DOCTORAL DISSERTATION

TOWARD PREDICTIVE MAINTENANCE IN A CLOUD MANUFACTURING ENVIRONMENT
A population-wide approach

BERNARD SCHMIDT
Industrial Informatics
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Industrial Informatics

UNIVERSITY OF SKÖVDE
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ABSTRACT

The research presented in this thesis is focused on improving industrial maintenance by using better decision support that is based on a wider range of input information. The core objective is to research how to integrate information from a population of similar monitored objects. The data to be aggregated comes from multiple disparate sources including double ball-bar circularity tests, the maintenance management system, and the machine tool’s controller. Various data processing and machine learning methods are applied and evaluated. Finally, an economic evaluation of the proposed approach is presented. The work performed is presented in five appended papers. Paper I presents an investigation of cloud-based predictive maintenance concepts and their potential benefits and challenges. Paper II presents the results of an investigation of available and potentially useful data from the perspective of predictive analytics with a focus on the linear axes of machine tools. Paper III proposes a semantic framework for predictive maintenance, and investigates means of acquiring relevant information from different sources (i.e., ontology-based data retrieval). Paper IV presents a method for data integration. The method is applied to data obtained from a real manufacturing setup. Simulation-based evaluation is used to compare results with a traditional time-based approach. Paper V presents the results from additional simulation-based experiments based on the method from Paper IV. The aim is to improve the method and provide additional information that can support maintenance decision-making (e.g., determining the optimal interval for inspections). The method developed in this thesis is applied to a population of linear axes from a set of similar multipurpose machine tools. The linear axes of machine tools are very important, as their performance directly affects machining quality. Measurements from circularity tests performed using a double ball-bar measuring device are combined with event and context information to build statistical failure and classification models. Based on those models, a decision-making process is proposed and evaluated. In the analysed case, the proposed approach leads to direct maintenance cost reduction of around 40% compared to a time-based approach.
SAMMANFATTNING


Papper I presenterar en undersökning av molnbaserade prediktiva underhållskoncept och deras potentiella fördelar och utmaningar.

Papper II presenterar resultaten av en undersökning av tillgängliga och potentiellt användbara data för prediktiv analys med fokus på maskinverktygens linjära axlar.

I papper III föreslås ett semantiskt ramverk för förebyggande underhåll, vilket söker relevant information från olika källor (dvs. ontologi-baserad datainläggning).


Papper V presenterar ytterligare resultat från simuleringsbaserade experiment baserat på metoden från papper IV. Syftet är att förbättra metoden och tillhandahålla extra information som kan stödja beslut gällande upplägg av underhåll (t.ex. definiera det optimala intervall för inspektioner).

Metoden som utvecklats i denna avhandling tillämpas på en population av linjära axlar från en uppsättning liknande fleroperationsmaskiner. Maskinernas linjära axlar är mycket viktiga, eftersom deras prestanda direktd påverkar den producerade produkternens kvalitet. Mätningar utförda med hjälp av en ballbarmätning kombineras med information om händelser och maskinens kontext, för att definiera statistiska felbeteendemodeller och klassificeringsmodeller. Baserat på dessa modeller föreslås en beslutsprocess som också utvärderas. I det analyserade fallet leder det föreslagna tillvägagångssättet till en reduktion av direkta underhållskostnader på cirka 40 % jämfört med ett tidsbaserat förebyggande underhållsprogram.
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PUBLICATIONS

This list of publications for which the author is responsible is divided into those that directly contribute to this research (high relevance) and those that indirectly support it (lower relevance). Publications that are less relevant to the research but to which the author contributed during the research period are listed as “Other”.

PUBLICATIONS WITH HIGH RELEVANCE

Paper I

Paper II

Paper III

Paper IV
Schmidt, B., Gandhi, K., Wang, L., Ng, A.H.C. (journal draft). "Integration of events and offline measurement data from a population of similar entities for condition monitoring”, to be submitted to International Journal of Computer Integrated Manufacturing, Special Issue on Smart Cyber-Physical System Applications in Production and Logistics.

Paper V
PUBLICATIONS WITH LOWER RELEVANCE


OTHER PUBLICATIONS


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INTRODUCTION
CHAPTER 1
INTRODUCTION

This chapter presents the structure of the thesis, background information, the problem identification, purpose of the research and the research questions.

1.1 STRUCTURE OF THE THESIS

The thesis is divided into following chapters:

**Chapter 1: Introduction** – sets out the background of the research and highlights its purpose, the research objectives, and the research questions.

**Chapter 2: Research Approach** – describes the methodology applied in the research process.

**Chapter 3: Frame of Reference** – introduces and explains basic concepts relevant to this thesis.

**Chapter 4: Summary of Included Articles** – summarises the five appended papers, highlighting the most important aspect of each paper.

**Chapter 5: Conclusions and Discussions** – presents the conclusions drawn from the research, discusses some aspects of the work, and suggests potential future work.

**References** – provides a list of works cited.

1.2 BACKGROUND

Maintenance of assets is important to ensure productivity, product quality, on-time delivery, and a safe working environment in the manufacturing industry. It is one of the pillars of asset management (AM), enabling the realisation of value from assets through their full life cycle (TWPL 2015).

Approaches to maintenance have evolved and continue to evolve. In earlier periods, the run-to-failure approach was used. This is also known as reactive maintenance or corrective maintenance. Later, attention turned to preventive maintenance (PM), which focused on taking action before failure occurred. This approach evolved to condition-based maintenance (CBM), where decisions are based on an evaluation of the machine condition through inspections or measurement systems. Predictive maintenance (PdM) and prognostics and health management are approaches that use condi-
tion monitoring data to predict the future condition of the machine and make decisions based on this prediction. According to the standard EN 13306 (CEN 2001), these approaches to maintenance can be categorised as shown in Figure 1.1.

Predictive maintenance is the preferred maintenance method in 89% of cases (Hashemian and Bean 2011). It provides the ability to ensure product quality, perform just-in-time maintenance, minimise equipment downtime, and avoid catastrophic failure (Jay Lee et al. 2013).

Implementation of effective prognosis for maintenance can yield a variety of benefits including increased system safety, improved operational reliability, increased maintenance effectiveness, reduced maintenance and inspection and repair-induced failure, and reduced life cycle cost (Bo et al. 2012).

In the manufacturing industry, machine tools are used to transform raw materials to finished parts with the required geometry, dimensions and surface quality (Moriwaki 2008). Figure 1.2 shows a schematic model of a machine tool with three simultaneously controlled linear axes (X, Y, Z).

The linear axis and linear drive of the machine tool are important subsystems as they are used to position the machine tool components carrying the cutting tool. Their performance directly affects the quality and productivity of machine tools (Altintas et al. 2011).

Linear axes are also very important from a maintenance perspective. Fleischer et al. (2009) analysed machine tool component failures and found that four main component groups are responsible for the most downtime: drive axes, spindle and tool changers, electronics, and fluidics. Drive axes cause the most downtime, as shown in Figure 1.3.
The main component of a linear axis is a ball screw. The lifetime of the same type of ball screw in the same machine or other machines of the same type can vary from six months to more than ten years. This information was obtained in the initial phase of the research project based on 29 multipurpose machine tools of the same type over a period of around 12 years.
One of the condition monitoring methods used to assess the health of linear axes is a circularity test. This offline measurement method can be performed using an external measuring device (Kakino et al. 1987). Some modern machine tools use internal sensors (Siemens 2016).

The double ball-bar (DBB) measuring system from Renishaw® is one of the available measuring systems for circularity and volumetric error tests. Those measurements are usually used to detect or confirm the existence of a failure in linear axes subsystems. More details about circularity tests and DBB measurements are provided in Section 3.5.1.

1.3 PROBLEM IDENTIFICATION

The current situation in industrial maintenance is not satisfactory. In Swedish industry more than one third of maintenance time is spent on unplanned corrective work due to breakdowns (Alsyouf 2009).

Initial observation was performed over a four-week period and included observation of the following aspects of maintenance:

- work of maintenance technicians
- preparation of monthly and yearly maintenance reports
- acquisition of condition monitoring data (vibration, double ball-bar measurements, and laser tracker)
- analysis of condition monitoring data and report preparation.

The study and observations performed in the companies studied found several issues related to maintenance of manufacturing assets. Figure 1.4 shows a histogram of different types of maintenance work orders. It is based on the number of work orders in one calendar year performed on 29 multipurpose milling/drilling machine tools of the same type. These machines consist of three Cartesian axes, an indexing table, and an automatic tool changer. Emergency work orders (EWO) constitute almost half of all work orders and are four times more frequent then time-based maintenance (TBM) work orders.

![Figure 1.4: Distribution of work order types on machines of interest in one calendar year: DWO – deferred work orders; EWO – emergency work orders; TBM – time-based maintenance work orders; other – aggregated work orders for improvements, follow-ups and refurbishment of reparable spare parts](image)

Figure 1.4: Distribution of work order types on machines of interest in one calendar year: DWO – deferred work orders; EWO – emergency work orders; TBM – time-based maintenance work orders; other – aggregated work orders for improvements, follow-ups and refurbishment of reparable spare parts
There was no holistic view of the maintenance requirements for these machines due to so-called islands of knowledge. Data about assets was gathered by different functional units within the company such as maintenance, production, and quality. The same issue has been reported by (Bjorling et al. 2013, Diego Galar et al. 2012). Similar machines and subsystems can be distributed in different lines, units, and factories, which causes the data to be gathered and analysed independently. Therefore, a lesson learned in one place is not applied elsewhere. Some data that could be used for maintenance decision-making, such as data from machine tool control systems, is analysed only in special cases or not at all. Yet Jay Lee et al. (2013) noted that algorithms could perform more accurately by including more information about the machine’s whole lifecycle, including system configuration, physical knowledge and working principles. Thus there is a need to systematically integrate, manage, and analyse machinery or process data during different stages of the machines’ life cycle.

A literature study revealed that there is a need for some means of synthesising smaller available data sets to generate extensive, representative, historical condition monitoring and event data sets (Gao et al. 2015).

1.3.1 DOUBLE BALL-BAR MEASUREMENTS
The advantages of DBB are its low cost, simplicity of use, and robustness (Zargarbashi and Mayer (2006). However, some problems related to double ball-bar measurements have been identified. One is that the measurement is time-consuming, as the measuring device needs to be installed in the machine each time. This can increase costs if production needs to be stopped to perform the measurement.

Another problem is that the measurement can only identify whether performance is within the required range. However, the challenge is to predict the progression of degradation once early deviations have been observed. In the case analysed in this thesis, the warning reports are created by CBM specialists, who qualitatively assess the plots and some trends based on their experience. Manual analysis of the data in each case is time-consuming. Moreover, it can be difficult to assess whether the machine will survive until the next inspection time. To avoid this uncertainty, a degradation model is needed to predict machine life.

1.4 PURPOSE OF THIS RESEARCH
This research has two purposes: to increase knowledge in the field of predictive maintenance of complex manufacturing equipment and to create a bridge between research and application in a real-world industrial setup. As used here, “knowledge” refers to awareness of existing data and information and of methods to acquire and process them. The aim is to provide better decision support to reduce the number of breakdowns and the amount of time spent in unplanned tasks, as presented in Figure 1.5.
1.5 AIM AND OBJECTIVES
The aim of this thesis is to increase knowledge of data science in the maintenance of manufacturing assets by using population data for predictive maintenance. The thesis has three objectives:

- Explore what can be improved in predictive maintenance when a population of similar monitored objects is considered.
- Research how the integration of information from a population of similar monitored objects can be achieved.
- Apply the method developed to a real case.

1.6 RESEARCH QUESTIONS
The following research questions have been formulated in order to fulfill the objectives:

1.6.1 PRIMARY RESEARCH QUESTIONS
PRQ1: In what ways can predictive maintenance activities be improved by utilising information from multiple similar entities?
PRQ2: How can the integration of information from a population of similar monitored objects be achieved by data science for maintenance prediction?

1.6.2 SECONDARY RESEARCH QUESTION
SRQ1: What potentially relevant data for condition monitoring of machine tool linear axes are available?
SRQ2: How could the relevant data be acquired?
SRQ3: Can double ball-bar measurements be used in predictive maintenance?

1.7 SCOPE AND DELIMITATION OF THE STUDY
The research project is based on the automotive manufacturing industry. The equipment that is the subject of the research was chosen from the assets available in the factories of the companies involved. The machines investigated include 29 multi-operation machine tools of the same type, on four different production lines and performing different operations in the same factory. The analysed data cover a period of
four years. The study is focused mainly on data and data analytics rather than on ma-
chine tools, physical sensing and measurement instrumentation. However, the engi-
neering context of the data is important and is considered in the data analysis process.
The subsystem selected for investigation was the linear axis of the machine tool. This
subsystem directly affects machining quality but, in comparison to the cutting tool and
main spindle, it is not well represented in research in the field of condition-based and
predictive maintenance.
Selecting which maintenance approach is most suitable in an individual case is beyond
the scope of this research.

1.8 RELATIONSHIP BETWEEN ARTICLES
An overview of the relationship between the included articles is presented in Figure
1.6, while their relationship to the research questions is indicated in Table 1.1.

Paper II (Schmidt et al. 2017) presents the results from an investigation of available and potentially useful data from the perspective of predictive analytics with a focus on machine tool linear axes.

In Paper III (Schmidt et al. 2017) a framework, which is visualised in Figure 1.6, is proposed. The paper also reports on ways to acquire relevant information from different sources, that is, ontology-based data retrieval. This paper was inspired by the work performed in Paper II and additional investigations (Schmidt et al. 2015, 2016, 2016).

Paper IV presents the method developed for data integration. The method is applied to the data described in Paper II. Simulation-based evaluation is applied to compare the results with a traditional time-based approach.

Paper V reports the results from additional simulation-based experiments using the method presented in Paper IV. The aim was to improve the method and provide additional information that could support maintenance decision-making, for example, determining an optimal interval for inspections.

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*Table 1.1: Relationship between the publications and the research questions*
RESEARCH APPROACH
CHAPTER 2
RESEARCH APPROACH

This chapter presents the research approach. Section 2.1 provides an overview of the philosophy of science, and Section 2.2 describes the applied research methodology. An overview of the research process is presented in Section 2.3, while Section 2.4 discusses the rigor and relevance of the research.

2.1 PHILOSOPHY OF SCIENCE

The philosophy of science is the study, from a philosophical perspective, of the elements of scientific inquiry (Kitcher 2017). A philosophical paradigm is a set of shared assumptions and ways of thinking about the nature of our world (ontology) and the ways knowledge about it can be acquired (epistemology) (Oates 2006).

Oates discussed three philosophical paradigms of research, namely positivism, interpretivism, and critical research. Positivism is appropriate for studying the natural world, while interpretivism and critical research are more appropriate when studying the social world as they assume that there are multiple subjective realities as social reality is created and re-created by people.

Positivism can be further subdivided into positivist and post-positivist approaches. In the positivist approach, it is assumed that the world is regular and ordered and can be investigated objectively. Research is based on the empirical hypothesis testing, leading to their confirmation or refutation. Finally, it aims to discover universal laws that can be shown to be true regardless of circumstances.

The post-positivistic approach argues that research evidence is always imperfect and fallible (Robson 2011). Therefore, reality can only be known imperfectly and probabilistically because of researcher limitations. In contrast to the positivist approach, it accepts that what is observed can be influenced by theories, hypotheses, background knowledge and the values of the researcher (Reichardt and Rallis 1994).

In my work, I hold to the positivist philosophical paradigm.

2.2 RESEARCH METHODOLOGY

In this research the guidelines presented by Hevner et al. (2004) and the methodology described by Peffers et al. (2007) have been applied.
Peffers et al. (2007) presented a design science research methodology for information systems research (Figure 2.1). The purpose of this model is to provide a framework to carry out design science research as well as a mental model for its presentation. The guidelines for design science research as presented by Hevner et al. (2004) cover the following aspects: design as an artefact, problem relevance, design evaluation, research contribution, research rigor, design as a search process, and communication of research.

Figure 2.1: Process model of design science research methodology developed by Peffers et al. (2007), based on (Takeda et al. 1990)

The iterative search process of design and development is captured in the information system research framework presented by Hevner et al. (2004). Figure 2.2 presents an instantiation of the framework.

Figure 2.2: Information systems research framework adapted from (Hevner et al. 2004)
The design and creation (development) research strategy is focused on developing new IT artefacts (Oates 2006). Researchers following this strategy can contribute to knowledge with a construct, model, method, instantiation, or combination of those. According to March and Smith (1995) and Oates (2006):

- construct is the concept or vocabulary used in a particular IT-related domain,
- model is a combination of constructs that represent a situation and is used to aid problem understanding and solution development,
- method is guidance on the models to be produced and process stages to be followed to solve the problems using IT,
- instantiation is a working system which demonstrates that constructs, models, methods, ideas or theories can be implemented in a computer-based system.

The main artefacts and contributions of the research are: (1) method to integrate and process disparate data from a population of entities to provide support for maintenance decisions; (2) instantiation of the method, applied to the machine tool linear axis.

### 2.3 RESEARCH PROCESS
The research process in this work is presented using the model by Peffers et al. (2007), as shown in Figure 2.1.

#### RESEARCH ENTRY POINT
The research project was initiated from the manufacturing side by Volvo Car Corporation (VCC) and Volvo Global Trucks Operation (VGTO). Their vision was to avoid faults and disturbances and secure the process quality of the selected equipment/subsystem. To be relevant, the project had to be aligned with business strategy, which meant that it had to

- maximise value with minimum cost,
- use collected data to predict events or changes in the status of equipment/subsystems,
- aim to support maintenance actions that reduce cost and improve quality,
- acquire the data from existing equipment/subsystems within VCC and VGTO.

The specified requirements were at a high level of abstraction, and a pre-study was performed to further shape the research.

#### PROBLEM IDENTIFICATION AND MOTIVATION
Problem identification and justification were done through a literature study and observation of maintenance work in the companies involved. This part is covered in chapter 1 of the thesis.

#### OBJECTIVES OF THE SOLUTION
From the company perspective, the developed artefact was required to have a positive impact (quantitative objective) on one or more key performance indicators (KPI), for example, cost, mean time to failure (MTTF), and overall equipment efficiency (OEE).

#### DESIGN AND DEVELOPMENT
This task was performed in an iterative way, starting with data acquisition through data processing to maintenance decision-making.
DEMONSTRATION
The developed methodology was applied to real data. Data obtained from manufacturing were used to build data-driven models.

EVALUATION
Evaluation was performed through simulation. The direct cost of maintenance actions based on different approaches was compared.

COMMUNICATION
Manuscripts were published in academic conference proceedings and academic journals. The work performed was disseminated at several meetings in the companies involved, with the level of attendees ranging from maintenance technicians to condition monitoring specialists to plant managers.

CONTRIBUTION
The method was developed and demonstrated on real-world industrial cases that are of high importance. A summary of contributions is presented in Section 5.2.

2.4 RIGOUR AND RELEVANCE
Information systems and computing research should be rigorous and relevant (Oates 2006). The objective of the design science research approach is to develop a technology-based solution for important and relevant business problems (Hevner et al. 2004). The project was initiated by industrial partners; moreover, the relevance and importance of the problem was confirmed through a literature study. “Relevance” is defined as having a direct bearing on practitioners. The practitioners in this thesis are other developers of CBM decision support systems. As the research conducted is closely related to the real industrial problem, it could be relevant to maintenance managers to justify putting more effort into CBM.

Design science research relies upon the application of rigorous methods in both the construction and evaluation of the design artefact (Hevner et al. 2004). The work presented follows a systematic process, applied methods are verified and evaluated, and validity is taken into account. For example, when the travelled distance for the axis of the machine tool was estimated based on NC code, the estimations were matched with ground truth data obtained from online monitoring of two machine tools performing different operations. When statistical methods were applied, the underlying assumptions were checked e.g., the assumption on the distribution of analysed signals in the feature selection step presented in Paper IV.

External validity is concerned with the level of generalisability. It depends on how representative the research samples are (Oates 2006). The external validity of method evaluation is lower, since data from a limited number of machines were analysed. This means that the results in a different case cannot be evaluated ahead of time. However, the method does not make many assumptions and can be applied to different cases.
FRAME OF REFERENCE
CHAPTER 3
FRAME OF REFERENCE

This chapter presents the theoretical background and provides context to the research. It begins with positioning the research with respect to recent concepts of cloud manufacturing and industry 4.0 (Section 3.1). Section 3.2 gives an overview of predictive maintenance with a brief description of the various methods. Then the population-based approach is explained in Section 3.3. Section 3.4 explains the ontology model that was utilised in data retrieval. Finally, machine tool condition monitoring with more focus on linear axes is presented in Section 3.5.

