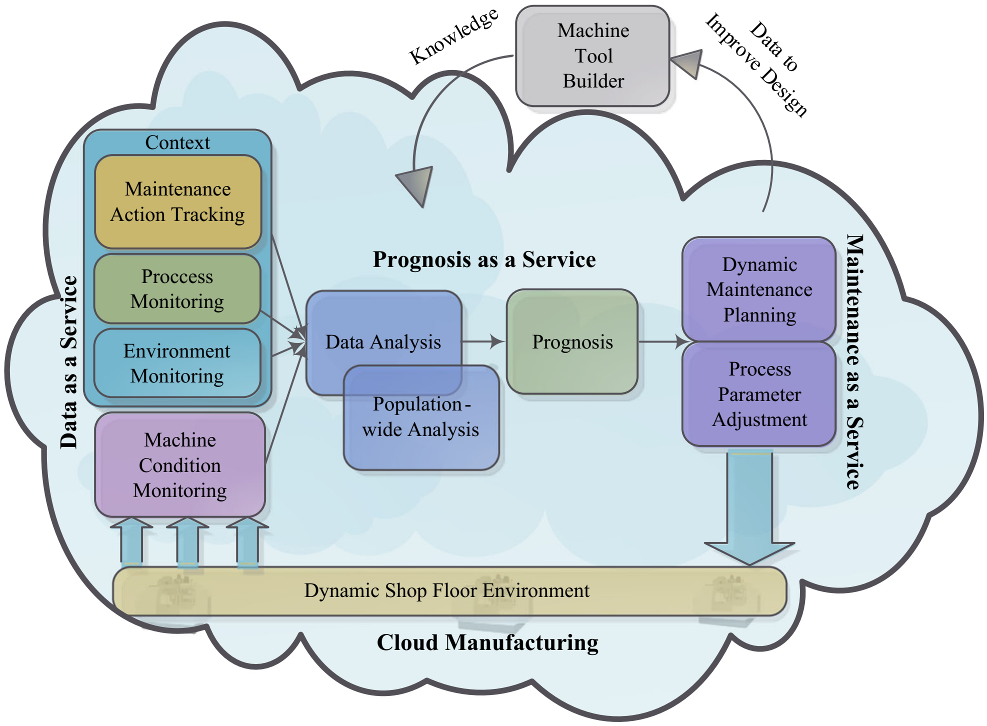
Other data utilised in our framework are event data that are important from different perspectives of prognosis. One is identification which and when component failed and/or has been replaced. Connecting event data with condition monitoring data allows mapping performed maintenance actions and occurrence of events to changes in performance. To achieve this, there is a need to fuse information of different type i.e. structured and unstructured data that are present as event descriptors.

Cloud-based concept is not limited to the cloud computing where IT resources such as infrastructure, platform, and applications are delivered as services, but it is a broader concept where the Internet of Things (IoT) and cloud manufacturing ideologies are considered.

By combining 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 including in steps of prediction, not only data from items under investigation but also data from whole population of identical or similar item. Data can be gathered and processed without or with minimal intervention of human operators. Moreover, it will allow for direct feedback to the machine, e.g. to modify controller parameters so as to maintain performance according to the current situation and machine health status. Further, having all equipment interconnected allows acquisition of better context information. In this concept, connected equipment can deliver Data-as-a-Service to the cloud-based predictive maintenance. On the other hand, equipment can subscribe Prognosis-as-a-Service or in more general case Maintenance-as-a-Service. An overview of this approach is presented in Fig. 4.

Fig. 4 Cloud approach for predictive maintenance



Within the cloud, data, knowledge, and resources could be exchanged. Example of one potentially fruitful data and information link is between machine tool builder (MTB) and machine user. When MTB can access and process data from all installed machines, it could improve future design and support services.

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 attention. To schedule maintenance actions, not only the value of remaining useful life prediction is needed but also the uncertainty associated with this value. To handle and process uncertainty probability theory, Evidence theory, Fuzzy Set, or Rough Set theory could be applied.

5 Case study

An initial case study has been settled in a production line of an automotive manufacturing industry. At first, a variety of data regarding one machine/subsystem is analysed. As a subject of investigation, a machine tool linear axis has been selected. Considered data sources are CMMS system with information of maintenance actions and the spear parts stock, SCADA system with production data, CM system with ball-bar measurements, and online machine tool monitoring system.

Example of result from ball-bar measurement of machine with some issues in X axis is presented in Fig. 5. A special software tool has been developed to parse folders with the ball-bar measurements stored in the XML files, and exported to an RDB (Relational Data Base).

To generate feature for single axis i.e., X axis, feature $X_{\mathrm{RMS}} = \mathrm{XY}_{\mathrm{RMS}} + \mathrm{XZ}_{\mathrm{RMS}} - \mathrm{YZ}_{\mathrm{RMS}}$ has been proposed, where $\mathrm{AB}_{\mathrm{RMS}}$ represent RMS (Root Mean Square) value calculated from recorded deviations of path radius when executing circular path in plane defined by axes A and B. This feature has been calculated for measurements exported to the RDB, and results have also been stored in the same RDB.

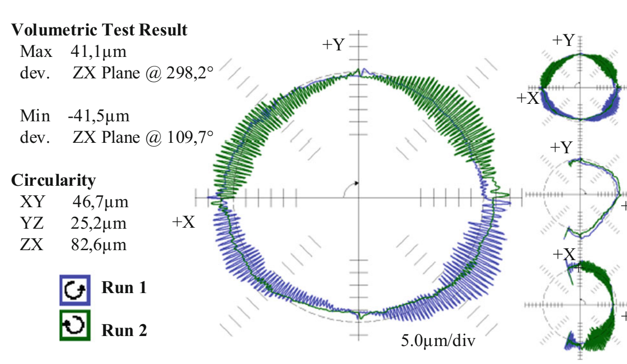


Fig. 5 Ball-bar measurements from Renishaw® tool

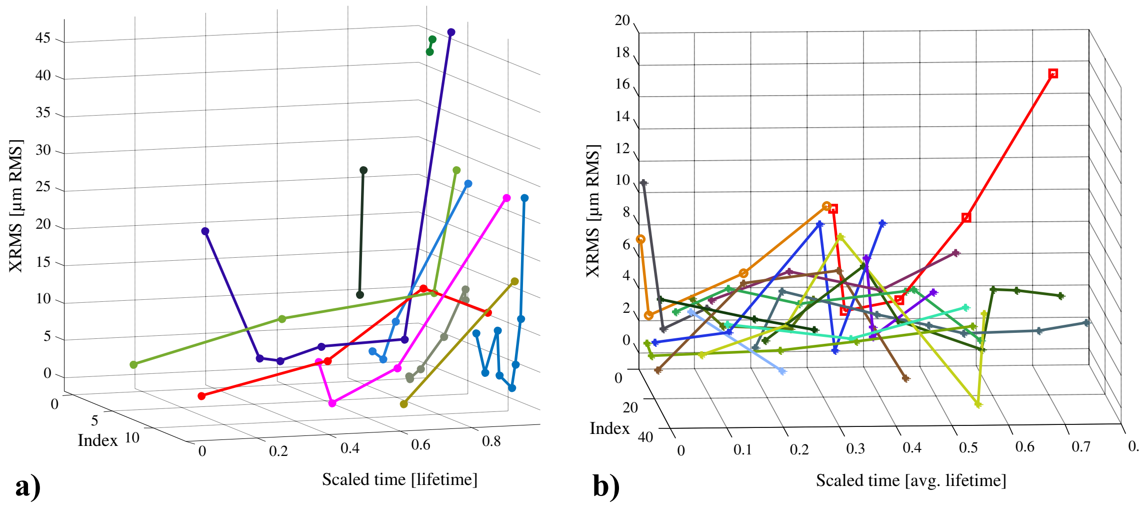


Fig. 6 Change of X_{RMS} feature over time for **a** failed ball-screws and **b** ball-screws in use

From CMMS, all machines of the same type as the machine selected for the case study have been identified and instances of X axis' ball-screw for all of those machines have been created. Those instances have been grouped into (1) ball-screws that have already been replaced (failed) and (2) ball-screws that are still in operation. For each instance, a corresponding RMS-based feature from ball-bar measurement has been queried. For the failed ball-screws depicted in Fig. 6a, it can be noticed an increasing trend for the selected feature over its lifetime. Looking at the operating ball-screws in Fig. 6b, some items with accelerated degradation process can be identified, i.e. the one represented with square marked line. Next step is to find the correlation between machine usage context and the differences in the degradation processes.

To obtain the context related information regarding machine tool usage, an online monitoring system has been installed in the machine tool's electrical cabinet. This data acquisition system retrieves and stores information about the machine's axes positions, velocities, and torques. A screenshot of live preview is presented in Fig. 7.

6 Conclusions

This paper presents a research framework for cloud-based predictive maintenance. The main aim of the present research is to improve 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 gathering, processing, and utilising the information according to the cloud-based concept. In the core of the approach, there is context modelling, retrieval, and processing that corresponds to knowledge management. This will allow processing and exchanging knowledge in a cloud environment to benefit from crowdsourcing. It is 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 of this research covers continuation of the case studies in real-world industrial settings. Future work will focus on analysing means to correlate machine condition with

Fig. 7 Oscilloscope-like continuous preview of data from machine tool online monitoring system; from the *top*, pairs of position and torque for X, Y and Z axes

context data, as well as on developing general cloud-based framework. More results will be reported separately in the future.

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