3.1 CLOUD MANUFACTURING

The cloud manufacturing paradigm is a result of combining 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. It is not a simple deployment of manufacturing software tools in the computing cloud. The physical resources integrated into the manufacturing cloud are able to offer adaptive, secure, and on-demand manufacturing services over the Internet of Things (Lihui Wang et al. 2014). According to the Federal Ministry of Education and Research, Germany (BMBF) quoting Monostori (2014), “Industry is on the threshold of the fourth industrial revolution, frequently noted as Industry 4.0. This revolution is led by development and implementation of cyber-physical systems”. One of the services included in the cloud manufacturing concept is maintenance-as-a-service (Ren et al. 2013). Cloud manufacturing increases the level of complexity of production equipment and requires high availability and robustness (Ylipää et al. 2017). Therefore, proper maintenance plays an important role.

Cloud-enabled prognosis for predictive maintenance combines information from similar machines and uses the power of cloud computing to more efficiently execute the prognostic models in the distributed cloud environment for improved decision-making (Gao et al. 2015). An overview of a cloud-enabled prognostics approach within a cyber-physical concept is visualised in Figure 3.1.
3.2 PREDICTIVE MAINTENANCE

Standard EN 13306 (CEN 2001) defines predictive maintenance as a CBM carried out following a forecast derived from the analysis and evaluation of significant parameters of the degradation of the item. CBM is defined as preventive maintenance based on performance and/or parameter monitoring and subsequent actions. Preventive maintenance is defined by the standard as maintenance carried out at predetermined intervals or according to prescribed criteria and intended to reduce the probability of failure or degradation. Three key steps of a CBM program, as mentioned by Jardine et al. (2006), are (1) data acquisition, (2) data processing, and (3) maintenance decision-making.

3.2.1 DATA ACQUISITION

Jardine et al. (2006) describe data acquisition as a process of collecting and storing useful data from targeted physical assets for the purpose of CBM. The collected data can be categorised into two main types: condition monitoring data and event data. Condition monitoring data are measurements related to the health condition or state of the physical asset. Si et al. (2011) defined condition monitoring (CM) data as any data that may have a connection with the prediction of remaining useful life, including operational data, performance data, environmental information, and degradation signals. Event data include information on what happened and/or what was done to the targeted physical asset. Event data and CM data are equally important in CBM.

Development and implementation of information and communication technologies (ICT) in industry over the past decade has brought new possibilities and challenges. More data are now gathered. However, the data are stored and processed in disparate and heterogeneous systems as computerised maintenance management systems (CMMS) for maintenance record-keeping, CM for asset health state monitoring, and
supervisory control and data acquisition (SCADA) systems for monitoring processes and controlling the asset (D. Galar et al. 2012, Diego Galar et al. 2016). Bjorling et al. (2013) indicated that attempts to integrate CMMS, CM and maintenance knowledge management will be a key part of maintenance technology in the future.

3.2.2 DATA PROCESSING

Data processing methods depend mainly on the type of data collected. Jardine et al. (2006) categorised CM data into three categories: value data such as oil analysis data, temperature, and pressure; waveform data such as vibration and acoustic data; and multidimensional data such as infrared and X-ray images.

Value data can be analysed using multivariate analysis techniques such as principal component analysis (PCA) and independent component analysis (ICA). For waveform data analysis, there are three main categories: time-domain analysis, frequency-domain analysis and time-frequency analysis. The data processing step to extract useful information from raw signals is called feature extraction (Jardine et al. 2006).

3.2.2.1 FEATURE SELECTION

A wide range of features can be extracted from signals when there are multiple sources of data, but it is important to determine which features are more promising. Feature selection should be performed without operator intervention (Teti et al. 2010).

Kohavi and John (1997) distinguished between filter and wrapper methods for feature selection. Filter methods make a selection based only on data by applying some heuristic evaluation for each feature individually (Figure 3.2). Wrapper methods use machine learning algorithms to evaluate selected features in a cross-validation process, and some search algorithm is used to find a subset of optimal features (Figure 3.3).

An example of a wrapper method is correlation-based feature selection (CFS), well described and evaluated by (Hall) and applied in tool CM by Binsaied et al. (2009). In the first step, all continuous features are discretized using the technique presented in (Fayyad et al. 1996). The same technique is used in algorithms in Decision Tree C4.5
to decide which branches to split. The metrics are based on mean feature-class correlation and mean feature-feature correlation. Then a greedy hill-climbing search algorithm is applied to find a feature subset that maximises the evaluation metrics.

If the degradation model is known, then model-based feature selection methods can be applied. When linear correlation can be assumed, linear techniques like the Pearson correlation coefficient can be used (Quan et al. 1998). The coefficient of determination provides a statistical measure of how well a model approximates the real data points. The coefficient of determination was used to avoid uncertain assumptions about the dependency of a feature on tool wear in (Jemielniak et al. 1998).

3.2.2.2 MACHINE LEARNING

A description of a broad range of machine learning algorithms and their statistical principles is provided by Mitchell (1997). The author describes machine learning as a multidisciplinary field that draws on artificial intelligence, probability and statistics, control theory, neurobiology, and other fields.

In this thesis machine learning is applied to a multiclass classification problem to determine the degradation state of a component. The set of applied methods was identified based on (Kiang 2003), who assessed several classification methods. The selected distribution-free classification methods are Back Propagation Feed Forward Neural Network (FFNN), k-Nearest Neighbour (kNN) (Wong and Lane 1981), and Decision Tree C4.5 (DT) (Quinlan 1993). In addition, Random Forest and a multiclass Support Vector Machine (SVM) classifier were included based on (Binsaeid et al. 2009, Prytz et al. 2013).

3.2.3 MAINTENANCE DECISION SUPPORT

In the CBM approach, techniques for maintenance decision support can be divided into diagnostics and prognostics (Jardine et al. 2006). Diagnostics is identifying and quantifying damage that has occurred, while prognostics tries to predict damage that is going to occur (Sikorska et al. 2011).

3.2.3.1 PREDICTION MODELS

The basic classification of modelling techniques for prediction is presented in Figure 3-4.

![Figure 3-4: Prediction models classification (Schmidt and Wang 2015)](image)

Physical models use the laws of physics to describe the behaviour of a failure. Models are usually described by analytical equations and the most accurate estimates are provided. However, such models require complete and detailed knowledge of the system. This is a common approach to evaluating cutting tool wear (Gao et al. 2015), which is directly affected by machining parameters such as cutting speed, feed rate, and temperature.

Knowledge-based models assess the similarity between an observed situation and a set of previously defined failures (Sikorska et al. 2011). Those models can be subdivided into expert and fuzzy systems. Expert systems use precise IF-THEN statements
to define rules, while fuzzy models use fuzzy rules and logic that can handle noisy or imprecise input data.

Data-driven models are based on acquired historical data. Within this type of model we can distinguish between stochastic models, statistical models, and artificial neural networks. Hybrid models use combinations of two or more modelling techniques.

### 3.2.3.2 STOCHASTIC MODELS

Stochastic models provide reliability-related information. One of the most common tools used by industry is aggregate reliability functions (Sikorska et al. 2011). This approach analyses the time to failure of the population to determine the probability density function. Various distributions can be used to model failure data, including Gaussian, lognormal, exponential and Weibull. Stochastic conditional probability is a subgroup of statistical models that use the Bayes theorem and are often referred as Bayesian models. Sikorska et al. (2011) placed Markov and semi-Markov models, hidden and semi-hidden Markov models, Kalman filters, and particle filters in this group. Markovian-based models assume that the future degradation state depends only on the current degradation state, which can be directly observed through CM (Si et al. 2011). Hidden Markov models are composed of two stochastic processes, a not directly observable Markov chain, which represents the real state of deterioration, and an observable process that corresponds to the observed CM information.

### 3.2.3.3 STATISTICAL MODELS

Prediction of a future state is often performed by comparison of the monitoring results with a model representing behaviour in the failure-free state (Sikorska et al. 2011). The simplest form is trend extrapolation, in which a single parameter or feature is represented as a function of time. Trend data are compared with configured limits to generate warnings. With regression methods, data can be extrapolated to predict when the limit will be reached. Autoregressive models like autoregressive moving average (ARMA) and autoregressive moving average with exogenous inputs (ARMAX) assume that all future values are linear functions of past observations. These models need to be identified based on observation data by estimating parameters that minimise the error between model output and observed data. An application of using the ARMA method for fault prediction is presented in (Jie et al. 2007). Also, SVM can be applied as a regression model (Benkedjouh et al. 2013). Other regression models that can be applied include Wiener and Gamma processes (Gao et al. 2015).

The proportional hazard model (PHM) can also be categorised as a statistical model (Sikorska et al. 2011). It was first proposed by (Cox 1972). This model extends the aggregate reliability functions by using so-called covariates. The PHM assumes that the hazard rate of a system consists of two multiplicative factors: a baseline hazard function and a function of covariates (Si et al. 2011). Ghodrati et al. (2017) used a Weibull distribution in a PHM to estimate the mean residual life of hydraulic systems in mining equipment.

### 3.2.3.4 ARTIFICIAL NEURAL NETWORKS

Artificial neural networks (ANN) is a technique that simulates the functions of brain neurons (Teti et al. 2010). Neurons are grouped in layers, where the outputs from one layer are connected to the inputs of the next layer. The typical structure of an ANN consists of the input layer, an output layer, and one or more hidden layers (Figure 3.5).
The output from the neuron depends on the chosen activation function and input values modified by input weights. Input weights are automatically adjusted during the learning or training process. An ANN approach can be used when there is no previous knowledge of the system and without a physical understanding of the process. However, a high number of samples is required to train the network, and its performance strongly depends on the selected structure (Gao et al. 2015).

![Artificial neural network structure](image)

### 3.3 Population-Based Approach

The population-based approach, also known as a fleet-wide approach, is an approach in which data from a set of entities are utilised. Three types of fleets can be distinguished based on the similarity between entities in the fleet (Al-Dahidi et al. 2016).

- An identical fleet consists of pieces of equipment that have identical technical features and work in the same operational conditions.
- A homogeneous fleet includes a set of entities that share some technical features and work in similar operating conditions; however, there are some differences in some features.
- A heterogeneous fleet consists of entities that undergo different usage with different operational conditions and have similar and/or different technical features.

Bahga and Madisetti (2012) adapted cloud-based case-based reasoning for fault prediction. Case-based reasoning (CBR) is an effective way of solving problems. The approach is to create cases based on fault data and sensor data retrieved from the maintenance database and machine sensor data respectively for a population of similar machines. The sensor data used to create the case can be treated as context information for faults which occur.

G. Medina-Oliva et al. (2014), Voisin et al. (2013) present an approach to fleet-wide diagnosis and prognosis. It takes advantages of all available knowledge about a set of similar units. By adding not only data from identical units but also from similar ones, a higher volume of data can be obtained to reduce uncertainty. They indicate the need to handle the heterogeneity of the knowledge, the similarity of the components, and the operational context. The approach in their research was focused on retrieving relevant context information with the use of ontology-based knowledge representation. The availability of CM data for heterogeneous fleets of equipment installed worldwide and experiencing different operational conditions drives the development of new data-driven approaches to capitalise on the information coming from the fleet in order to
improve the remaining useful life estimation (Al-Dahidi et al. 2016). Unsupervised ensemble clustering is applied to obtain a number of states in a homogeneous discrete-time finite-state semi-Markov model (HDTFSSMM). Maximum likelihood estimation (MLE) and a Fisher information matrix (FIM) are used to estimate state transition parameters and their uncertainty. Finally, direct Monte-Carlo simulation of the degradation progression is applied to estimate remaining useful life. The proposed approach has been validated in several simulated cases:

- aluminium electrolytic capacitors (simulated): 2-dimensional data vector (1 – degradation, 1– condition)
- aircraft engine turbomachinery (NASA simulated): 24-dimensional data vector (21 – degradation, 3– condition); 15 signals used.

Prytz (2014) applied machine learning methods to data from a fleet of vehicles for predictive maintenance of vehicle compressors. Off-board maintenance records and on-board monitoring data were used. Prytz et al. (2013) evaluated the performance of three classifiers on the data obtained: k-Nearest Neighbour, Decision Tree, and Random Forest. Prytz et al. (2015) used a Random Forest classifier with two feature selection methods were used: a statistical filter using a Kolmogorov-Smirnov test, and a wrapper-based method. Finally, the approach was evaluated by estimating profitability.

### 3.4 ONTOLOGY MODEL

In computer and information science, ontology is a formal specification of knowledge in a domain, explicit specification of the objects, concepts, and other entities that exist in some area of interest, and the relationships between them (Gruber 2009). An ontology model can be described as a set $O= \{C, RS, I\}$. In this model, $C$ is a collection of concepts also called classes, $I$ is set of particulars (instances of classes, individuals), and $RS$ is set of relationships between two concepts or particulars. Ontology Web Language (OWL) (McGuinness 2004) is one of the common ontology formalisation languages.

(X. H. Wang et al. 2004) indicated that ontology-based modelling allows:

- knowledge sharing between computational entities by having a common set of concepts about a 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, that is, large-scale context ontology can be composed without starting from scratch.

3.5 MACHINE TOOL CONDITION MONITORING

Considerable research has been conducted in the field of machine CM (Jay Lee et al. 2014). The majority of this research focuses on applications involving common rotating machine components such as bearings and gears. The most popular CM technique for rotating equipment is vibration monitoring (Al-Najjar 1997, Higgs et al. 2004). Vibration-based CM is a very large research area with a long history, and powerful diagnostic techniques are currently available (Randall and Antoni 2011).

3.5.1 MONITORING OF LINEAR AXES

Condition monitoring of linear axes can be subdivided into online indirect measurement and offline direct measurements. There are a few examples of online approaches. Verl et al. (2009) proposed an approach using signals relating to position, speed, and motor current in position-controlled drives to detect wear of the drive unit. Feng and Pan (2012) developed a temperature and vibration sensor unit embedded in the ball screw nut to detect different levels of preload through supervised learning of an SVM classifier. Garinei and Marsili (2012) used a Hall-effect sensor to detect the presence of damaged balls in the ball screw. Tsai et al. (2014) used an accelerometer to monitor ball pass frequency to detect decreasing ball screw preload. Vibration signals from an accelerometer placed on the ball screw nut in a laboratory test rig were used by W. G. Lee et al. (2015) to detect artificially introduced failures in the ball screw race. Vogl et al. (2016) developed a method to use data from an inertial measurement unit (IMU) to identify changes in the axis errors due to degradation.

A well-established method for offline measurement of axes accuracy is the DBB measurement that was first presented by Bryan (1982) and later standardised in ISO 230-1 (ISO 2012). Its advantages are low cost, simplicity of use, and robustness (Zargarbashi and Mayer 2006). The DBB test is designed to perform circular trajectory interpolation of two prismatic axes. The test results are a good representation of the results that would be obtained on machined parts in ideal machining conditions with the same motion parameters. Figure 3.6 shows a result from machine tool with faulty X-axis. For 3-axis machines the test is performed on three planes defined by pairs of machine main axes (Figure 3.7), for both rotation directions and for two feed rates.

![Figure 3.6: Example of results from a double ball-bar test](image)

The drawback of performing double ball-bar measurement is that it is performed in an unloaded condition, without the forces and torques generated during cutting operations. Moreover, it cannot be performed automatically and requires time to install the external measuring device. However, in modern machine tools, a circularity test can
be performed automatically using internal position sensors (Siemens 2016). This provides an opportunity to acquire measurements more frequently, with less disturbance to production.

![Figure 3.7: Concept of double ball-bar measurement on a 3-axis machine](image)

Most of the research using the DBB test focuses on identifying sources of deviation (Kakino et al. 1987), its application to multi-axis and/or non-prismatic axis tools (Chen et al. 2015, Uddin et al. 2009, Hong-jian Xia et al. 2017, Zargarbashi and Mayer 2006), modelling thermal deviations (Dehnavi et al. 2012, Delbressine et al. 2006, Florussen et al. 2003), improving the measurement to include dynamic conditions (Archenti et al. 2012), and prediction of the machined part accuracy (Archenti 2014). It is hard to find reported research where data from double ball-bar measurements were used for predictive maintenance. The data are mainly used to identify existing problems, not to indicate when problems could occur.

Axes accuracy can be also assessed using other measuring techniques and principles. For example, axis straightness can be measured using an autocollimator or a laser interferometer (ISO 2012).

### 3.5.1.1 CIRCULARITY TEST FEATURES

Standard ISO 230-4 (ISO 2005) defines four types of features:

- circular deviation $G$ is defined as the minimal radial separation of two concentric circles enveloping the actual path of a clockwise or anticlockwise contoured path (Figure 3.8 a),
CHAPTER 3 FRAME OF REFERENCE

- bi-directional circular deviation $G(b)$ uses the radial separation of circles enveloping two actual paths, clockwise and anticlockwise (Figure 3.8 b),
- radial deviation $F$ is defined as the deviation between the actual path and the nominal path and is given by the maximum value $F_{max}$ and minimum value $F_{min}$,
- mean bi-directional radial deviation $D$ is defined as the deviation between the radius of the nominal path and the radius of the least squares circle of two (clockwise and anticlockwise) full circle actual paths.

![Figure 3.8: Circular test features according to ISO 230-4 (ISO 2005)](image)

The features utilised in this research come from Renishaw® ball-bar diagnostic analysis. The analysis can be used to identify the cause of any circularity error when the executed circular path is a complete circle or a $220^\circ$ degree circular arc. Table 3.1 presents an example of some features that can be retrieved from DBB by the Ball-bar diagnostics. Some possible deviations caused by machine errors are visualised in Figure 3.9.

<table>
<thead>
<tr>
<th>Features for individual axis</th>
<th>Features common for two axes</th>
</tr>
</thead>
<tbody>
<tr>
<td>BACKLASH_X</td>
<td>BEST_RADIUS_XY</td>
</tr>
<tr>
<td>CENTRE_OFFSET_X</td>
<td>CALCULATED_FEEDRATE_XY</td>
</tr>
<tr>
<td>CYCLIC_ERROR_X</td>
<td>CIRCULARITY_XY</td>
</tr>
<tr>
<td>CYCLIC_PHASE_X</td>
<td>GLOBAL_SCALE_XY</td>
</tr>
<tr>
<td>CYCLIC_PITCH_X</td>
<td>POSITIONAL_TOLERANCE_XY</td>
</tr>
<tr>
<td>LATERAL_PLAY_X</td>
<td>RADIUS_CHANGE_XY</td>
</tr>
<tr>
<td>OFFSET_X</td>
<td>SCALE_MISMATCH_XY</td>
</tr>
<tr>
<td>REVERSAL_SPIKES_X</td>
<td>SERVO_MISMATCH_XY</td>
</tr>
<tr>
<td>SCALE_ERROR_X</td>
<td>SIN_4_THETA_XY</td>
</tr>
<tr>
<td>STRAIGHTNESS_X</td>
<td>SQUARENESS_XY</td>
</tr>
<tr>
<td></td>
<td>RMS_XY</td>
</tr>
</tbody>
</table>

*Table 3.1: Example of features from the ball-bar diagnostics*
3.5.2 BALL SCREW LIFETIME

According to ISO 3408 (ISO 2006) the nominal life expectancy $L$ of a ball screw based on material fatigue can be estimated using Equations 1–3.

$$L = \left( \frac{C_a}{F_{ma}} \right)^3 \cdot 10^6$$  \hspace{1cm} (1)

$$F_{ma} = F_{pr} \left( 1 + \frac{F_m}{3F_{pr}} \right)^{\frac{2}{3}}$$  \hspace{1cm} (2)

$$F_m = \sqrt[3]{\frac{q_1 \cdot n_1 \cdot F_1^3 + q_2 \cdot n_2 \cdot F_2^3 + \cdots + q_n \cdot n_n \cdot F_n^3}{q_1 \cdot n_1 + q_2 \cdot n_2 + \cdots + q_n \cdot n_n}}$$  \hspace{1cm} (3)
where \( C_a \) is dynamic load capacity, \( F_{ma} \) is equivalent mean load, \( F_m \) is mean load, \( F_{pr} \) is preload tension, \( F_i \) is thrust, \( n_i \) is speed, and \( q_i \) is time percentage. An extended version of Equation 1, presented in Equation 4, includes an additional factor \( f_w \) that correlates life expectancy with different operational conditions. Different sources provide different values for the \( f_w \) parameter. Some approximations of the parameter values are presented in Table 3.2.

\[
L = \left( \frac{C_a}{F_{ma} f_w} \right)^3 \cdot 10^6
\]

(4)

<table>
<thead>
<tr>
<th>Use condition</th>
<th>( f_w )</th>
<th>Use condition</th>
<th>( f_w )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Smooth movement without impacts</td>
<td>1.0 – 1.2</td>
<td>Vibrations/Impact</td>
<td>Very low V&lt;0.25</td>
</tr>
<tr>
<td>Normal movements</td>
<td>1.2 – 1.5</td>
<td>Speed (V)[m/s]</td>
<td>Slow 0.25&lt;V&lt;1</td>
</tr>
<tr>
<td>Movement with impacts and vibrations</td>
<td>1.5 – 2.5</td>
<td>Medium</td>
<td>Medium 1&lt;V&lt;2</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Strong</td>
<td>High 2&lt;V</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>(UTHAH 2006)</th>
<th>(THK 2015)</th>
</tr>
</thead>
</table>

Table 3.2: Values of condition-related factor \( f_w \) in the model for life expectancy

The nominal life expectancy model was simulated by Mauro et al. (2015). Ball screw life was evaluated with different kinematic parameters used to generate the reference trajectories. The results indicate that limits on the maximum jerk, acceleration, and velocity can have a strong influence on the expected life of the ball screw of a feed drive. Higher limits yield a shorter machining cycle time; however, the ball screw lifetime is expected to be reduced as the ball screw is exposed to higher loads.
SUMMARY OF INCLUDED ARTICLES
CHAPTER 4
SUMMARY OF INCLUDED ARTICLES

A summary of the five appended papers is provided with the most important aspects of each paper highlighted.

4.1 PAPER I: CLOUD-ENHANCED PREDICTIVE MAINTENANCE


This paper, published in IJAMT, presents the outcome of the initial step of the research and provides the base for further research. With an aim of improving maintenance, some current issues and relevant research areas are identified. The initial version of the research question is stated. The paper highlights the need to integrate data from different available sources and presents a cloud approach for predictive maintenance. As a step toward answering research question PRQ1, it provides an example of potential improvements (Figure 4.1).

In addition, initial results from data integration are provided. Combined trends from double ball-bar measurements for a fleet of machines are presented for visual data assessment. Assessing data visually made it possible to identify patterns like accelerated degradation on some instances of ball screws.

**Figure 4.1:** Potential population-based improvement in prediction
4.2 PAPER II: CONTEXT PREPARATION FOR PREDICTIVE ANALYTICS - A CASE FROM MANUFACTURING INDUSTRY


To answer research question SRQ1, this paper presents results from analysis of available data that could be relevant for predictive maintenance of machine tool linear axes. The acquired data come from CMMS, SCADA systems, maintenance reports, double ball-bar measurements, and implemented online monitoring system.

The implemented online monitoring system of the linear axes allowed acquisition of different signals from the axes controller. Values of velocity and torque were used to calculate power delivered to the axis. Analysis revealed some abnormal behaviour on one of the monitored machines. Although the root cause was not discovered, the results indicate the potential of this type of monitoring to detect some anomalies.

Acoustic emission signals were recorded and analysed on a machine with audible noise. Energy in the frequency band 935Hz–1560Hz shows correlation with the motion of one the axes that was the source of the sound (Figure 4.2).

![Figure 4.2: Correlation of acoustic emission (blue solid) and velocity of axis motion; green (--) in positive direction, red (--) in negative direction](image)

Theoretical lifetime, based on nominal life expectancy (ISO 2006) with load parameters obtained from online monitoring, was compared with real failure data. The results indicate that ball screws could be working in harsher operational conditions than “normal” (see Section 3.5.2).
The user interface developed allows the user to browse and visualise the acquired information (Figure 4.3). It allows browsing through: ➊ available machines; ➋ the machine structure that includes machine units, subunits, and components; and ❼ available features obtained from CM. The charts in the main window present: ➊ trends of selected features; ➋ maintenance work orders and acquired spare parts; and ➋ machine utilisation indicated by the number of machining cycles per time unit. It allows comparison of the performed maintenance actions and replaced components with relevant CM indications.
4.3 PAPER III: SEMANTIC FRAMEWORK FOR PREDICTIVE MAINTENANCE IN A CLOUD ENVIRONMENT


In this paper, a semantic framework using an ontology-based approach for data aggregation is proposed to support cloud-enabled diagnostics and prognostics applied to the maintenance of manufacturing assets (Figure 4.4). The framework provides the basis for answering research question PRQ2.

![Figure 4.4: Semantic framework for data aggregation](image)

A way to retrieve relevant information, based on examples of asset hierarchy ontology, functional ontology, and measurement ontology, is presented to answer research question SRQ2.

This approach, providing types and amounts of available relevant data, could be used to support the selection of suitable diagnostic and prognostic methods. Moreover, data from the whole population of identical or similar components could be retrieved.
4.4 PAPER IV: INTEGRATION OF EVENTS AND OFFLINE MEASUREMENT DATA FROM A POPULATION OF SIMILAR ENTITIES FOR CONDITION MONITORING

Schmidt, B., Gandhi, K., Wang, L., Ng, A.H.C. "Integration of events and offline measurement data from a population of similar entities for condition monitoring" (journal draft for International Journal of Computer Integrated Manufacturing)

This paper describes in detail a method to integrate event and CM data from a population of similar machines. The paper provides answers to research question PRQ2. The proposed method is applied to ball screw components as follows:

- Event data are used to create component instances that allow reliability analysis (lifetime distribution) and alignment of measurements with respect to time to failure,
- Context-related data are used to scale time-based data to usage-based data (expressed in calendar days, processing days, number of machining cycles, or travelled distance),
- Data are divided and labelled into three classes: long (TC1), medium (TC2) and short (TC3) time before failure,
- Different processing and feature selection methods are evaluated,
- Evaluation is based on the accuracy of several classification methods applied in the cross-validation process (Figure 4.5),
- The result of the evaluation is visualised (Figure 4.6) and the best combination of processing and classification method is indicated,
- A condition-based decision process, based on the number of detected observations in state TC2 and TC3 is proposed,
- A reliability-based model and a CM accuracy model are applied in a Monte-Carlo simulation to estimate cost, failure rate, and to optimise prediction method parameters.

The indicated improvement of the direct cost (in imaginary currency unit U) of the analysed case is from 706 ± 16 U/year to 416±5 U/year, a cost reduction of 41%. Moreover, the number of unplanned work orders is reduced from 53% to 8%, which could result in a reduction of consequential costs.

Figure 4.5: Cross-validation evaluation procedure
Figure 4.6: Comparison of different pre-processing and processing methods based on the accuracy of several classification methods. Dots indicate all combinations that are not significantly different from the best solution marked with a bigger dot. Asterisks indicate solutions that are not significantly different from a random classifier. Values on the right and bottom represent number of dots in a corresponding row or column.

The visualisation method for the results from the accuracy calculation (Figure 4.6) allows assessment of how different combinations of processing and classification methods perform on the data set. In the paper, some observed patterns are discussed.

Independent component analysis (ICA) was proposed for the analysis because of the characteristics of the data from the double ball-bar measurements. Combining ICA with statistical feature selection (SFS) and PCA (ICA+SFS+PCA), used with the SVM classification method, produced good results.
4.5 PAPER V: DIAGNOSIS OF MACHINE TOOLS: ASSESSMENT BASED ON DOUBLE BALL-BAR MEASUREMENTS FROM A POPULATION OF SIMILAR MACHINES


This paper describes results from simulations performed on models obtained using the method reported in Paper IV. The effect of CM inspection intervals as well as inspection cost is assessed through simulation. The paper shows how the method can be used to support maintenance decisions. The simulation was also applied to optimise the division into classes (Figure 4.7). The indicated improvement of the direct cost of the analysed case is from 706 U/year to 396 U/year, a cost reduction of 44 %. Moreover, the number of unplanned work orders is reduced from 53 % to 7 %.

![Figure 4.7: Minimal cost for CBM policy for different clusters sizes for conditions TC1, TC2, and TC3 that relate to long, medium and short time to failure. The white asterisk indicates the clustering with the lowest cost](image)

This paper answers research questions SRQ3 and PRQ1. Table 4.1 shows the results, which indicate that applying the proposed method to the analysed case of ball screw CM using double ball-bar measurements could be economically beneficial.
<table>
<thead>
<tr>
<th>Maintenance policy</th>
<th>Mean cost [U/year]</th>
<th>Mean lifetime [days]</th>
<th>Mean EWO ratio [%]</th>
<th>Inspection interval $T_{CM}$ [days]</th>
</tr>
</thead>
<tbody>
<tr>
<td>RM</td>
<td>767</td>
<td>1143</td>
<td>100</td>
<td></td>
</tr>
<tr>
<td>TBM</td>
<td><strong>706</strong></td>
<td>857</td>
<td><strong>53.4</strong></td>
<td></td>
</tr>
<tr>
<td>CBM*, $C_{CM}=10$</td>
<td><strong>395.9</strong></td>
<td>1030</td>
<td><strong>6.9</strong></td>
<td>50</td>
</tr>
<tr>
<td>CBM, $C_{CM}=10$</td>
<td>407.9</td>
<td>962.7</td>
<td>8.6</td>
<td>70</td>
</tr>
<tr>
<td>CBM, $C_{CM}=20$</td>
<td>460.0</td>
<td>966.0</td>
<td>8.5</td>
<td>70</td>
</tr>
<tr>
<td>CBM, $C_{CM}=50$</td>
<td>560.1</td>
<td>966.3</td>
<td>21.1</td>
<td>140</td>
</tr>
<tr>
<td>CBM, $C_{CM}=80$</td>
<td>635.2</td>
<td>982.0</td>
<td>24.0</td>
<td>150</td>
</tr>
</tbody>
</table>

Table 4.1: Comparison of results from the simulation for different costs of condition monitoring $C_{CM}$, with obtained optimal $T_{CM}$. Results for simulation with improved division into classes are marked with *. 
CONCLUSIONS AND DISCUSSIONS
CHAPTER 5
CONCLUSIONS AND DISCUSSIONS

This chapter concludes with how the research questions have been answered and what the contribution of the research is. It also discusses some results and suggests further work.

5.1 REVISITING THE RESEARCH QUESTIONS

**PRQ1:** In what ways can predictive maintenance activities be improved by utilising information from multiple similar entities?

This research question was formulated to investigate and justify the need for data integration from a population of entities in condition-based predictive maintenance. Initial justification was performed based on observations and literature study (Paper I). Quantitative results from Paper V show that the cost and number of failures could be reduced. A suitable interval for inspections could also be obtained. In the case analysed, the potential cost reduction is 44%, with breakdowns reduced from 53% to 7% compared to the time-based approach.

**PRQ2:** How can the integration of information from a population of similar monitored objects be achieved by data science for maintenance prediction?

This research question was formulated to investigate how information from a population of similar objects could be acquired and processed to support better maintenance decisions. The answer to this question is supported by answers to secondary research questions SRQ1 and SRQ2. The integration of information from a population of similar monitored components can be achieved by following the method developed and evaluated in Paper IV.

**SRQ1:** What potentially relevant data for condition monitoring of machine tool linear axes are available?

This research question was formulated with the goal of exploring and describing available information. The result was reported in Paper II. Identified sources include maintenance work orders, reports, cycle information from SCADA, signals from the controller, NC code, and double ball-bar measurements. The answer to this question
allowed the development of a method for data integration. It is possible that awareness of existing data and its importance has increased in the company involved.

**SRQ2: How could the relevant data be acquired?**
This research question was formulated to investigate how available relevant information could be identified and acquired. To answer this question, the ontology-based framework is presented in Paper III. The use of semantic querying and ontology base mapping allows accessing of relevant information from disparate sources. Moreover, provision of a service-oriented data access within the cloud concept allows relevant information to be obtained regardless of its location.

**SRQ3: Can double ball-bar measurements be used in predictive maintenance?**
This question was formulated to determine whether available data from offline double ball-bar measurements can be used not only for diagnostics but also for prognostics. The obtained evidence shows that double ball-bar measurements can indeed be used in predictive maintenance. The results from applying the proposed method to the data, reported in Paper IV and V, indicate the potential for the method to improve maintenance decisions.

### 5.2 RESEARCH CONTRIBUTION

The presented research contributes to the body of knowledge and to the industry.

**SCIENTIFIC CONTRIBUTION**
- Method to integrate event, CM, and context data from a population of similar machines:
  - event data are used to create component instances that allow reliability analysis and alignment of measurements with respect to time to failure,
  - context-related data are used to scale time-based data to usage-based data,
  - different processing and feature selection methods are evaluated,
  - a condition-based decision process is proposed,
  - a reliability-based model and a CM accuracy model are applied in a Monte-Carlo simulation to estimate cost, failure rate, and to optimise prediction method parameters.
- Numerous scientific publications.

**INDUSTRIAL CONTRIBUTION**
- Identified and described available and potentially useful data.
- Evaluated the method using data from a real manufacturing setup.
- Proposed economic evaluations to allow the assessment of the consequences of different scenarios; this could be used to optimise the maintenance procedure.
- Indicated potential benefits of double ball-bar measurements.
- Provided support in analysing ball-bar measurements.
5.3 DISCUSSION

5.3.1 VALIDITY OF RESULTS
In this thesis a population-wide approach is presented. Data from the population of similar components are analysed and the estimations obtained are valid for a similar population.

The main assumption affecting the results regards the failure time. It is assumed that component replacement is equivalent to component failure. When replacements are performed before actual failure and information on the degradation level of the replaced component is not available, the life distribution model will be biased. Lifetime predicted based on this model will be shorter than the actual lifetime, and replacements based on the model will be premature. The consequences are that the potential useful life is not fully utilised.

In the research, the analysed components (ball screws) are replaced based on CM (double ball-bar measurements) or because of failure. There is no time-based preventive replacement of the ball screw.

5.3.2 QUALITY OF DATA

In this subsection, different sources of data are discussed.

5.3.2.1 EVENT DATA

Information about component replacement can be retrieved from maintenance records, that is, work orders stored in CMMS. However, it is not always obvious what was replaced and where.

Each machine, its subsystems, and components have a unique ID in the system and can be unambiguously identified. Nevertheless, very often the performed work is labelled with an ID of the machine or one subsystem, while the work was performed on several subsystems. Information on what exactly was done is provided in the free-form text description. Moreover, each component has an ID of the corresponding spare part, but several components of the machine can use the same spare part. An example is the end bearings for ball screws in these machines. There are three different types of ball screws in the three main axes; however, the end bearings are the same type and have the same spare part ID. It is not possible to identify on which axis the end bearings were replaced based solely on the spare part ID if the axis is not explicitly logged. This makes it difficult or impossible to retrieve information automatically about component lifetimes.

5.3.2.2 DOUBLE BALL-BAR MEASUREMENTS

Measurements come from the standardised procedure in the company. The test for each machine is prepared based on common configuration templates. Each machine is measured in an operational area close to where the workpiece is located. There could be some deviation in location between machines, as well as between different occasions of measurement on the same machine.

Most machines are scheduled to be measured every 3 months. Sometimes additional measurements are performed when disturbances are noticed and measurements are needed to identify and/or confirm the source of the problem. DBB measurements are also performed after component replacement to confirm that the problem has been solved. When the measurements are taken during other maintenance work, it is not possible to automatically distinguish whether the measurement was taken on an old part before replacement or a new part just after replacement.
The distribution of intervals between measurements, based on data from the machines analysed, is presented in Figure 5.1. The median value of the interval between measurements is 119 days, which is almost four months. In the modelling step of the method presented in the thesis, no assumption about the distribution of the measurement interval was made. However, in the prediction step for economic evaluation, it was assumed that measurements are performed at fixed intervals.

![Figure 5.1 Distribution of intervals of double ball-bar measurements based on 276 intervals from the case analysed](image)

5.3.2.3 **ONLINE AXES MONITORING**

An external acquisition system was needed to obtain the internal signals of the machine tool axis controller. The machine tool controller allowed recording of its internal signals, but recording could not be performed continuously and also affected the performance of the human machine interface (HMI) However, it was possible to select two internal signals and forward them through a digital to analogue converter to create analogue outputs. An external data acquisition unit with an analogue to digital converter captured those signals. The data are limited to only two signals per axis, and the resolution of the internal digital to analogue converter is only 8 bits. Moreover, electrical noise was present in the signals transmitted. For modern machine tool controllers with more powerful processing units, access to the internal signals should not be an issue.

Analysis revealed some differences in behaviour between the monitored machines. On one machine, the average energy per machining cycle was consistently high after each break in operation every day, and slowly down during continuous operation, see Figure 5.2. While on another machine, see Figure 5.3, the deviations in the level of energy per machining cycle were much smaller.
It is possible that the energy signals could be used to diagnose some problems in the linear axes. Higher torque applied to the linear axis also causes faster degradation. Monitoring its value over the lifetime of the ball screw could improve the lifetime modelling.

In this research, controller data were acquired over a relatively short period of time (a few months) and only on two machines. As a result, the data were not used directly in the population-based modelling. However, the data were used to validate estimation of the distance travelled by the machine tool axes, based on the controller’s NC code and information on the number of machining cycles performed.

5.3.2.4 CONTEXT INFORMATION

Based on the literature and discussions with experts, the potential causes of ball screw degradation were identified and are shown in Figure 5.4. However, in the case analysed most of this information was not available at all, or only to a limited extent. As a result, this information was not used in creating the data-driven model.
5.3.3 FAILURE MODEL
A two-parameter Weibull distribution (Eq. 5.1) with parameters \( \beta = 1.75 \) and \( \lambda = 1285 \) estimated with p-value < 0.01 was obtained from statistical analysis on failures of ball screws.

\[
w(t) = (\frac{\beta}{\lambda}) \left( \frac{t}{\lambda} \right)^{\beta-1} e^{-\left( t/\lambda \right)^\beta}
\]

\( (5.1) \)

The shape parameter \( \beta > 1 \) represents an increasing failure rate (Figure 5.5) and only in this case can there be an optimal interval for time-based maintenance (Ahmad and Kamaruddin 2012). Using assumed costs for planned and unplanned work orders, the optimal TBM results in an estimated yearly cost of 704 U and 50% non-preventable failures. The best proposed CBM method gives a cost of 396 U and 7% non-preventable failures. According to (Hashemian and Bean 2011, Nowlan and Heap 1978), only 11% of industrial equipment can benefit from TBM. Nevertheless, the results of this
research indicate that even in those cases CBM could be beneficial and should be considered.

5.3.4 CLASSIFICATION EVALUATION
Classification accuracies were compared in the intermediate evaluation process of different combinations of processing and classification methods. However, the goal is to provide support for maintenance decisions that include economic aspects. In a later step, the simulation-based economic evaluation, a 3 x 3 confusion matrix was used. Classification evaluation metrics other than accuracy could be applied to improve the model. The new metrics should be derived from dependencies between the confusion matrix and economic evaluation results. In this research, this is not a trivial task as multiclass classification was used.

5.4 FUTURE RESEARCH
Future work needs to be done to improve the predictive part of the presented method. A possible option is using a hidden semi-Markov Model. To improve the feature and method selection step of presented approach, the data mining techniques could be applied to analyse how the accuracy of classification affects the predicted cost. This could lead to the classification evaluation metrics that will reflect the estimations from the predictive step.

It would be interesting to apply this method to other types of machines. As the method is not constrained by the source of CM (that is, the monitored components) it would be beneficial to apply the method to other types of components and CM. For example, features could be extracted from monitoring the machine tool main spindle.

Another extension of this work is to utilise identified data sources such as the signals of the internal machine tool controller. It would be beneficial if the offline double ball-bar measurements could be partially replaced by an automatic method based on online monitoring and automatic testing.

Further to presented work, it could be investigated if and to what extend the classification model build on one linear axis, can be applied to remaining linear axes of the machine tool. In applied data-driven approach, predictions were done with use of models built based on historical observations. It means that only earlier observed failure could be predicted. The idea is to enchase historical data for one axis, where there is no previous observation of failure, with artificial failure data generated based on models built for another axis with previously observed failures.
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INCLUDED ARTICLES

PAPER I

PAPER II

PAPER III

PAPER IV
Schmidt, B., Gandhi, K., Wang, L., Ng, A.H.C. (journal draft). "Integration of events and offline measurement data from a population of similar entities for condition monitoring", to be submitted to International Journal of Computer Integrated Manufacturing, Special Issue on Smart Cyber-Physical System Applications in Production and Logistics.

PAPER V
PAPER I
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

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.
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 (RVM) 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).

$$I_{inK_{Ax}} \forall i \sum I_{inK_{Ax}} < \sum I_{inK_{Ax}} \bigcup \forall i$$

where $I_{inK_{Ax}}$ is the information that can be obtained from $x$th knowledge area, $\sum$ is a fusion operator for information, and $\bigcup$ 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
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 several 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 question 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

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**Fig. 2** Modes for information fusion and predictive maintenance

![Diagram](chart.png)

**Fig. 3** Modes for information fusion and predictive maintenance

![Diagram](chart2.png)
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.
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 maintenance actions and 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 $\lambda_{RMS} = XY_{RMS} + XZ_{RMS} - YZ_{RMS}$ has been proposed, where $AB_{RMS}$ 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.
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
context data, as well as on developing general cloud-based framework. More results will be reported separately in the future.

References

PAPER II
Context preparation for predictive analytics – a case from manufacturing industry

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Abstract

Purpose – The purpose of this paper is to exemplify and discuss the context aspect for predictive analytics where in parallel condition monitoring (CM) measurements data and information related to the context are gathered and analysed.

Design/methodology/approach – This paper is based on an industrial case study, conducted in a manufacturing company. The linear axis of a machine tool has been selected as an object of interest. Available data from different sources have been gathered and a new CM function has been implemented. Details about performed steps of data acquisition and selection are provided. Among the obtained data, health indicators and context-related information have been identified.

Findings – Multiple sources of relevant contextual information have been identified. Performed analysis discovered the deviations in operational conditions when the same machining operation is repeatedly performed.

Originality/value – This paper shows the outcomes from a case study in real world industrial setup. A new visualisation method of gathered data is proposed to support decision-making process.

Keywords Predictive maintenance, Context awareness, Condition monitoring

Paper type Case study

1. Introduction

A large number of smart devices and sensors is producing a huge amount of data that need to be processed in a useful way, to provide relevance and context that can be understood by the right personnel (Lee et al., 2013). Moreover, algorithms can perform more accurately when more information throughout the machine’s lifecycle, such as system configuration, physical knowledge and working principles, are included. Therefore, there is a need to systematically integrate, manage and analyse machinery or process data during different stages of the machine’s lifecycle.

The contribution of operation and maintenance data to the different asset management stages has been triggered by the emergence of intelligent sensors for measuring and monitoring the health state of a component, the gradual implementation of information and communication technologies (ICT), and the conceptualisation and implementation of e-maintenance (Galar et al., 2016).

Computer maintenance management systems (CMMS) and condition monitoring (CM) systems are two main systems deployed in maintenance departments. CMMS are a great organisational tool and the core of traditional maintenance record-keeping practices while CM systems are capable of directly monitoring asset components parameters. However, the attempts to link observed CMMS events to CM sensor measurements have been fairly limited.
in their approach and scalability. Moreover, information from SCADA which is mainly used in operation for supervisory purposes is seldom fused with the data mentioned above. Bjorling et al. (2013) indicated that all attempts to integrate CMMS, CM and maintenance knowledge management are going to be a key part of maintenance technology in the future, and pointed out that currently this integration consists of a common framework for data exchange, however, no real relations and context information is extracted from the huge amount of data included in these data warehouses.

Predictive analytics information can be distinguished into two sets of information, namely, CM and context. Estimation of health state of monitored equipment utilises the CM data while the context provides support to understand it. Context information consists of factors that affect health state estimation and degradation processes. Examples of factors that belong to the first context group are type of used sensors, acquisition parameters and operational conditions at measurement time. Schmidt et al. (2016) provided an overview of different context modelling techniques and their usage in predictive maintenance.

The purpose of this paper is to exemplify and discuss the context-based approach in a real word setup. It is based on an industrial case study, conducted in a company in manufacturing industry. The remaining structure of the paper is as follows: Section 2 provides brief overview of related works; applied research methodology is presented in Section 3; Section 4 describes performed case study; the findings are presented in Section 5; finally, Section 6 outlines the conclusions and discusses the future work.

2. Related work

Context awareness in industrial applications attracts more attentions in recent years. In (Dannecker et al., 2011) the context-aware approach has been used in energy domain for predicting the future load. The prediction model parameters are stored in repository with context in which they were valid; this allows to retrieve them when similar context occurs.

Thaduri et al. (2014) presented a computational intelligence framework for context-aware decision making to demonstrate the utilisation of soft computing techniques in context-aware industrial areas. Johansson et al. (2014) presented a concept of context-driven prognosis for RUL based on fingerprint and available operational data. A fingerprint consists of data obtained in standardised way and represents the status of a machine. Changes in it corresponds to degradation of the machine and can be correlated with the operational data that represents the way the machine has been used.

Galar et al. (2015) proposed a hybrid model-based maintenance decision system where operating conditions are related to degradation accumulation in a system with consideration of context-driven aspects. It combines information from the expertise of the maintenance workers, physical models of degradation based on known damage mechanisms and the data-driven models.

Al-Dahidi et al. (2016) reported new data-driven approaches to capitalise the information coming from the CM data of heterogeneous fleets of equipment installed worldwide and experiencing different operational conditions for improving the RUL estimation. The proposed approach has been validated in simulated cases of aluminium electrolytic capacitors and aircraft engine turbomachinery.

In Mauro et al. (2015) a model-based simulation has been performed to assess how different parameters, i.e. kinematic limits of a jerk, acceleration and velocity as well as a proportional gain of position control loop of the control affect the expected life of the ball screw of feed drive. Dependencies between those parameters, machine response time and expected ball-screw time have been indicated. Expected life was calculated according to ISO 3408 (ISO, 2006). The analysis was performed to provide a general instrument for the machine tool user to set the controller parameters in order to optimise the balance between productivity, which is strictly connected to axis performance, and ball screw life.
However, not much research can be found that correspond to real industrial setups. Moreover, integration of the maintenance works into a context remains as a challenge and requires further investigation.

3. Methodology
To carry out this research the case study research strategy has been adopted. According to Yin (1984): “A case study is an empirical inquiry that investigates a contemporary phenomenon within its real-life context, especially when the boundaries between phenomenon and context are not clearly evident”. According to Oates (2006), a case study is characterised by: focus on depth rather than breadth, natural setting, holistic study, and multiple sources and methods.

There are three basic types of case studies (Yin, 1984): exploratory, descriptive and explanatory. An exploratory study is performed to define the questions or hypotheses to be used in a subsequent study. A descriptive study leads to rich, detailed analysis of a particular phenomenon and its context. An explanatory study aims to explain why events happened as they did or particular outcomes occurred.

Our research is conducted as the descriptive study, where available sources of information are identified and analysed. Analysed phenomenon is a degradation process in natural industrial setup and its context. An outcome of this research is to be used in following explanatory study that will investigate why the particular failure occurred with the aim to predict future failures or affect the time of the future failure.

The selection of cases was performed in multiple steps. The type of the selected component was based on typical instances in manufacturing industry. In other words, linear axes with ball-screws are typical components of machine tools. In one of the involved companies, it was possible to obtain a history of condition monitoring data related to the health state of linear axes. This aspect determined the main area of the study. Finally, a particular type of machine has been selected with the considerations that:

- machines of the selected type should be distributed over multiple production lines; and
- some instances should be installed on a production line with convenient access.

In our case study, 29 machines of the same type distributed over four production lines are included, and over 60 individual instances of ball-screws for linear X-axis are considered.

4. Case study
This paper presents a case study performed in machining area in an automotive manufacturing plant. In a machine tool, two subsystems responsible for the accuracy of the machine can be distinguished. One is related to cutting process that includes cutting tool and main spindle, while the other is responsible for positioning. There has been not much research focussed on the second area in comparison to the main spindle and cutting tool. However, as Verl and Frey (2010) indicated, “The efficiency and reliability of ball screw feed drives is a major issue concerning the productivity of modern machine tools”.

In the presented research, the machine tool subsystem related to the positioning is considered with a focus on linear drive and ball-screws.

4.1 Available data
There are several ICT systems that create, process and store data related to maintenance: CMMS, SCADA and CM systems.

4.1.1 From CMMS. Asset data information about machine tools across factory (a taxonomy of the assets) includes: types of machines and their locations across production
lines; hierarchical structure of machine tool with the division into units, subunits, components and spare parts.

Work orders (WO) include information regarding machine/unit/component on which maintenance action was performed; type of maintenance action; descriptions (symptoms, comments on performed actions); list of acquired spare parts.

4.1.2 From SCADA. In SCADA system, information about production process are gathered. For each station information about performed cycles includes processing time, waiting time, produced variant and reasons for stop.

4.1.3 From CM. For monitoring of machine accuracy and health status of axes, periodic off-line measurements are performed by using a ball-bar measuring device. In this test, the geometric errors present in machine tool are measured. It allows detecting inaccuracies induced by its controller and linear-drive system (Kuric et al., 2013).

Ball-bar measurement (BBM) indicates the health status of the machine axis. An example of the measurement result from a machine tool with some issues is presented in Figure 1. Each single test corresponds to two axes – a planar motion. Performance of the axis depends not only on the ball screw but also other components like end-bearings, bearing housing, control system, etc.

Several features are extracted from the measurement, to mention some: circularity, backlash, reversal spikes, lateral play, cyclic error and servo mismatch.

4.1.4 From reports. There are also available reports from ball-bar CM measurements. Those reports are created when symptoms of degradation or malfunction are observed in data. Based on the analysis performed by expert, suggestion to inspect or replace components of specific linear axes is provided. Moreover, some of the reports from measurements that have been performed confirm that maintenance action solved the problem, includes the analysis of replaced components. Those reports depict the real damage to the components, how severe it was and in some cases indicate the potential cause that initiated the degradation.

4.2 Physics of failure

According to ISO 3408 (ISO, 2006) nominal life expectancy $L$ of a ball screw based on material fatigue can be estimated as presented in Equations (1)-(3):

$$L = \left( \frac{C_a}{F_{ma}} \right)^3 \cdot 10^6$$

![Figure 1. Result of ball-bar measurement (BBM) obtained with use of Renishaw® measuring system](image)
\[ F_{ma} = F_{pr} \left(1 + \frac{F_m}{3F_{pr}}\right)^\frac{3}{2} \]  
\[ F_m = \sqrt[3]{\frac{q_1 \cdot n_1 \cdot F_{1}^3 + q_2 \cdot n_2 \cdot F_{2}^3 + \cdots + q_n \cdot n_n \cdot F_{n}^3}{q_1 \cdot n_1 + q_2 \cdot n_2 + \cdots + q_n \cdot n_n}} \]  

where \( C_a \) is dynamic load capacity, \( F_{ma} \) is equivalent mean load, \( F_m \) is mean load, \( F_{pr} \) is preloading tension, \( F_i \) is trust, \( n_i \) is speed, \( q_i \) is time percentage. An extended form of Equation (1) presented in Equation (4) includes additional factor \( f_w \) that correlates life expectancy with different operational conditions:

\[ L = \left(\frac{C_a}{f_w \cdot F_{ma}}\right)^3 \cdot 10^6 \]  

The value of \( f_w \) can vary in ranges from 1-1.2 for smooth movement without impacts up to 2-3.5 for movements with high velocity and strong vibrations and impacts.

4.3 Additional monitoring

Over already recorded and stored data, an online system to acquire information directly from linear-drive controllers has been deployed. The selected machine tool controller has the capabilities to configure and record selected parameters. However, there are limitations regarding the length of recording and negative effects on performance of the human machine interface of the machine. An external acquisition system is implemented to overcome those issues. It enables the online monitoring of torque and velocity applied in linear axes of the selected machine tool. Those data have been configured with respect to ball-screw fatigue-based degradation model (ISO, 2006).

4.4 Data acquisition

At initial stage safety and security issues do not allow direct connection between the implemented framework and the mentioned ICT systems. For the purpose of this case study, data has been imported through CSV and Excel files. The architecture of implemented data acquisition and processing is presented in Figure 2.

4.4.1 Data description. Data from CMMS and SCADA systems are available through user interfaces. It is possible to export those in CSV/Excel formats. BBMs data are stored in XML files, with raw recorded measurements, as well as calculated predefined indicators.
Following data has been imported to a local SQL database: WO, spare parts acquisition; machine tools structure; machining cycle information; ball-bar recordings and indicators parsed from the XML files.

4.4.2 Machine accuracy CM. Machine accuracy is periodically measured by performing a volumetric test with use of ball-bar measuring equipment. Acquired data are stored in XML files. One complete test consists of six measurements and is stored in six separate files. Those measurements are from runs in three planes repeated for two different feed rates, namely, low and high. Each measurement covers running in the clockwise and counterclockwise directions. In the presented work, a simple tool has been developed to parse folder structure and XML files, to import measurement data into a relational database.

4.4.3 Data from axes controller. In the selected machine tool, the controller does not allow obtaining internal parameters directly through the digital interface without affecting the performance of GUI. However, each servo drive provides 2 analogue output channels that could be configured to provide values of controller’s internal variables. It uses 8-bit D/A with a 4 kHz refresh rate. The refresh rate is consistent with working frequency of inner control loop of torque stabilisation. Those signals are acquired with use of acquisition card with 12 bit A/D converter, connected through a USB interface to a portable computer placed in a control cabinet with the capability for remote access.

Signals from three main axes, namely, X, Y, Z are acquired simultaneously with the sampling frequency of 100 Hz for continuous monitoring, and 4 kHz for periodic detailed analysis. In Figure 3, an example of recorded data from one axis for one working cycle is presented.

4.4.4 Sound measurements. To test other possible sources of information for CM of linear axes, in addition to previously mentioned data and measurements, sound has been recorded with use of handheld data acquisition device. Several recordings of 10-minute in length with 25 kHz sampling frequency has been acquired. The microphone was located outside the machine tool in proximity to the compartment with main axes.

**Figure 3.**
Position (a) and driving torque (b) of machine tool’s axis from online monitoring system.
4.5 Processing
In this section, the performed processing and analysis on the acquired data are presented.

4.5.1 Component instances. By analysing WO and spare parts acquisition unique instances of ball-screws can be created. Those instances have been grouped into: ball-screws that have already been replaced (failed), and ball-screws that are still in operation. The record for each instance contains information about the installation date as well as the replacement date of past instances. Among considered 29 machines of the same type, 65 instances of ball-screws for X-axis have been identified.

4.5.2 BBM. To assess the health state of a linear axis several features are considered including circularity and the presence of oscillations/vibrations in recorded measurements. However, these vibrations are evaluated only by experts through the plot, and no feature related to this is calculated.

A root mean square (RMS) feature for this type of measurement has been proposed and implemented according to Equations (5)-(8):

\[
\text{RMS}_{\text{bbm}} = \sqrt{\sum_{i=\text{begin}}^{\text{end}} \text{bbm}_i^2 / (\text{end} - \text{begin} + 1)}
\] (5)

\[
\text{RMS}_{\text{bbmX}} = \text{RMS}_{\text{bbmXY}} - \text{RMS}_{\text{bbmYZ}} + \text{RMS}_{\text{bbmZX}}
\] (6)

\[
\text{RMS}_{\text{bbmY}} = \text{RMS}_{\text{bbmXY}} + \text{RMS}_{\text{bbmYZ}} - \text{RMS}_{\text{bbmZX}}
\] (7)

\[
\text{RMS}_{\text{bbmZ}} = -\text{RMS}_{\text{bbmXY}} + \text{RMS}_{\text{bbmYZ}} + \text{RMS}_{\text{bbmZX}}
\] (8)

where begin and end are, respectively, indexes of the first and last sample of considered path in recorded data, \(\text{RMS}_{\text{bbm}}\) represents calculated feature, indexes X, Y, Z indicate main axes while pairs XY, YZ, ZX indicate planes in which individual test has been performed.

A simple tool of this framework has been implemented to make those calculations and return results into the database for further use. The proposed feature has been aggregated with obtained information about instances of the ball screw. Figure 4 visualises the values of the feature in respect to a relative point of the ball-screw lifetime on which the measurement has been taken for several instances of ball-screws component.

4.5.3 Controller data. The first analysis of data from axes controller consists of histogram analysis as shown in Figure 5. This could be used as a context factor in the
comparison between different machines. According to ISO 3408 ball-screw standard (ISO, 2006), velocity and torque are factors that affect the wear process.

In addition, with consideration of energy efficiency in sustainable manufacturing, acquired data are used to compute mechanical energy delivered to machine's axes. As indicated by Mori et al. (2011) spindle rotation and servo-driven axis motion are the major components of machine tool power consumption. Analysis of energy consumption for the same machining operation on different days revealed the phenomenon that could be expected, however, it gives new perspective. Energy in the axis per machining cycle has been visualised for the following two days, named A and B, respectively, in Figures 6 and 7. Day A corresponds to the case when there was no production on the previous day, and during the day there was not much disturbance. Following day B depict the case when the day before production was running and ended with low energy level for the cycle. However, during this day, there were disturbances in processing cycles in form of longer waiting times.

Similar changes in energy level are observed on other days, as well as for all three main axes of the machine tool. The reason of this behaviour has not been verified yet. However, it
is suspected that thermal effects are responsible for this. Some observations from obtained characteristics are as follows. Each additional break during the work shift increases energy level for the following operation, which is leading to some practical implications. This phenomenon should be considered when performing CM measurements as it may affect the measurement results.

Furthermore, based on the acquired monitoring data and technical documentation of the machine the life expectancy has been calculated according to Equations (2)-(4). The nominal life expectancy in revolutions, has been converted into years, with consideration of working days, number of machining cycles per day and revolutions per cycle. Results from calculations for assumed different value of factor $f_w$ are presented in Table I, while statistics of real lifetime of ball-screws from the case study is presented in Table II. The challenge is to identify in advance what value of $f_w$ factor should be applied in each individual case if this theoretical model is going to be applied.

4.5.4 SCADA data. Knowing that stops affect working conditions, those information can be obtained from cycle time measurement. In Figures 8 and 9, a distribution of times between starts of following cycles is presented. It is a relative time in respect to the median

<table>
<thead>
<tr>
<th>$f_w$</th>
<th>90% to survive</th>
<th>50% to survive</th>
<th>10% to survive</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>16.8</td>
<td>83.8</td>
<td>234.7</td>
</tr>
<tr>
<td>1.2</td>
<td>9.7</td>
<td>48.5</td>
<td>135.8</td>
</tr>
<tr>
<td>1.5</td>
<td>5.0</td>
<td>24.8</td>
<td>68.6</td>
</tr>
<tr>
<td>2</td>
<td>2.1</td>
<td>10.5</td>
<td>28.3</td>
</tr>
<tr>
<td>2.5</td>
<td>1.1</td>
<td>5.4</td>
<td>15.0</td>
</tr>
<tr>
<td>3.5</td>
<td>0.4</td>
<td>1.9</td>
<td>5.48</td>
</tr>
</tbody>
</table>

Table I. Theoretical life expectancy for a new ball screw in considered machine tool

<table>
<thead>
<tr>
<th>Monitored machine – single instance</th>
<th>Population of 45 instances</th>
</tr>
</thead>
<tbody>
<tr>
<td>10 years</td>
<td>90th percentile</td>
</tr>
<tr>
<td>10 years</td>
<td>0.8 year</td>
</tr>
</tbody>
</table>

Table II. Real lifetime of ball-screws
of processing times. Calculations have been performed individually for each machine. Presented machines are from the same production line, A.1 and A.2 perform in parallel one operation while B.1 and B.2 perform in parallel another operation. Deviation of median processing times for all those machines is within range $\pm 1.5$ per cent.

The increase for value range 15-20 corresponds to stops over night while last values in histogram correspond to longer stops such as weekends and holidays. Differences between machines in respect to short cycle time disturbances is presented in Figure 9.

Moreover, difference in machine utilisation between instances has been noticed. The difference in averaged machining time per day for individual machine could deviate from $-20$ to $+50$ per cent in respect to the averaged utilisation of all machines.

4.5.5 Sound measurements. By analysing spectrogram, some band frequencies with noticeable energy variation over time can be identified. Recorded sound has been correlated with data from axis controller. Figure 10 shows sound energy in frequency band 935-1560 Hz in solid blue line and an absolute value of X-Axis velocity with the direction of motion indicated by the type of line.

The observations that an operator can make that audible sound appearing during operation is related to the movement of the machine’s X-axis, can also be retrieved from the analysis of those data.
4.6 Issues in real data

Sometimes, it is observed that the indicated object in the reported/Performed maintenance WO is not as per the required level of details for the component, units and machines. In that case, an object has to be identified from spare parts indicated in the WO and the description provided in free text form.

As an example, when end-bearing has been replaced with an indication that maintenance action has been performed on a machine level, real replaced component can only be identified by WO description, as the same type of end-bearing is used in all three main axes of the machine tool.

When the BBM is performed during maintenance work related to the replacement of a ball screw it is difficult to automatically assign it. Detailed information when the measurements have been taken during performed maintenance action are required to decide if a measurement should be assigned to an old or newly installed instance of ball screw or should be discarded.

4.7 Information visualisation

The user interface has been developed to browse through and visualise the acquired information. In the screenshot presented in Figure 11, there are panels to browse
through: machines; machine structure with decomposition to units, subunits and components; and available indicators obtained from CM. The charts in the main window are presenting: trend of selected indicator; maintenance WO and acquired spare parts; and machine utilisation indicated by the number of machining cycles per time unit. It allows comparing the performed maintenance actions and replaced components with CM indications.

5. Discussions
To apply context-based prediction modelling with utilisation of fleet data, it is important to identify which operational conditions vary over time as well as what makes the differences between considered units within the fleet.

In the analysed machine, if energy delivered to axis per machining cycle is considered, the difference between steady working conditions and state after cold start could differ more than 25 per cent. Level for cold start differs from one day to another. Moreover, short stops affect working conditions as well. This brings several implications. As conditions for each machining cycle are different, therefore, it is important to continuously monitor working conditions, not only a number of machining cycles and a profile of cycle averaged from the limited number of runs.

The impact of tracking the manufacturing process of a machine is important in all stages of the process. Identifying the operational condition’s factor $f_w$ can help in obtaining the more accurate life estimation of the ball screw. The factor explains the survival rate of the ball screw and operational conditions as the usage and handling of the machine. Those working conditions can also affect CM measurements that should be taken in the same operational conditions.

After analysing the performed work on data acquisition, a semantic framework for relevant information retrieval has been proposed as shown in Figure 12. This work will be reported in more detail in a separate future publication.
6. Conclusions and future work

This paper shows the outcomes from a case study in real-world industrial setting. Multiple sources of relevant contextual information have been identified. The analysis reveals the deviations in operational conditions when the same machining operation is repeatedly performed. Moreover, a new visualisation method of gathered data are proposed to support the decision-making process.

Our future work will focus on using different data mining techniques among gathered information for descriptive and predictive modelling. The techniques from data mining can be used for identifying and classifying the contexts and their respective factors that may affect the degradation process. From the perspective of health evaluation of a machinery or important component, finding critical factors from the measurements can be an important area of research.

References


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1. Introduction

Maintenance plays an important and supportive role in the production. Effective maintenance policy improves quality, efficiency, and effectiveness of manufacturing operation and could influence the productivity and profitability of a manufacturing process [1]. Diagnostics and prognostics are two important aspects in a Condition-based Maintenance (CBM) program [2]. In literature several approaches for machining operation and machine tool condition monitoring have been reported [3].

To improve diagnostics and prognostics for better maintenance decision making, there is a need to better correlate process and inspection data with machine condition to differentiate between process and machine degradation [4]. Generally, diagnostics and prognostics models require significant amounts of historical condition monitoring and event data, as the uncertainty of these models decreases when data become more extensive. The means to synthesise smaller available data sets to generate extensive, representative historical condition monitoring and event data sets remains an open research question [5].

To solve those problems more detail information about manufacturing asset across its lifetime need to be gathered, accessed and processed. Targeting cloud-based predictive maintenance, this research aims at developing a semantic framework for the context-aware approach.

The remainder of the paper is organised as follows. Section 2 reviews background. Section 3 highlights available sources of data and benefits of its aggregation. Proposed semantic framework is presented in Section 4. Section 5 provide an example how this framework can be used to retrieve relevant information. Finally, Section 6 conclude the paper.

2. Backgrounds

2.1. Disparate data sources

Development and implementation of Information and Communication Technologies (ICT) in the industry in past decade brings new possibilities and challenges. More data are gathered, however, stored and processed in disparate and heterogeneous systems as Computerised Maintenance Management System (CMMS) for maintenance record-keeping, Condition Monitoring (CM) for asset health state...
monitoring and Supervisory Control and Data Acquisition (SCADA) systems for monitoring process and controlling the asset.

2.2. Industry 4.0

According to the Federal Ministry of Education and Research, Germany (BMBF) after Monostori [6], “Industry is on, the threshold of the fourth industrial revolution frequently noted as Industry 4.0. This revolution is led by development and implementation of Cyber-Physical Systems. A similar concept is also researched under the name of Cloud Manufacturing. Cloud Manufacturing paradigm is a result of a combination of cloud computing, the Internet of Things, service-oriented technologies and high-performance computing [7]. 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 into the manufacturing cloud are able to offer adaptive, secure and on-demand manufacturing services over the Internet of Things [8].

2.3. Context

Recently a context awareness is an approach gaining more focus from researchers in the field of CBM and predictive maintenance. This well-known concept in some other fields could be beneficial when employed in CBM and Asset Management [9].

2.3.1. Context definition

In predictive analytics, two sets of information can be distinguished namely condition monitoring and context. Condition monitoring data are used to estimate health state of monitored equipment while context information provides support for a better understanding of it. Context information consists of two types of factors: conditions that affect health state estimation, and condition that affects degradation processes. An example of factors that belongs to the first context group is types of used sensor, acquisition parameters, and operational condition at measurement time. Operational conditions and performed maintenance actions are the examples of contextual information belonging to the other group. Overview of different context modelling techniques and its usage in predictive maintenance has been reported in [10].

2.4. Ontology

In computer and information science, ontology determines formal specifications of knowledge in a domain explicit specification of the objects, concepts, and other entities (vocabulary) that exist in some area of interest and the relationships that hold among them [11]. Ontology model O can be described as a set $O=\{C, RS, I\}$, where C is a collection of concepts in the ontology called also classes, I is set of particulars (instances of classes, individuals), and RS is set of relations between two concepts or particulars. Ontology Web Language (OWL) [12] is one of common ontology formalization languages. Reasoning over ontology specified with OWL is done with the use of Descriptive Logics that makes it more powerful than just reasoning within Resource Description Framework (RDF), as more complicated relations can be represented. Moreover, Semantic Web Rule Language (SWRL) [13] extend the capability of OWL to represent knowledge by means of more complex rules. According to [14], 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.

2.4.1. Standards

There are some standardisation initiatives to enable the integration of disparate maintenance IT systems. MIMOSA (Machinery Information Management Open Systems Alliance) [15] is a not-for-profit trade association dedicated to developing and encouraging the adoption of open information standards for Operations and Maintenance in manufacturing, fleet, and facility environments. MIMOSA’s open standards enable collaborative asset lifecycle management in both commercial and military applications. OSA-EAI (System Architecture for Enterprise Application Integration), OSA-CBM (Open Systems Architecture for Condition Based Maintenance), MIMOSA standards are compliant with and form the informative reference to the published ISO 13374-1 standard for machinery diagnostic systems. According to [16] MIMOSA and OSA-CBM are the most evolved standards that cope with CBM technology.
Another standard that provides maintenance taxonomy is ISO 14224: Petroleum and Natural gas industries – Collection and exchange of reliability and maintenance data for equipment. Some typical oil and gas equipment related terms have been categorised as to taxonomy, boundary definition, inventory data and failure modes. These data are specific for each equipment unit. A standardization approach has been applied for classification and subdivision of units. This reduces the total number of different data categories and definitions, while at the same time there are fewer tailor-made definitions and codes for each individual equipment unit.

2.5. Machine Tool condition monitoring

Zhou at al. [17] proposed integrated condition monitoring and fault diagnosis for modern manufacturing system with the use of internal controller signals and sensors. Remote monitoring and maintenance system for thousands of machine tools linked to a central server has been developed in [18]. There exists high potential in knowledge capitalisation in population width approach, as for example existing system reported in [19] connects to over 14 000 machine tools worldwide.

Condition monitoring in [20] dynamically affect the entries in the capability ontology by providing the current status of the machines. If the machine is overloaded or faulty then it will be not shown up in results from a query of the machine that can perform specified task.

3. Valuable data/information

Across industrial ICT systems, there exist a big amount of valuable information from diagnostics and prognostics perspective. To mention some of them:

- Asset related data: information about machine tools across factory – type of machines and their location; hierarchical structure – division into units, subunits, components, spare parts.
- Work orders (WO): machine/unit/component on which maintenance action was performed; type of maintenance action (corrective, preventive); descriptions (symptoms, comments on performed actions); list of acquired spare parts for WO.
- Condition monitoring: vibration, ball-bar measurements; geometry measurements.
- SCADA: number of cycles, type of produced variant.
- Internal Machine Tool Controller data.

The ideal scenario is to have access to all those data and be able to retrieve relevant information, that could be utilised within context-aware approach and provide support for predictive maintenance, see Fig. 2.

Examples provided in following part of the section are based on real data retrieved from ICT systems in one company within the automotive manufacturing industry.

Aggregated information can be presented to the human decision maker in a new way, as depicted in Fig. 3, where trend information from condition monitoring are enriched with indications of performed maintenance actions, and replaced spare parts. Automatic query of information related to specified machine/unit/component will improve interpretation of data by including that information as contextual information.

Fig. 2. Information access for context-aware prediction.

Fig. 3. Aggregation of information from disparate sources in one view: XY, YZ, XZ – trends from ball-bar measurements; MaintMatReq – acquired spare parts; WO – performed work orders.

Fig. 4. Condition monitoring data aligned to component instances.
Querying for components of the same type and associated condition monitoring data can increase the amount of available datasets that can be used to train the diagnostics and prognostics models. In Fig. 4. an example of ball-bar measurements aligned with instances of replaced ball-screws of the same type across the available population of machines is presented. Taking into consideration the type of performed maintenance work (corrective or preventive) involved in the replacement, obtained trends can be differentiated to ones related to actual lifetime, and to ones related to censored lifetime.

Continuously acquired information from machine tool controllers can provide additional contextual information about machine utilisation. As an example in Fig. 5. calculated mechanical energy delivered to machine tool’s linear axes is presented. It is based on on-line acquired information about axes velocities and applied torque. Energy corresponds to the load axes have been exposed to, and could be used as a context information. Despite the same operation is performed, the average energy consumption per cycle varies noticeably.

4. Semantic Framework

Overview of the semantic framework for predictive maintenance is presented in Fig. 6. With the use of ontology base mapping and semantic querying, it allows accessing information from disparate sources. Moreover, provision of a service-oriented data access within the cloud concept allows obtaining the relevant information despite its location.

4.1. Ontology-based data retrieval

To be able to access the local data sources through the domain ontology, there is need to maintain the link between the domain ontology and the data sources. There exist some technology that allows performing this mapping with different autonomy levels.

RDB to RDF mapping language (R2RML) [21], D2RQ Mapping Language [22], RDB2RDF Direct Mapping [23].

After that semantic query language e.g. simple protocol and RDF query language (SPARQL) [24] can be used to retrieve local data represented in RDF (R2RML, D2RQ). Ontology-based information representation and retrieve are similar to the one proposed in the semantic framework presented in [25].

4.1.1. Manual mapping

Manually create a mapping using e.g. R2RML. This is the case when vocabulary and local ontology of RDB differ much from a domain ontology, see Fig. 7.a.

4.1.2. Automatic and semi-automatic mapping

In this case, local ontology is retrieved from RDB by direct mapping. Than ontology, alignment tool has to be applied to automatically generate R2RML file corresponding to this alignment. When two ontologies cannot be fully automatically aligned, there is a need for human intervention to manually modify or add mappings between ontologies, as depicted in Fig. 7.b.

To facilitate the automatic mapping, the standardization of common ontology for data represented in RDBs are needed. Some initiatives in this direction have been mentioned earlier in section 2.4.1.

4.2. Domain ontologies

Domain ontology captures knowledge within the domain, specific area, and perspective. Examples of different perspectives that the same asset in a manufacturing environment can be looked from could be: production, maintenance, quality.

Potential domain ontologies that could be distinguished are: Asset ontology – structure of asset, Functional ontology – performed function, Work Order ontology – performed maintenance actions. In most cases, ontologies overlaps and it allows to make bridges between them and this provides an opportunity to use data and knowledge across linked domains.
However, those bridges if not explicit have to be defined by expert across the domains.

5. Demonstration Case

To illustrate the potential usefulness of proposed approach a demonstration case based on part of data that have been explained in section 3 is presented.

In a relational database of CMMS, there are tables that represent the hierarchical structure of the asset. Data model is depicted in Fig. 8. This model corresponds to ontology’s classes and dependencies presented in Fig.9. Retrieving data stored in RDB, the ontology can be enriched with instances of individuals that corresponds to existing physical machines, units, components and its hierarchical structure.

Additional ontologies that have been creating are Functional ontology presented in Fig.10. and Measurement ontology depicted in Fig.11. A functional ontology defines functions that can be performed by objects. In presented part, there have been defined three functions related to a linear movement that are translations in 3 main directions (Tr_X, Tr_Y, and Tr_Z). Measurement ontology can describe different types of measurements with an indication of what function performance it corresponds to. In depicted case, the ball-bar measurement is represented that corresponds to a measurement in plain created by motion in two main directions at a time.

Ball-bar measurements are retrieved form of XML files. It includes a field that consists of machine_id, an identification number of a machine tool on which the measurement has been performed. It is the same number as Object_ID key in the asset database. This leads to straightforward connections between those ontologies as in Table 1.

The used sameAs property belongs to OWL vocabulary, and indicates that two terms are synonyms, e.g. identify the same class or individual.

Next step in defining ontologies and connections is to map defined functions with objects that are responsible for it. In presented case of machine tool axes it can be done by following a set of rules from Table 2. represented in human readable form (? denotes a variable).

In this case value of one property of an object (has_name) is used to assign the value of another property (has_function). Up to this point following mappings have been performed: measurements to machines, and machines’ components to its functions. Table 3. presents rule specified to map measurement instances with relevant objects within the machine tool hierarchical structure (units or components).
Table 3. Mapping of measurements to corresponding asset objects.

<table>
<thead>
<tr>
<th>Measurement:measures(?measurement,/function)</th>
<th>Measurement:performed_on(?measurement,?objectX)</th>
<th>Object:has_function(?objectY,/function)</th>
<th>Object:part_of(?objectY,?objectX) =&gt; Object:has_measurement(?objectY/?measurement)</th>
</tr>
</thead>
</table>

Now combined ontology can be queried for has_measurement property to retrieve all relevant measurements. For example, for individual corresponding to the X axis of machine A, it will return all ball-bear measurements performed on machine A that has been executed in XY plane and XZ plane, as those measurements involve the motion in X direction.

This approach can be used as a support in selecting suitable diagnostics and prognostics method on its early stages by checking what types of data are available and the amount of available relevant data. Moreover, data from the whole population of identical or similar components could be retrieved. Identical components could be defined as the ones that uses the same spare part. However, data from a population of components cannot be simply aggregate, without consideration of contextual information. It needs to be mentioned, that defining similarity in context domain is not a trivial task.

6. Conclusions

This paper presents important data available within ITC systems in the manufacturing industry that have to be integrated to facilitate improvement in diagnostics and prognostics for CBM. A semantic framework with the use of ontology-based approach for data aggregation is proposed to support context-aware cloud-enabled diagnostics and prognostics in application to the maintenance of manufacturing asset. To indicate potential benefits, some advanced context modelling and prediction method that will be able to utilise the contextual information to improve prediction reliability.

References


PAPER IV
Integration of events and offline measurement data from a population of similar entities for condition monitoring

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In this paper, an approach for integration of data from different sources and from a population of similar monitored entities is presented with evaluation procedure based on multiple machine learning methods that allows selection of a proper combination of methods for data integration and feature selection. It is exemplified on the real-world case from manufacturing industry with application to double ball-bar measurement from a population of machine tools. Historical data from the period of four years from a population of 29 similar multitask machine tools are analysed. Several feature selection methods are evaluated. Finally, simple economic evaluation is presented with application to proposed condition based approach. With assumed parameters, potential improvement in long term of 6 times reduced amount of unplanned stops and 40% reduced cost has been indicated with respect to optimal time based replacement policy.

Keywords: condition monitoring; population-wide data; double ball-bar measurement; feature selection; machine learning

Subject classification codes: include these here if the journal requires them

1 Introduction

Maintenance of manufacturing equipment is essential to ensure productivity and product quality. Jardine, Lin and Banjevic (2006) indicated that diagnosis and prognosis are two important aspects of Condition Based Maintenance (CBM) and consists of three key steps: data acquisition, data processing, and maintenance decision-making step. Diagnostics provides useful outputs on its own, while prognostics relies on diagnostic outputs as for example fault indicators or degradation rates, and cannot be done in isolation (Sikorska, Hodkiewicz and Ma 2011). Implementation of effective prognosis can bring a variety of benefits for industry including increases in maintenance effectiveness and system safety as well as reduced maintenance inspection and repair-induced failure (Bo, Shengkui, Rui et al. 2012). To improve diagnosis and prognosis for complex systems, one possibility is to utilise more data and knowledge obtained from a population of similar systems (Medina-Oliva, Voisin, Monnin et al. 2014). Cloud approach enables usage of data and information from across the manufacturing hierarchy (Gao, Wang, Teti et al. 2015). A number of obtained signals and features can be very large. To obtain relevant feature in an industrial application, it is preferred to perform feature selection automatically without operator intervention (Teti, Jemielniak, O’Donnell et al. 2010). Binsaeid, Asfour, Cho et al. (2009) proposed and applied correlation-based feature selection on features obtained from multiple sensors for tool condition monitoring. Authors indicated that in most cases better results are for a selected subset of features than for all. In (Kang, Islam, Kim et al. 2016) authors proposed an outlier-insensitive hybrid feature selection that employs the filter-wrapper approach. The k-fold cross-validation is used and for evaluation the k-Nearest Neighbour (k-NN) classification accuracy is employed.

Fleischer, Broos, Schopp et al. (2009) presented an analysis of failures of components in machine tools. There are four main component groups responsible for most of the downtimes: drive axes, spindle and tool changer, electronics and fluidics. Drive axes are the one that causes the most downtime with 38% contribution.
Condition monitoring of linear axes can be divided into the online indirect measurement and offline direct measurements. Examples of online approaches are: Verl, Heisel, Walther et al. (2009) proposed approach of using signals available in position controlled drives such as position, speed and motor current to detect wear of drive unit; Feng and Pan (2012) developed a temperature and vibration sensory unit embedded in ball screw nut, to detect different levels of preload through supervised learning of Support Vector Machine (SVM) classifier; Garinei and Marsili (2012) used hall-effect sensor to detect presence of damaged balls in ball-screw; in (Tsai, Cheng and Hwang 2014) authors use accelerometer to monitor ball pass frequency and detect loose of ball screw preload; Lee, Lee, Hong et al. (2015) use vibration signals from accelerometer placed on ball screw nut in laboratory test rig, and detect artificially introduced failures on ball screw race. In (Vogl, Donmez and Archenti 2016) authors developed method to use data from an internal measurement unit for identification of changes in the axis errors due to its degradation. Those approaches are mainly performed in laboratory setup, based on artificially introduced failures.

A well-established method for off-line direct measurement of axes accuracy is double ball-bar (DBB) measurement that was first presented by Bryan (1982) and later standardised in ISO 230-1. Its advantages are low cost, the simplicity of use and robustness (Zargarbashi and Mayer 2006). The DBB test is designed to perform circular trajectory interpolation of two prismatic axes and is mainly applied for three-axis machines. Most of the research that utilises this test is focused on identification of sources of deviation (Kakino, Ihara, Nakatsu et al. 1987), its applications to multi-axis and/or not-prismatic axis (Chen, Dong, Bian et al. 2015, Uddin, Ibaraki, Matsubara et al. 2009, Xia, Peng, Ouyang et al. 2017, Zargarbashi and Mayer 2006), modelling the thermal deviations (Dehnavi, Movahhedy, Naebi et al. 2012, Delbressine, Florussen, Schijvenaars et al. 2006, Florussen, Delbressine and Schellekens 2003), improvement of measurement to dynamic conditions (Archenti, Nicolescu, Casterman et al. 2012), prediction of the machined part accuracy (Archenti 2014). It is hard to find reported research where data from double ball-bar measurements have been used for predictive maintenance. It is mainly used to identify existing problem, not to indicate when the problem can occur.

Most of the approach for prediction works with time trends from run to failure – for each individual instance e.g. like in similarity-based approach presented in (Wang, Yu, Siegel et al. 2008) or in research presented in (N. Gebraeel 2006, Nagi Z. Gebraeel, Lawley, Li et al. 2005). In presented work focus is on analysing data from a population of similar entities. Data are of high dimension, and for each individual unit, only several points on the trend are available.

In the context of emerging cloud approach for prognosis, establishing guidelines for designing prognosis system, including sensor selection, prognostic method selection and intelligent decision, would significantly advance the state of prognosis (Gao, Wang, Teti et al. 2015). In this paper, an approach for the integration of data from different sources and from a population of similar monitored entities is presented. Key part of the approach is an evaluation procedure (see Fig.1) that allows selection of a proper combination of methods for data integration and feature selection applied in earlier steps. Presented evaluation methodology could be applied in automatic method selection step of predictive maintenance in a cloud environment approach presented by Schmidt, Wang and Galar (2017). Presented approach is exemplified based on application to the real-world industrial case with consideration of population of the linear axes. Data cover 4 year period and are gathered from machining area.
Remaining of the paper is organised as follows: Section 2 presents the methodology; Section 3 explains in details application of the methodology to a case study; Section 4 presents results and discussion including some Monte Carlo simulation results based on an assumed cost model to illustrate the economic benefits of proposed approach; Finally, Section 5 highlights the conclusions and indicate our future work.

2 Integration methodology

Applied methodology for integration of data from different sources and from a population of similar monitored entities consists of several steps, namely: domain selection, trend aggregation, feature selection, dimensionality reduction, and evaluation method. Those steps are described in more details in following sections.

2.1 Domain selection

The first proposed step is to select the proper domain that minimises the variability in lifetimes within the population. It is assumed that population is heterogeneous, understood as being undergone different operational conditions.

Based on the acquired information, the lifetime can be expressed in time domain – calendar based or usage based. Usage itself can be represented in different ways e.g. operational time, a number of performed cycles, or be a function of specific events e.g. starts, stops.

It is assumed that performing analysis in the domain that provides lower variability is more beneficial – e.g. in reliability analysis where MTTF (mean time to failure) is estimated, lower variability implies lower dispersion of real times to failure from estimated mean value.

A commonly used measure of variability is a standard deviation that is expressed in the same units as a measured quantity. To compare variability between measures expressed in different units, a unit-less – relative measure of variability is required. The coefficient of variation $c_v$ is one of such measures defined as the ratio of the standard deviation $\sigma$ to the mean as in Eq. 1.

$$c_v = \frac{\sigma}{\bar{x}}$$

It is regarded as a measure of stability or uncertainty and can indicate the relative dispersion of data in the population to the population mean (Pang, Leung, Huang et al. 2005).

Weibull distribution is widely used in reliability analysis of technical equipment, as in the wide range of cases it describes well the failure rate. Two-parameter Weibull distribution $w(x)$ can be parametrised as in Eq. 2.

$$w(x) = (k/\lambda)(x/\lambda)^{k-1}e^{-(x/\lambda)^k}$$
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where \( k \) is a shape parameter, \( \lambda \) is a scale parameter, and variable \( x \) is used to express the life of entity.

The coefficient of variation of the two-parameter Weibull distribution is expressed as in Eq. 3.

\[
c_v = \sqrt{\Gamma(1+2/k)/\left(\Gamma(1+1/k)\right)^2} - 1
\]

where \( \Gamma \) is the gamma function.

For a family of Weibull distributions, \( c_v \) depends only on the shape parameter \( k \) and is a monotonically decreasing function (see Figure 2). The bigger the shape parameter \( k \) the lower the \( c_v \) value.

Figure 2. Coefficient of variation of Weibull distributions depending on the shape parameter \( k \).

2.2 Alignment of trend data

In applications where degradation process is not affected by the cumulative damage, a linear functional form may be used (Alaa H. Elwany and Gebraeel 2008), while the exponential functional form is more suitable for cases where the initial degradation level accelerates the subsequent degradation. This type of degradation process is common in many mechanical systems, especially rotating machinery and rolling element bearing applications (A.H. Elwany 2012). Exponential models have been applied in (N. Gebraeel 2006, N. Gebraeel, Lawley, Liu et al. 2004).

In some cases, at begin of life, there are no symptoms of degradation. This period varies significantly from unit to unit. When degradation process is initialized, the time to failure does not vary so significantly for exponential-like degradation process. This behaviour could be observed in accelerated life tests performed on bearings in (Medjaher, Tobon-Mejia and Zerhouni 2012). In those cases, all CM measurements performed on the components from a population that failed can be presented with the use of a \( ttf \) (time to failure), see Eq. 4. A similar concept of rearrangement was presented in (Wang, Yu, Siegel et al. 2008).

\[
ttf_{ij} = T_j - t_{ij}
\]

where \( ttf_{ij} \) is time to failure from the time of measurement \( i \) performed on unit \( j \), \( T_j \) is a lifetime of unit \( j \), \( t_{ij} \) is a time when measurement \( i \) was performed on unit \( j \) in respect to begin of unit \( j \). A similar approach for aggregation of data from a population of monitored objects has been also presented by Prytz, Nowaczyk, Rögnvaldsson et al. (2013). Example of this rearrangement, based on artificial data is illustrated in Fig. 3.
2.3 Selection of features

In presence of multiple sources of data, wide range of features that can be extracted from the signal, there is a need to identify which features are more promising to be used. Feature selection should be performed without operator intervention (Teti, Jemielniak, O’Donnell et al. 2010).

Kohavi and John (1997) made a distinction between filter and wrapper methods for feature selection. Filter methods make a selection based only on data alone applying some heuristic evaluation. Wrapper methods use machine learning algorithms to evaluate selected features in cross-validation process, and some search algorithm to find a subset of optimal features.

An example of wrapper method is correlation-based feature selection (CFS) well described and evaluated by Hall (1999) and applied in tool condition monitoring by Binsaeid, Asfour, Cho et al. (2009). In our research, this method has been implemented for comparison with other proposed methods. In the first step, all continuous features are discretized using technique presented in (Fayyad, Piatetsky-Shapiro and Smyth 1996). The same technique is used in algorithms for decision tree C4.5 for making a decision about splitting branches. Then symmetrical uncertainty coefficient (SUC) defined as in Eq. 5 is used for measuring feature-feature correlation, as well as feature-class correlation by treating the class as a feature. $H(Y)$ is the measure of the information entropy of feature represented as a random variable $Y$ defined as in Eq. 6, while $H(Y|X)$ defined by Eq. 7 is the conditional entropy of feature $Y$ given the occurrence of $X$.

$p(Y=y)$ represents the probability that random variable $Y$ will take value $y$, while $p(Y=y|X=x)$ is conditional probability that feature $Y$ will have value $y$, given that feature $X$ has value $x$.

\[
SUC = 2 \frac{H(Y) - H(Y|X)}{H(Y) + H(X)}
\]  

\[
H(Y) = - \sum_{y \in Y} p(Y = y) \log(p(Y = y))
\]
\[
H(Y|X) = - \sum_{x \in X} p(X = x) \sum_{y \in Y} p(Y = y|X = x) \log(p(Y = y|X = x))
\] (7)

\[
M_s = \frac{N \overline{r_{cf}}}{\sqrt{N + N(N-1) \overline{r_{ff}}}}
\] (8)

\(M_s\) is a heuristics used to evaluate a selected subset of features, expressed as in Eq. 8 where: \(\overline{r_{cf}}\) is the average feature-class correlation, \(\overline{r_{ff}}\) is the mean feature-feature correlation, and \(N\) is a number of features. Then greedy hill-climbing search algorithm, as in (Hall 1999), is applied to find a feature subset that maximises the \(M_s\). Search algorithm starts with a feature that has the highest correlation coefficient with classes, and then add next feature that makes the highest improvement. Adding is continued as long as there is an improvement.

Some feature selection methods are model based. When the linear correlation can be assumed, e.g. Pearson correlation coefficient (Eq. 9) could be used (Quan, Zhou and Luo 1998).

\[
\rho = \frac{\left( \sum_i (x_i - \bar{x})(y_i - \bar{y}) \right)}{\left( \sum_i (x_i - \bar{x})^2 \cdot \sum_i (y_i - \bar{y})^2 \right)}
\] (9)

The coefficient of determination provides a statistical measure, of how well a model approximates the real data points. In (Jemielniak, Kwiatkowski and Wrzosek 1998), the coefficient of determination has been used, to avoid uncertain assumption about the dependency of a feature on tool wear.

\[
R^2 = \frac{\left( \sum_i (y_i - \bar{y}) - \sum_i (y_i - \bar{y}_i) \right)}{\sum_i (y_i - \bar{y})^2}
\] (10)

where \(y_i\) \(\bar{y}\) are single and mean value of the feature respectively, \(\bar{y}_i\) is feature value estimated based on a proposed model.

From measurement performed on failed components, two sample sets could be taken – from the period just before the end of life, and from period fare from the end of life. The first set is assumed to represent the fault behaviour, the second one is assumed to be of good health. Scheffer and Heyns (2004) for feature selection proposed usage of correlation coefficient (Eq. 9) together with statistical overlap factor (SOF) (Eq. 11) applied to data samples from new and worn tool conditions. The higher value of both the better.

\[
\text{SOF} = \left| \frac{\bar{x}_1 - \bar{x}_2}{\sigma_1/2 + \sigma_2/2} \right|
\] (11)

However, these approaches assume that the degradation model is known. The proposed approach is to use statistical hypothesis testing methods to verify if there is a statistically significant difference in values of the feature between samples from good health and from the end of life.

Welch’s \(t\)-test is a two-sample location test which is used to test if two populations have equal means. Welch’s \(t\)-test is more reliable then Student’s \(t\)-test when the two samples have unequal variances and unequal sample sizes. The test statistics is presented in Eq. (12). Satterthwaite’s approximation (Satterthwaite 1946) can be used for estimation of the degree of freedom.

\[
t = \frac{\bar{x}_1 - \bar{x}_2}{\sqrt{\frac{\sigma_1^2}{n} + \frac{\sigma_2^2}{m}}}
\] (12)

If normal distribution cannot be assumed then non-parametric test should be applied. One possibility is
Mann–Whitney U test (Mann and Whitney 1947) (also called the Wilcoxon rank-sum test or Wilcoxon–Mann–Whitney test). It is a nonparametric test to check if it is equally likely that a randomly selected value from one sample will be less than or greater than a randomly selected value from a second sample. Unlike the t-test and the Welch-t test, it does not require the assumption of normal distributions, and it is nearly as efficient as the t-test on normally distributed samples. In this paper, statistical feature selection (SFS) is applied based on this test. The statistics applied in the test is used to rank features.

If multiple failure modes are expected, or nonlinearity is present, then, e.g., Kolmogorov-Smirnov test can be used to test for difference in distribution between signals from good and failing components. The two-sample Kolmogorov-Smirnov test (Massey 1951) is a nonparametric hypothesis test that evaluates the difference between the cumulative distribution functions (CDFs) of the distributions of the two sample data vectors. The two-sided test uses the maximum absolute difference between the CDFs. This test has been applied in (Prytz, Nowaczyk, Rögnvaldsson et al. 2015) to select a predetermined number of relevant feature.

When data are aggregated from a population of machines with the presence of multiple failure modes and multiple failing components than it is hard to make normality assumption, as visualised in Fig. 4.

![Figure 4](image)

Figure 4. Numerical simulations, histograms representing distributions, with fitted Gaussian distribution, of: a signal with Gaussian noise; b signal with Gaussian noise and influence of linear degrading component, c and d signals with Gaussian noise and influence of exponentially degrading components.

There are several methods for testing if samples have been drawn from a population with a normal distribution. In (Yap and Sim 2011) the Anderson–Darling, Kolmogorov–Smirnov, Lilliefors, and Shapiro–Wilk tests have been compared. It has been indicated that Shapiro–Wilk has the best power for a given significance, followed closely by Anderson–Darling test (Anderson and Darling 1954).

### 2.4 Dimensionality reduction

As presented earlier, the feature selection step aims to reduce dimensionality of data by leaving only relevant one. Dimensionality can be also reduced by projecting data into lower dimensional space. Principal component analysis (PCA) is a multivariate statistical analysis technique which is very commonly used for dimension reduction, fault detection, and isolation (Halligan and Jagannathan 2011). Comparative study of PCA approaches in process monitoring and fault detection has been presented in (Tien, Lim and Jun 2004). In (Malhi and Gao 2004) a PCA-based approach for selecting the most representative features for the classification of defective components of rolling bearings was presented.

In this work, Independent Component Analysis (ICA) technique is also applied with the use of Fast ICA (Hyvarinen 1999) algorithm. ICA is one of method for blind source separation (BSS), which consists of recovering the contributions of different physical sources (Eq. 13) from a finite set of observations (Eq. 14), without any a priori knowledge on the sources and independently from the propagation medium (Gelle, Colas and Serviere 2001). The assumption for ICA is that no more than one signal source can have a Gaussian distribution. In presence of the measurement noise e (Eq. 15), that is assumed to be
Gaussian, all remaining signal sources have to be non-Gaussian and independent to be separated. The goal of ICA is to find matrix $B$ that provides a transformation from observation space to signal source space (Eq. 16).

$$X(t) = [x_1(t), \ldots, x_n(t)]$$  \hspace{1cm} (13)

$$Y(t) = [y_1(t), \ldots, y_m(t)]$$  \hspace{1cm} (14)

$$Y(t) = AX(t) + e = \sum_{i=1}^{m} a_{ki}(t)x_k(t) + e$$  \hspace{1cm} (15)

$$\hat{X}(t) = BY(t)$$  \hspace{1cm} (16)

One of the approaches is to find matrix $B$ that maximises the non-Gaussianity of the $X$. Mixture of non-normal distributions is more Gaussian than each individual signal. It corresponds to finding rotation matrix that will align preprocessed observation signal $Y_w$ with source signal $X_w$ presented in Fig. 5. It can be achieved by minimising the Gaussianity of the rotated signals. In (Hyvarinen 1999) some approaches for measuring how far the given distribution is from Gaussian distribution and corresponding metrics are described.

![Figure 5. Background of ICA presented based on joint distributions of two independent signal sources with uniform distribution and two observation signals: $X$ – true non-Gaussian source signals, $Y$ – observed signals, $X_c$, $Y_c$ centred true and observed signals respectively, $X_w$, $Y_w$ whitened centred true and observed signals respectively.](image)
Preparation consist of centring the observation signals $Y(m \times N_t)$ as in Eqs. 17 and 18.

$$\bar{y}_i = \frac{1}{N_t} \sum_{j=1}^{N_t} y_{i,j}$$

(17)

$$Y_C : \bar{y}_{c,i,j} = y_{i,j} - \bar{y}_i$$

(18)

Whitening (Eqs. 19-21) is to make the variance equal to 1, and it is achieved with the use of singular value decomposition of the covariance matrix.

$$E = \text{singular vectors}(\text{cov}(Y_c))$$

(19)

$$D = \text{singular values}(\text{cov}(Y_c))$$

(20)

$$Y_W = ED^{-1/2} E^T Y_C$$

(21)

The main steps of Fast ICA procedure: initialise matrix $W$ with weights vectors, e.g. with random values (Eq. 22); calculate new weights for each signal (Eq. 23); normalise vector-wise to unit length (Eq. 24) and perform singular value decomposition (Eq. 25) to get set of independent vectors; calculate the convergence (Eq. 26). Repeat steps described by Eqs. 23 to 27 until an end condition is met i.e. $d$ smaller than threshold or reached the number of iteration. Approximation of source signals is then calculated as in Eq. 28.

$$W : w_i = \{r_{i,1}, r_{i,2}, \ldots r_{i,m}\}, i = 1, n$$

(22)

$$w_i^# = E[Y_W g(w_i^T Y_W)] - E[g(w_i^T Y_W)] w_i$$

(23)

$$\hat{w}_i^# = w_i^#/\|w_i^#\|$$

(24)

$$\hat{W} = E_{w_i^#} D^{-1/2} E_{w_i^#}^T \hat{W}^#$$

(25)

$$d = \max_{i=1,n} \left(1 - |\hat{w}_i \cdot w_i|\right)$$

(26)

$$W = \hat{W}$$

(27)

$$X_W = W Y_W$$

(28)

Function $g(u)$ and its derivative $g'(u)$ are defined as in Eq. 29 for kurtosis base measure of non-Gaussianity or Eq.30 that is based on the estimation of the quantity of differential entropy, called negentropy, as a measure.

$$g(u) = 4u^3 \Rightarrow g'(u) = 12u^2$$

(29)

$$g(u) = u \exp\left(-u^2/2\right) \Rightarrow g'(u) = \left(1-u^2\right) \exp\left(-u^2/2\right)$$

(30)

In (Arifianto 2011) the ICA has been applied to source separation for machine fault detection in the presence of background noise. In (Schimert 2008), the comparison of results from PCA and ICA with
application to fault detection in aeroplane maintenance has been presented. The initial evidence indicates that trends based on ICA decomposition indicate degradation earlier than the one based on PCA.

Usage of this method is proposed because of characteristics of the double ball-bar measurements. It is assumed that failures on each individual axis are independent of each other. Every single measurement is a mixture of contributions from two axes. Features obtained from measurements can be a group in triplets ($F_{kXY}$, $F_{kYZ}$, $F_{kZX}$), that each corresponds to the same entity $F_k$ measured on three combinations of two out of three axes ($XY$, $YZ$, $ZX$). The goal is to obtain a set of new features ($F_x$, $F_y$, $F_z$) where the cross-influence between axes is reduced. In presented case signals do not follow a Gaussian distribution, as it was explained earlier. An example of results from the application of ICA to simulated data from circularity tests on 3 axes is presented in Fig. 6.

![Figure 6. Example of ICA decomposition a artificial data simulating a set of features from DBB and b decomposition to source signals with use of FastICA.](image)

2.5 Evaluation

The steps of data preparation and processing presented here are with the goal to improve diagnosis and prognosis step in predictive maintenance. In the evaluation step, the influence of different options on the output has to be considered.

In the currently presented approach, different processing options are evaluated by its impact on the classification accuracy on several machine learning (ML) methods. Classification accuracy is defined as ratio of correctly classified observations to all observations. In work by Dash and Liu (1997), the classification accuracy has been indicated as an evaluation function for feature selection that has very high power. The disadvantage is that it has low generality, it indicates goodness of selected features for use with classifier selected for evaluation. To overcome this issue, several classifiers can be used in parallel for the evaluation purpose. The advantage of such approach is that not only the processing part is evaluated, but also the appropriate classification method could be suggested for the specific case.
In (Kiang 2003), several classification methods have been assessed. Selected distribution-free classification methods are Back Propagation Feed Forward Neural Network (FFNN), k Nearest Neighbour (kNN) (Wong and Lane 1981), and Decision Tree C4.5 (DT) (Quinlan 1993). Moreover, a multiclass Support Vector Machine (SVM) classifier has been included.

To validate a particular classification method and estimate its accuracy, usually the dataset is split into a training data set and a testing data set. This is to check how methods work on data that were not presented to it during the learning process. If the amount of data is not big enough than cross-validation method can be applied that uses repeated random sub-sampling or k-fold splitting.

In this work, multiple time repeated k-fold cross-validation with different splits into folds is used. This provides a better Monte-Carlo estimate to the complete cross-validation (Kohavi 1995). The stratified 10-fold has been applied for splits into folds, as it was recommended by Kohavi (1995) based on a case study on several real-world datasets. Stratification ensures, that in training and testing datasets, all classes are represented in similar proportion.

Both steps; processing and classification, are included in cross-validation process. It means that analysis in processing step, are performed only on training data set and obtained transformation applied later on testing data set.

At last state in the analysis process, the statistical method shall be applied to verify the significance of differences and to select proper methods. If the assumption of the normally distributed sample population is not fulfilled, instead of one-way analysis of variance (ANOVA), a non-parametric method, the Kruskal-Wallis Test (Kruskal and Wallis 1952) should be applied. Test indicate whether at least one population median of one group is significantly different from the population median of at least one other group against the null hypothesis that the medians of all groups are equal. If there is an indication of the existence of differences, multiple comparison tests can be applied to check which groups are significantly different.

3 Case study

The presented approach is exemplified in a case study on machine tool’s linear X axis. As condition monitoring, data obtained from double ball-bar measurement are utilised, as well as information from CMMS, SCADA systems and NC code. The acquisition of data has been detailed described in (Schmidt, Gandhi, Wang et al. 2017).

The main condition monitoring data are measurement obtained from Renchaw® measuring device. Each test is performed in three planes: XY, YZ, and ZX with two feed rates. As an extension, additional information has been extracted from NC code. Available data from CMMS and SCADA do not contain information about distance travelled by axes of the machine tool. Moreover, this information has not been stored in the considered controller of the machine tool. To overcome this limitation, the NC G code has been parsed with the use of a Perl script to retrieve travelled distance per machining cycle, a number of motions with division into different types as well as a number of tool changes. Combining information extracted from NC code with information on a number of performed machining cycles from SCADA allows calculation of distance travelled by considered axes.

A tool implemented for visualisation of gathered data (see Figure 7) was used to assess the data acquisition process. It allowed checking if all data have been imported and if there exist dependencies that can be directly observed.
A lifetime of the linear axis can be expressed in different entities based on different data sources. Based on data from CMMS system, a lifetime of the component can be expressed in calendar days. From SCADA additional information can be retrieved, that allows expressing lifetime in processing days or number of performed processing cycles. Data from NC code executed by the machine tool controller allows expressing lifetime in the travelled distance, the number of tool changes, or the number of specific type of performed motions.

To select the proper domain of lifetime the Weibull distributions have been fitted with use of R environment (Team 2016) with ‘survival’ package (Therneau 2015). Information on 23 failed instances and 26 in use instances of ball-screw have been used.

The two-parameter Weibull distribution (see Eq. 31) was assumed, where k is the shape parameter, while \( \lambda \) is the scale parameter.

\[
w(t) = (k/\lambda) (t/\lambda)^{k-1} e^{-(t/\lambda)^k}
\]  

(31)

Associated cumulative distribution function \( W_{cdf}(t) \) and reliability function \( R(t) \) are presented in Eq. 32.

\[
W_{cdf}(t) = 1 - e^{-(t/\lambda)^k} = F(t) \\
R(t) = 1 - F(t) = e^{-(t/\lambda)^k}
\]

(32)

Lifetime expressed in processing cycles does not follows the Weibull distribution, while there were no statistically significant differences between obtained parameters for lifetime distributions expressed in calendar days (\( k = 1.75 \)), processing time (\( k = 1.77 \)), and travelled distance (\( k = 1.51 \)). Fitted Weibull distribution of ball-screw lifetimes in Figure 8, has been scaled with use of the nominal life expectancy value. Nominal life expectancy \( L \) is a lifetime that 90% of the population should reach – survival ratio is 90%. Theoretical model is based on ball-screw’s manufacturer information that for 5*L the survival rate is 50%, therefore the shape parameter of the Weibull distribution is \( k = 1.17 \).
The significant difference between data-driven and theoretical model for lifetime distribution, could be caused by the fact that theoretical distribution is assigned to ball-screw as to an isolated component, working in an ideal conditions that are different from real operational conditions.

![Figure 8. Weibull failure distributions: fitted to data and theoretical.](image)

3.2 Processing application and evaluation

Offline condition monitoring data come from double ball-bar measurements performed with use of RENISHAW® QC20-W measuring device. Measurements from a period of 4 years and from 29 similar machines have been parsed. In total there were 303 measurements from 59 instances of ball-screws. From this data set, 32 instances that have failed during this period and have at least one measurement available have been selected. This gives 145 measurements utilised in the further part. For each of two feed rates, there are 88, 82 and 82 features available for the tests performed in XY, YZ, ZX plane respectively. In total 504 features are available for each of the 145 tests.

All measurements have been aligned with respect to time to failure in four ways based on different utilisation measures: calendar days (CD), processing time (PT), travelled distance (TD), and a number of cycles (C). Then measurements can be normalised with use of the z-score method, that centres each feature in 0 by subtracting the mean value and scale that the standard deviation become equal to 1. In the evaluation, not normalised (nN) and z-score normalised (zN) data are considered. A set of combination of processing and feature selection methods have been implemented: 1. PCA; 2. SFS+PCA; 3. ICA+SFS; 4. ICA+SFS+PCA, 5. CFS. Moreover, a PCA+SFS has been tested, however, it resulted in behaviour between PCA and SFS+PCA with only 3 to 5 factors selected. Those results are not included in the further analysis.

Used classifiers are respectively: 1. k-Nearest Neighbour (kNN); 2. Back-propagation Feed-forward Neural Network (FFNN); 3. Decision Tree (DT); 4. Naïve Bayesian (NB); 5. Random Forest (RF); 6. Support Vector Machine (SVM).

Moreover, classification algorithms have been applied to different sets of n selected features. Features are selected as n first most significant features, without searching for the optimal subset.

For comparison, a following number of dimensions has been selected: 1, 2, 3, 4, 5, 10, and 15.
3.3 Configuration of methods

3.3.1 Statistical Feature Selection

For SFS two sample sets of the size of $n_1=30$ samples with the longest time to failure and $n_2=50$ samples with the shortest time to failure are selected. This corresponds to data from good health state, and from degraded health state respectively and are drawn each time from a training population of around 130 samples. The assumption is that, as a lifetime of ball-screws is relatively long, and only measurements from one that had failed are considered there is more measurement available from the degraded state than from good state.

3.3.2 Correlation-based Feature Selection

This method has been implemented as one of the reference methods, used in similar studies presented (Binsaeid, Asfour, Cho et al. 2009). In process of feature discretisation and searching for optimal feature subset it requires the information of class labels – supervised learning. The same labels are used as later for supervised learning of classification method.

3.3.3 Independent Component Analysis

For ICA only 492 features have been considered, while 12 features have been discarded as there were no corresponding features to group them in triplets. Discarded features come from measurement on XY plane, where the full circular path is performed, while on YZ, and ZX planes only a 270-degree arc is executed, and not all features can be retrieved.

3.3.4 Labelling for supervised learning

There is no information available for each measurement about true degradation state that could be used to label the data. The whole data set (145 samples) has been divided based on time to failure into three classes: 1. good health state; 2. initiation of degradation; and 3. degraded/faulty state. The threshold used to calculate the size of classes was selected as 135 processing days, and 50 processing days before failure. To set threshold, trends on several features selected by SFS has been analysed. Sizes of those classes are 41, 49 and 55 respectively. For each time usage domain (CD, PT, TD, C) the size of respective classes is kept the same.

3.3.5 $k$-Nearest Neighbour

To select the proper size of the neighbourhood the $k$ value, a wrapper like optimisation has been performed. The 10-fold cross-validation has been performed 50 times on not normalised (nN) data ordered with use of Processing Time (PT). The classification has been performed with value of $k$ from 1 to 40 and with use of 1 to 40 features from SFS. Then for each fold, $k$ has been selected that maximise the average accuracy of classification on the test dataset. Accuracy has been averaged among 40 results obtained from different feature sets. Value $k=15$ has been selected, as one that was occurring most often among giving optimal results. Because of this optimisation, there could be a bias in further results, toward methods that have been applied at this stage.

3.3.6 Neural Network

Tests have been performed with different numbers of hidden neurons (5, 10, and 15). No difference has been noticed and the default value of 10 neurons in hidden layer has been selected. The output layer consists of three neurons, while a number of neurons in the input layer is equal to the number of input signals.
3.3.7 Random Forest
The classification’s parameter selection has been performed in a similar way as for kNN algorithm. A bigger number of trees in a random forest prevents overfitting problem, however, makes the algorithm very time-consuming. Value of 40 trees has been selected as a tradeoff between accuracy and execution time.

3.3.8 Support Vector Machine
Linear SVM and Radial Kernel SVM have been checked. As Radial Based SVM performed much better, only this classifier is included in further steps. To select proper parameters for the kernel, a grid search has been performed on a set of training data, and the optimal parameters that occur most often have been selected. Those parameters are \( c=4, \ g=0.0014, \) and \( c=2, \ g=0.002 \) for not normalised and normalised features respectively.

3.4 Cross-validation step
Combining different pre-processing and feature selection method with classification methods gives in total 2016 possible configurations. All those configurations are applied in 10-fold cross validation repeated 30 times for different folds sampling, producing 300 classification accuracy values for each configuration. In none of the 2016 cases, the distribution of accuracy follows the normal distribution. This has been verified with use of Anderson–Darling test (Anderson and Darling 1954) with a significance level of \( p=0.05 \). For analysing the results the nonparametric Kruskal-Wallis test (Kruskal and Wallis 1952) is applied.
4 Results and discussion

Results from applying cross-validation on selected processing and classification methods are presented in Fig. 9. In the analysed setup, the best solution in respect to classification accuracy has been obtained with use of SFS on z-score (zN) normalised data with time to failure represented in Calendar Days (CD), and with kNN classifier with use of 2 features. However, from a statistical point of view, there are additional 143 among the 2016 configurations that are not significantly different from the mentioned one. All top solutions that are not significantly different from each other are marked with a black dot. For comparison purposes, all results that are not statistically significantly different from the random classifier, are marked with an asterisk. For each row and column, the number of present dots, if there are any, is provided from the left and bottom side respectively with a cumulative sum for classification methods and processing methods. This gives an overview of which combination of methods can or should be applied in the tested case, and which should be avoided. In applied non-parametrical statistical testing the significance of the difference in medians is analysed. For visualisation purpose, instead of median accuracy, the mean accuracy is used in the colourmap. This is due to the fact that in the test sets there are only 14 or 15 samples so the values of accuracy are discretized into only 28 distinct values.

![Figure 9. Comparison of different pre-processing and processing methods based on accuracy of several classification methods. Dots indicate all combinations that are not significantly different from the best solution marked with bigger dot. Asterisks indicate solutions that are not significantly different from a random classifier. Values on the right and bottom represent number of dots in corresponding row or column.](image-url)
4.1 Marginal statistics

More insight can be obtained by analysing marginal statistics when only the subset of configuration parameters are considered (see Table 1). Options from analysed subset of parameters has been ordered in descending order in respect to obtained accuracy, with consideration of statistical significance in differences. This could provide some generalisation of which configuration to choose. However, it needs to be noticed, that if some method, in general, gives good results, it does not means it always is better than other methods.

Table 1. Marginal statistics of cross validation results

<table>
<thead>
<tr>
<th>Ordered options*</th>
</tr>
</thead>
<tbody>
<tr>
<td>Domain 1. CD; 2. TD; 3. [PT, C]</td>
</tr>
<tr>
<td>Normalisation 1. zN; 2. nN</td>
</tr>
<tr>
<td>Processing method 1. SFS; 2. CFS; 3. ICA+SFS+PCA; 4. ICA+SFS; 5. PCA+SFS; 6. PCA</td>
</tr>
<tr>
<td>Classification method 1. SVM; 2. kNN; 3. RF; 4. FFNN; 5. NB; 6. DT.</td>
</tr>
<tr>
<td>Dimension no 1. [10, 15]; 2. [3, 4, 5]; 3. 2; 4. 1.</td>
</tr>
<tr>
<td>Processing method and Classification method 1. ICA+SFS+PCA x SVM; 2. SFS x SVM; 3. [SFS x kNN, SFS x FFNN, SFS x SVM, ICA+SFS+PCA x SVM]</td>
</tr>
</tbody>
</table>

*options in square brackets holding the same position are statistically not significantly different from each other

4.2 Correlation-based Feature Selection

Analysing results obtained for Correlation-based Feature Selection, it can be noticed, that good results are obtained when Random Forest or Decision Tree classifiers are applied. It is due to fact that CFS is a wrapper based method that evaluates selected subset of features with the use of a similar method that is used in mentioned classification method. One needs to be careful applying such method for feature selection when in a later stage another classification method is used.

4.3 Limitations

The results of analysis depend on selected analyses ranges. Considering the different set of numbers of selected features the results can be different. In the presented analysis, lower dimensionality is overrepresented, and this could cause bias toward methods that work better with a lower number of selected features.

4.4 Economic justification

To analyse results, from the perspective of potential benefits of its application, an economic evaluation method is defined. A simple condition based maintenance strategy is proposed and compared with time based maintenance. Obtained results are from Monte Carlo simulation where 100000 of instances is being simulated in each scenario. The considered key performance indicators (KPI) are the cost and ratio of emergency work orders. Cost is expressed in imaginary currency unit U. All times presented in this section are expressed in calendar days if not indicated differently.

Assumptions for the economic model: $T_{CM} = 90$ – an interval for CBM offline measurements; $T_{PL} = 14$ – time required to schedule planned work order, if component fails within this time it is an emergency work order; $C_{CM} = 10U$ – cost for condition monitoring inspection; $C_{EWO} = 2400U$ – cost for unplanned emergency work order (EWO); $C_{PWO} = 800U$ – cost for planned preventive work order (PWO). Cost for unplanned work order is equal to cost for planned work order increased by direct cost of stopped production for the time needed for the replacement that is assumed to be the same as for planned work order.
Lifetime values are generated from assumed two-parameter Weibull distribution (see Eq. 31 in section 3.1) with parameters obtained from statistical analysis on failures of ball screws considered in this research, i.e. \( k=1.75 \) and \( \lambda=1285 \). Weibull distribution is used as lifetime data do fit well. In general any parametric or non-parametric distribution obtained from data can be applied in this step.

4.4.1 TBM policy

A simple model for the cost of time-based maintenance based on replacement interval is presented in Eq. 33. The integral in denominator gives the expected lifetime of the component and is used to scale cost per time unit. Optimal replacement interval is obtained by minimising this cost function as shown in Eq. 34.

\[
C_{TBM}(T) = \frac{C_{EWO} \cdot F(T) + C_{PWO} \cdot R(T)}{\int_{t=0}^{T} R(t) \, dt}
\]

(33)

\[
T_{TBM} = \min_{t} C_{TBM}(t)
\]

(34)

4.4.2 CBM policy

The assumption for the predictive model are as follows:

Lifetimes are generated from the same distribution as in TBM scenario. Two best classifiers from an earlier analysis are selected, respectively CBM1: CD+zN+SFS x kNN+2features and CBM2: CD+zN+SFS x DT+1feature that have average accuracy respectively 64% and 63%.

Time to failure \( t_{tf} \) is split into three intervals \( T_{C1}: t_{tf}>465, T_{C2}: 465\geq t_{tf}>175, \) and \( T_{C3}:175\geq t_{tf}. \) This corresponds to splits of classes in the domain of calendar days that have been used in the cross-validation procedure.

Based on this and accuracy of considered CBM methods the classification is being made according to confusion matrices in Table 2 and Table 3 in \( T_{CM}=90 \) intervals. This simulate an outcome from condition monitoring and diagnosis process that includes signal processing and classification in respect to selected combination.

Table 2. Confusion matrix, conditional probability of predicted state \( PC_x \) given the true state \( TC_x \) for CBM1: CD+zN+SFS x kNN+2features.

<table>
<thead>
<tr>
<th></th>
<th>PC1</th>
<th>PC2</th>
<th>PC3</th>
</tr>
</thead>
<tbody>
<tr>
<td>TC1</td>
<td>0.7772</td>
<td>0.2220</td>
<td>0.0008</td>
</tr>
<tr>
<td>TC2</td>
<td>0.3531</td>
<td>0.5245</td>
<td>0.1224</td>
</tr>
<tr>
<td>TC3</td>
<td>0.1042</td>
<td>0.2545</td>
<td>0.6412</td>
</tr>
</tbody>
</table>

Table 3. Confusion matrix, conditional probability of predicted state \( PC_x \) given the true state \( TC_x \) for CBM2: CD+zN+SFS x DT+2features.

<table>
<thead>
<tr>
<th></th>
<th>PC1</th>
<th>PC2</th>
<th>PC3</th>
</tr>
</thead>
<tbody>
<tr>
<td>TC1</td>
<td>0.8008</td>
<td>0.1407</td>
<td>0.0585</td>
</tr>
<tr>
<td>TC2</td>
<td>0.3728</td>
<td>0.3912</td>
<td>0.2361</td>
</tr>
<tr>
<td>TC3</td>
<td>0.0479</td>
<td>0.2345</td>
<td>0.7176</td>
</tr>
</tbody>
</table>

Proposed approach for the CBM policy is a simplification, where decision is made based on the counts of specific observations, i.e. PC3 and PC2. This numbers depends, despite the classification accuracy, on
used life (number of performed observations) and states (C1, C2, C3) in which the component has been during those times. This is the point where traditional reliability based approach is being merged with condition monitoring approach.

The assumption for the CBM policy are:

- Condition-based work order (CBWM) is scheduled after the first occurrence of observation classified as PC3 or m occurrences of state PC2, where m is a parameter from range 1 to 10.
- If CBWO is scheduled later than \( T_{PL} = 14 \) days before failure, it is treated as unplanned work (EWO).
- If CBWO is scheduled earlier than \( T_{PL} = 14 \) days before failure, it is treated as a planned maintenance (PWO).
- If state PC1 is detected, we do nothing.

If the machine fails between measurements we treat it as EWO.

The cost model for CBM is presented in Eq. 35 where \( N_{EWO} \) is a number of emergency work orders across simulation, \( N_{PL} \) is a number of planned maintenance action, \( N \) is a total number of simulated instances.

\[
C_{CBM}(m) = C_{EWO} \cdot N_{EWO}(m) + C_{PWO} \cdot N_{PL}(m) + \frac{C_{CM}}{\sum N_T(m)}
\]

(35)

### 4.4.3 Results

Results from the simulation for the run to failure reactive maintenance (RM) policy, TBM policy and two approaches of CBM with different variants are presented in Table 4.

Table 4. Comparison of results from simulation for different maintenance policies.

<table>
<thead>
<tr>
<th>Maintenance policy</th>
<th>Cost [U/year]</th>
<th>std(^a) [U/year]</th>
<th>Lifetime [days]</th>
<th>std(^a) [days]</th>
<th>EWO ratio [%]</th>
<th>std(^a) [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>RM</td>
<td>767</td>
<td>13</td>
<td>1143</td>
<td>20</td>
<td>100</td>
<td>0</td>
</tr>
<tr>
<td>TBM</td>
<td>706</td>
<td>16</td>
<td>857</td>
<td>9</td>
<td>53.4</td>
<td>1.55</td>
</tr>
<tr>
<td>CBM1,m=1</td>
<td>1051</td>
<td>7</td>
<td>298</td>
<td>9</td>
<td>1.6</td>
<td>0.04</td>
</tr>
<tr>
<td>CBM1,m=2</td>
<td>627</td>
<td>6</td>
<td>526</td>
<td>10</td>
<td>2.8</td>
<td>0.05</td>
</tr>
<tr>
<td>CBM1,m=3</td>
<td>499</td>
<td>5</td>
<td>691</td>
<td>13</td>
<td>4.1</td>
<td>0.06</td>
</tr>
<tr>
<td>CBM1,m=4</td>
<td>447</td>
<td>5</td>
<td>805</td>
<td>14</td>
<td>5.9</td>
<td>0.07</td>
</tr>
<tr>
<td>CBM1,m=5</td>
<td>428</td>
<td>6</td>
<td>876</td>
<td>14</td>
<td>8.1</td>
<td>0.09</td>
</tr>
<tr>
<td>CBM1,m=6</td>
<td>420</td>
<td>6</td>
<td>922</td>
<td>16</td>
<td>9.8</td>
<td>0.09</td>
</tr>
<tr>
<td>CBM1,m=7</td>
<td>417</td>
<td>6</td>
<td>948</td>
<td>18</td>
<td>11.0</td>
<td>0.09</td>
</tr>
<tr>
<td>CBM1,m=8(^b)</td>
<td>416</td>
<td>5</td>
<td>961</td>
<td>19</td>
<td>11.7</td>
<td>0.09</td>
</tr>
<tr>
<td>CBM1,m=9</td>
<td>417</td>
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<td>20</td>
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<td>0.10</td>
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<td>CBM2,m=7</td>
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<td>646</td>
<td>16</td>
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<td>647</td>
<td>17</td>
<td>5.6</td>
<td>0.72</td>
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</tbody>
</table>

\(^a\) std is a standard deviation of corresponding mean estimator (Cost, Lifetime, EWO ratio), obtained from 100 values of mean each calculated based on simulated 1000 instances of component

\(^b\) cost optimal solution
It can be noticed that in most of the cases, the CBM approaches in the simulated case are more beneficial than the TBM. If we consider for example strategy CBM1 with m=5, then with similar expected lifetime (876 vs. 857), the ratio of emergency work orders EWO is reduced over 6 times with respect to TBM (8.1% vs. 53.4%), and it reduces cost by almost 40% (428 vs. 706). The difference in classification accuracy between CBM1 and CBM2 is not big, however, the economical KPI looks differently. This is due to differences in classifier sensitivity for individual classes. It can be noticed, that for CBM2 in Table 3 there is a high ratio of false positive detection of PC3 than for states TC1 and TC2. This would cause that the components are replaced earlier than it is required.

In this study, inappropriate use of condition based approach (e.g. CBM1, m=1 and CBM2, m=1), despite the low ratio of EWO, is inefficient in terms of direct cost. The potential improvement is noticeable; however, there is a need for more thorough analysis that will include the effect of the model’s inaccuracies on the estimation of KPI’s.

5 Conclusions and future work

In this work, we presented an approach for integration of data from different sources (CMMS, SCADA, and CM) and from a population of similar objects with the aim to provide decision support system that will improve maintenance actions. Real data related to the population of 29 similar linear axes of the machine tools are analysed. Presented cross-validation framework allows to compare different processing and feature selection method, and at the same time gives suggestion which from used machine learning methods shows better performance in each individual case. It has been shown that proposed SFS method performs very well being statistically significantly better than other processing methods when considering independently from ML method. While the proposed combination of ICA+SFS+PCA method together with SVM gives statistically best combination of the method when analysing independently from other attributes. The obtained classification method is applied as a decision support tool for making maintenance actions. Economic evaluation is shown with application to the simulated case. Results show that in analysed case the condition based approach can reduce the number of unplanned stops and the cost of maintenance. Future work will be focused on including presented economic justification model in the statistical evaluation framework. Moreover, the Condition Based Maintenance policies could be improved by considering more advanced predictive models, e.g. Hidden Semi Markov Model (HSMM). Further optimisation can be applied to find an optimal interval for condition monitoring, i.e. the double ball-bar measurements.

6 Acknowledgements

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7 References


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PAPER V
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Diagnosis of machine tools: assessment based on double ball-bar measurements from a population of similar machines

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Abstract

The presented work is toward population-based predictive maintenance of manufacturing equipment with consideration of the automatic selection of signals and processing methods. This paper describes an analysis performed on double ball-bar measurement from a population of similar machine tools. The analysis is performed after aggregation of information from Computerised Maintenance Management System, Supervisory Control and Data Acquisition, NC-code and Condition Monitoring from a time span of 4 years. Economic evaluation is performed with use of Monte Carlo simulation based on data from real manufacturing setup.

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Keywords: Population based maintenance; Condition monitoring; Automatic signal selection

1. Main text

In Smart Manufacturing, the predictive and proactive maintenance is of paramount importance to ensure efficiency, product quality, on-time delivery, and a safe working environment. One of the possibilities to improve diagnosis and prognosis for complex systems, is to utilise more data and knowledge obtained from a population of similar systems [1]. Cloud approach in Smart Manufacturing enables usage of data and information from across the manufacturing hierarchy [2]. The challenge is to select relevant data and to integrate them. It is preferred to perform feature selection automatically without operator intervention [3].

An analysis of failures of components in machine tools, presented in [4], indicates four main component groups responsible for most of the downtimes: drive axes, spindle and tool changer, electronics and fluidics. Drive axes cause the most downtime with 38% contribution.

There are several reported research related to condition monitoring of linear axes. In [5] authors proposed an approach of using signals available in position controlled drives to detect wear of drive unit; hall-effect sensor to detect presence of damaged balls in ball-screw has been used in [6]; in [7] authors used accelerometer to monitor ball pass frequency and detect loose of ball-screw preload; Lee et al. [8] used vibration signals from accelerometer placed on a ball-screw nut to detect artificially introduced failures on the ball-screw race. However, those approaches are mainly performed in a laboratory setup.

A well-established method for offline measurement of axes accuracy, first presented by Bryan [9], is double ball-bar (DBB) measurement. This method implements circular trajectory test, where two linear axes are programmed to follow a full or partial circular trajectory in a plane defined by the two moving linear axes [10]. In the DBB test, a telescoping measuring device records radius deviation for the performed circular trajectory. The test results are a good representation of the results that would be obtained on machined parts in ideal machining conditions with the same motion parameters [10]. Advantages of this method are low cost, the simplicity of use and robustness [11]. Most of the research that utilises this test is focused on identification of sources of deviation [12], improvement of measurement to dynamic conditions [13], prediction of the machined part
accuracy [14]. It is hard to find reported research where data from double ball-bar measurements have been used for predictive maintenance.

In this paper, an approach for the integration of data from different sources and from a population of similar monitored entities is presented. The condition monitoring data, in form of DBB measurements, from a population of similar machines are combined with information from other sources, namely Computerised Maintenance Management System (CMMS), Supervisory Control and Data Acquisition (SCADA), NC-code, and analysed to provide maintenance decision support based on estimated cost. Steps of the approach are: data integration, automatic method selection, and an economic evaluation procedure.

The rest of the paper is organised as follows. Section 2 describes the data integration and method selection step; Section 3 provides the details of economic evaluation method; Section 4 depicts the results; and finally, Section 5 concludes the paper and highlights our future work.

2. Data integration and method selection

The first step is the acquisition of available data. The acquisition of disparate data from different available sources with an initial analysis has been described in [15].

2.1. Acquired data overview

DBB measurements are obtained from the Renishaw® QC20-W measuring device. Each test is performed in three planes: XY, YZ, and ZX with two feed rates selected in compliance with ISO 230-4 [23], respectively 1000 and 4000 mm/min. In plain XY the full circular trajectory is measured. Due to mechanical constrains, in plains YZ and ZX the trajectory is a circular arc with the angle of 220 degrees. For each of two feed rates, there are respectively 88, 82 and 82 features obtained from the Renishaw® Ballbar diagnostics tool with the analyses in version 2.

Event data from CMMS includes information about replacement of components (ball-screws), which allows the definition of instances of the component.

From SCADA system, information on performed machining cycles has been retrieved: number and duration of machining cycles.

By parsing NC-code, information about a number of different motions and distance travelled by axes have been obtained. Data from SCADA and NC-code are contextual information related to machines utilisation.

Measurements from a period of 4 years and from 29 similar machines have been analysed. Considered multi-purpose machine tools are of the same type, but utilised in different operational conditions as they are distributed over 4 production lines with different utilisation and performed different machining operations. There were 32 instances of ball-screws in the X-axis that have failed during the analysed period and have at least one measurement available. There were 145 measurements performed on a selected population of 32 ball-screws. In total 504 features extracted from double ball-bar measurements are available for each of the 145 tests.

2.2. Data processing

All measurements have been aligned with respect to time to failure (ttf) based on different utilisation measures: calendar days (CD), processing time (PT), travelled distance (TD), and number of cycles (C). In the evaluation, not normalised (nN) and z-score normalised (zN) data are considered. In this research following processing method are considered: Principal Component Analysis (PCA) [16], Statistical Feature Selection (SFS) based on Mann–Whitney U test [17], Independent Component Analysis (ICA) [18], Correlation Feature Selection (CFS) [19]. The following set of combination of processing and feature selection methods have been implemented: 1. PCA; 2. SFS+PCA; 3. ICA+SFS; 4. ICA+SFS+PCA, 5. CFS.

Six different classification method has been applied based on [20]: 1. k-Nearest Neighbour (kNN) [21]; 2. Back-propagation Feed-forward Neural Network (FFNN); 3. Decision Tree (DT) [22]; 4. Naïve Bayesian (NB); 5. Random Forest (RF); 6. Support Vector Machine (SVM).

2.3. Method selection

The proper combination of proposed methods is selected based on classification accuracy. To obtain the accuracy of all combinations of the processing and classification methods, multiple time repeated stratified 10-fold cross-validation with different splits into folds is used. Overview of the approach is presented in Fig. 1.
There is no information available about true degradation state that could be used to label the data. Therefore, the data set has been divided based on time to failure into three classes: TC1 – a long time to failure that corresponds to good health state; TC2 – initiation of degradation; and TC3 – a short time to failure, degraded/faulty state. To set threshold, trends on several features selected by SFS has been analysed.

An overview of applied steps is illustrated in Fig. 2. Data integration step and method selection, where the combination of processing and classification methods that results in best classification accuracy is selected, followed by Monte-Carlo simulations of lifetimes and observations. Applying this procedure to data from double ball-bar measurements, simulation allows estimating economic consequences of using double ball-bar measurements in CBM for the machine tool linear axis.

3. Economical evaluation

To analyse results, from the perspective of potential benefits of its application, a Monte-Carlo simulation-based economic evaluation method is defined. The considered key performance indicators (KPI) are the cost and ratio of emergency work orders (EWO). Cost is expressed in an imaginary currency unit U, and have been estimated based on real cost of spare parts, man-hours, and production stop. All times presented in this section are expressed in calendar days if not indicated differently.

In the simulation there are two models used. The first is the statistical model of component lifetimes. Lifetime values are generated from assumed two-parameter Weibull distribution (see Eq. 1) with parameters obtained from statistical analysis on failures of ball-screws considered in this research, i.e. $k=1.75$ and $\lambda=1285$. Weibull distribution is used as it fits well to lifetime data (parameters estimated with p-value < 0.01). Cumulative distribution function $F(t)$ and reliability function $R(t)$ are presented in Eq. 2.

$$F(t) = 1 - e^{-\frac{t}{\lambda}}$$
$$R(t) = 1 - F(t) = e^{-\frac{t}{\lambda}}$$

The second model is the statistical model of selected CBM – the accuracy of the selected combination of processing and classification method. This model is obtained in the earlier mentioned step of cross-validation.

Assumptions for the economic model are as follows: cost for an unplanned emergency work order (EWO): $C_{EWO} = 2400U$; cost for a planned preventive work order (PWO): $C_{PWO} = 800U$. Cost for unplanned work order is equal to cost for planned work order increased by the direct cost of stopped production for the time needed for the replacement that is assumed to be the same as for planned work order. Moreover, for CBM approach: an interval for offline measurements: $T_{CM} = [30, ..., 180]$; time required to schedule planned work order: $T_{PL} = 30$, if component fails within this period of time it is an emergency work order; cost for condition monitoring inspection: $C_{CM} = [10U, ..., 80U]$, value of 10U corresponds to measurement performed without disturbing production, while 80U is a cost of measurement that includes cost of stopped production. The assumed inspection time required to take the DBB measurement is 20 minutes.

CBM approach is compared with run-to-failure reactive maintenance (RM) and time-based maintenance (TBM). Cost models are described in the following sections.

3.1. Reactive Maintenance

Direct cost for reactive maintenance is defined in Eq. 3.

$$C_{RM} = C_{EWO} \int_0^{\infty} R(t) dt$$

where the integral in denominator gives the average lifetime of the component and is used to scale, per time unit, the cost of the maintenance approach.

![Fig. 2. The procedure of condition monitoring and event data integration for a population of instances with economical evaluation for decision support.](image-url)
3.2. Time Based Maintenance

A simple model for the cost of time-based maintenance based on replacement interval $T$ is presented in Eq. 4. Optimal replacement interval $T_{TBM}$ is obtained by minimising the cost function (see Eq. 5).

$$C_{TBM}(T) = \int_{t=0}^{T} F(t) + C_{PWO} \cdot R(t) \ dt$$

$$T_{TBM} = \arg \min_{t} C_{TBM}(t)$$

3.3. Condition Based Maintenance

The cost model for CBM is presented in Eq. 6., where $N_{EWO}$ is the number of emergency work orders across simulation, $N_{PWO}$ is the number of planned maintenance actions, $N$ is the total number of simulated instances, and $T$ is used lifetime of the component: the time between component installation and replacement due to scheduled work or failure.

$$C_{CBM} = (C_{EWO} \cdot N_{EWO} + C_{PWO} \cdot N_{PWO}) / \sum_{N} T + C_{CM} / T_{CM}$$

The assumptions for the simulation model of CBM are as follows. Lifetimes are generated from the same Weibull distribution as in RM and TBM scenarios. The best processing method and classifier from an earlier analysis is selected, i.e. $CD+zN+SFS \times kNN+2$ features that have an average accuracy of 64%. Accuracy model has been obtained by stratified 10-fold cross-validation repeated 30.

Time to failure, $ttf$, is split into three intervals of true condition (TC): long time before failure $TC1$ with $ttf_{TC1}$>465; medium time to failure $TC2$ with 465>$ttf_{TC2}$>175; and short time to failure $TC3$ with 175>$ttf_{TC3}$. This corresponds to the splits of classes in the domain of calendar days that have been used in the cross-validation procedure.

Based on this and the accuracy of considered CBM methods the classification is being made according to the confusion matrix in Table 1 in $T_{CM}$ intervals. For each simulated observation predicted classification (PCx: x = 1,2,3) result is obtained with use of following algorithm:

IF (r <= P(PC1|TCx) THEN PCx = PC1;
ELSE IF ( r > (1 - P(PC3|TCx)) THEN PCx = PC3;
ELSE PCx = PC2;

where, $r$ is a random variable drawn from a uniform distribution from the range [0;1].

This simulates an outcome of condition monitoring and diagnosis process that includes signal processing and classification with respect to selected combination.

The assumptions for the CBM decision making step are:

- Condition-based work order (CBWO) is scheduled after the first occurrence of observation classified as PC3 or $m$ occurrences of state PC2, where $m$ is a parameter from range 1 to 30.
- If CBWO is scheduled later than $T_{PL} = 30$ days before failure, it is treated as unplanned work (EWO).
- If CBWO is scheduled earlier than $T_{PL} = 30$ days before failure, it is treated as a planned maintenance (PWO) and $T_{PL}/2$ is included in the final lifetime of the component.
- If state PC1 is detected, no action is taken.
- If the component fails between measurements, it is treated as EWO.

3.3.1. Effect of clustering

The additional experiment has been performed to check how division into classes $TC1$, $TC2$, and $TC3$ affect the final results of the economical evaluation. The thresholds have been selected in the way that numbers of samples assigned to each of classes vary in range 20 to 105 with the step of 5. This gives in total 171 combinations. For each combination, the classification accuracy has been calculated and applied in the simulation with different values of parameters $m$ and $T_{CM}$, with assumed $C_{CM}$=10U.

4. Results

In this section, results from the simulation of different scenarios of CBM are presented. Moreover, results from the run to failure reactive maintenance (RM) policy and TBM policy are presented for comparison. Presented estimates are expected (mean) cost per year, expected lifetime of ball-screw and expected ratio of unplanned work orders (EWO). Those values are estimated base on simulation of $N$=30000 instances of ball-screws.

Table 2. Comparison of results from simulation for different maintenance policies for $C_{CM}$=10U and $T_{CM}$=90.

<table>
<thead>
<tr>
<th>Maintenance policy</th>
<th>Cost [U/year]</th>
<th>Lifetime [days]</th>
<th>EWO ratio [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>RM</td>
<td>767</td>
<td>1143</td>
<td>100</td>
</tr>
<tr>
<td>TBM</td>
<td>706</td>
<td>857</td>
<td>53.4</td>
</tr>
<tr>
<td>CBM,$m$=1</td>
<td>1002.4</td>
<td>315.3</td>
<td>1.9</td>
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<td>616.5</td>
<td>540.2</td>
<td>3.2</td>
</tr>
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<td>702.6</td>
<td>5.2</td>
</tr>
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<td>449.2</td>
<td>817.6</td>
<td>7.2</td>
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<td>CBM,$m$=5</td>
<td>432.9</td>
<td>890.9</td>
<td>9.8</td>
</tr>
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<td>CBM,$m$=6</td>
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<td>934.5</td>
<td>12.0</td>
</tr>
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<td>CBM,$m$=7</td>
<td>429.8</td>
<td>961.0</td>
<td>14.0</td>
</tr>
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<td>CBM,$m$=8</td>
<td>429.2</td>
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<td>14.8</td>
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<tr>
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<td>429.6</td>
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<td>986.3</td>
<td>15.9</td>
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</table>

Table 1. Confusion matrix, conditional probability $P(PCx|TCx)$ of predicted state PCx given the true state TCx for CBM: $CD+zN+SFS \times kNN+2$ features.
Results from simulation with fixed parameters $T_{CM}=90$ days, the usual interval of inspections in analysed case, and $C_{CM}=10U$ and different decision threshold $m$ are presented in Table 2. The highlighted row indicates the configuration with minimal obtained cost. With our proposed approach to decision making, the estimated yearly cost is 428U that is respectively 39% and 44% less than in TBM and RM policies.

Results for simulation with different condition monitoring intervals $T_{CM}$ are presented in Table 3. Presented values are for parameter $m$ from range 1 to 30 that results in a lower estimated cost for a given $T_{CM}$. For the assumed cost of condition monitoring ($C_{CM}=10U$) optimal interval for measurements is 70 days and expected yearly cost is 408U, that is respectively 42% and 47% less than in TBM and RM policies. The improvement in respect to CBM policy with interval $T_{CM}=90$ days is 5%.

Table 3. Comparison of results from the simulation for different maintenance policies when $C_{CM}=10U$, with optimal $m$.

<table>
<thead>
<tr>
<th>Maintenance policy</th>
<th>Cost [U/year]</th>
<th>Lifetime [days]</th>
<th>EWO ratio [%]</th>
<th>$m$</th>
</tr>
</thead>
<tbody>
<tr>
<td>RM</td>
<td>767</td>
<td>1143</td>
<td>100</td>
<td></td>
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<tr>
<td>TBM</td>
<td>706</td>
<td>857</td>
<td>53.4</td>
<td></td>
</tr>
<tr>
<td>CBM,$T_{CM}=30$</td>
<td>464.8</td>
<td>866.3</td>
<td>0.9</td>
<td>30</td>
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<tr>
<td>CBM,$T_{CM}=40$</td>
<td>427.7</td>
<td>900.6</td>
<td>1.8</td>
<td>24</td>
</tr>
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<td>CBM,$T_{CM}=50$</td>
<td>412.5</td>
<td>924.9</td>
<td>3.7</td>
<td>25</td>
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<td>945.5</td>
<td>6.3</td>
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<td>CBM,$T_{CM}=80$</td>
<td>418.3</td>
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<td>934.5</td>
<td>12.0</td>
<td>6</td>
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<td>435.1</td>
<td>961.6</td>
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<td>6</td>
</tr>
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<td>980.6</td>
<td>18.6</td>
<td>6</td>
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<tr>
<td>CBM,$T_{CM}=120$</td>
<td>450.2</td>
<td>971.2</td>
<td>19.8</td>
<td>5</td>
</tr>
</tbody>
</table>

Table 4. Comparison of results from the simulation for different cost of condition monitoring $C_{CM}$, with optimal $T_{CM}$ and $m$.

<table>
<thead>
<tr>
<th>Maintenance policy</th>
<th>Cost [U/year]</th>
<th>Lifetime [days]</th>
<th>EWO ratio [%]</th>
<th>$T_{CM}$</th>
<th>$m$</th>
</tr>
</thead>
<tbody>
<tr>
<td>RM</td>
<td>767</td>
<td>1143</td>
<td>100</td>
<td></td>
<td></td>
</tr>
<tr>
<td>TBM</td>
<td>706</td>
<td>857</td>
<td>53.4</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CBM,$C_{CM}=10$</td>
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<td>70</td>
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<td>CBM,$C_{CM}=20$</td>
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<td>960.0</td>
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<td>14</td>
</tr>
<tr>
<td>CBM,$C_{CM}=30$</td>
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<td>15.9</td>
<td>110</td>
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<tr>
<td>CBM,$C_{CM}=40$</td>
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<td>967.9</td>
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<td>140</td>
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<td>CBM,$C_{CM}=50$</td>
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<td>CBM,$C_{CM}=70$</td>
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<td>17.8</td>
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<td>982.0</td>
<td>24.0</td>
<td>150</td>
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</tbody>
</table>

Results for simulation with different costs of condition monitoring $C_{CM}$ are presented in Table 4. The grid search has been applied for parameter $m$ from range 1 to 30 and $T_{CM}$ from range 30 to 180 with the step of 10 to find values that result in a lower estimated cost for a given $C_{CM}$. It can be noticed, that stopping production for making an inspection, in the considered case when $C_{CM}=80$, is economically justified in comparison to TBM.

Results of simulation for the different threshold for splitting into classes TC1, TC2, and TC3 are presented in Fig. 3. The grid search has been applied for parameter $m$ from range 1 to 30 and inspection interval $T_{CM}$ from range 30 to 180 with the step of 10 days to find values that result in a lower estimated cost for a given split into classes. The minimal obtained value of the cost is 396U, marked by the white asterisk in Fig. 3. This solution has a ratio of undetected failures on the level of 6.9%. It has been obtained, when data are clustered respectively into 70, 30 and 45 samples in TC1, TC2, and TC3. This corresponds to thresholds $ttf_{TC1}>259$ days, time to failure of predicted class $PCx$ given the true state $TCx$: $ttf_{TC1}>259 \geq ttf_{TC2}>136 \geq ttf_{TC3}$, Confusion matrix obtained from cross-validation step is presented in Table 5. Parameters of the CBM policy that gives the minimal cost value are $m=3$ and condition monitoring interval $T_{CM}=50$ days.

Table 5. Confusion matrix, conditional probability $P(PCx|TCx)$ of predicted state $PCx$ given the true state $TCx$: $ttf_{TC1}>259 \geq ttf_{TC2}>136 \geq ttf_{TC3}$ with CBM: CD+$zN$+SFS x kNN+2features.

| $P(PCx|TCx)$ | PC1 | PC2 | PC3 |
|--------------|-----|-----|-----|
| TC1          | 0.958 | 0.042 | 0.000 |
| TC2          | 0.610 | 0.246 | 0.144 |
| TC3          | 0.187 | 0.136 | 0.678 |

Finally, the analysis of prediction accuracy has been performed. Prediction model and maintenance policy for the best solution from Table 3 where $C_{CM}=10$, $T_{CM}=70$ and $m=20$, has been analysed. Results are presented in Table 6. Estimations have been done for two sizes of population $n=1000$ and $n=30$. Estimation indicated by "rw" is based on
utilises an integration of data from different sources.

Moreover, the Condition Based Maintenance economic justification model and clustering in the cross-data is that replacement of the ball-screw means that it failed. The quality of used data. The main assumption regarding the data related to the population of 29 similar linear axes of the support system that will improve maintenance actions. Real data related to the population of 29 similar linear axes of the machine tools are analysed. Used cross-validation framework allows to compare different processing and feature selection method, and select a combination that performs the best, as well as to create the accuracy model. The selected classification method is applied in a Monte Carlo simulation-based economic evaluation. Through the simulation, the effect of condition monitoring inspections interval and cost on the final cost of maintenance approach can be assessed. Comparison with traditional reactive maintenance and time based maintenance indicate the economic benefits: the direct cost is decreased by around 40% and a number of unplanned stops is decreased 6 times, with the application of the proposed condition based approach. Moreover, the presented approach provides the support to select optimal intervals for the offline double ball-bar measurements.

The presented approach is data driven and relies on estimated lifetime and accuracy models based on population data. The predictions are provided for a population of machines that will operate in similar conditions as the population from which the data have been obtained. Moreover, quality of future data is assumed to be similar to the quality of used data. The main assumption regarding the data is that replacement of the ball-screw means that it failed.

Future work will be focused on including presented economic justification model and clustering in the cross-validation step. Moreover, the Condition Based Maintenance policies could be improved by considering more advanced predictive models, e.g. Hidden Semi Markov Model (HSMM).

5. Conclusions

In this work, we presented an approach for diagnosis of machine tool based on double ball-bar measurements. It utilises an integration of data from different sources (Computerised Maintenance Management System, SCADA, and double ball-bar condition monitoring) and from a population of similar objects with the aim to provide decision support system that will improve maintenance actions. Real data related to the population of 29 similar linear axes of the machine tools are analysed. Used cross-validation framework allows to compare different processing and feature selection method, and select a combination that performs the best, as well as to create the accuracy model. The selected classification method is applied in a Monte Carlo simulation-based economic evaluation. Through the simulation, the effect of condition monitoring inspections interval and cost on the final cost of maintenance approach can be assessed. Comparison with traditional reactive maintenance and time based maintenance indicate the economic benefits: the direct cost is decreased by around 40% and a number of unplanned stops is decreased 6 times, with the application of the proposed condition based approach. Moreover, the presented approach provides the support to select optimal intervals for the offline double ball-bar measurements.

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Acknowledgements

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References

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Table 6. Prediction sensitivity for CCM=10, TCCM=70 and m=20, based on 1000 repeated simulations.

<table>
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<th>Estimation parameters</th>
<th>Cost [U/year]</th>
<th>min</th>
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<th>median</th>
<th>95%</th>
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<tr>
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PUBLICATIONS IN THE DISSERTATION SERIES
PUBLICATIONS IN THE DISSERTATION SERIES


Bernard Schmidt received his M.Sc. in Automatics and Robotics from AGH University of Science and Technology in 2005. For 5 years he worked in a company that delivers software and services for condition monitoring. Since 2011 he has been working as a research assistant at the University of Skövde.

In this thesis Bernard investigates how data from a population of machines can be used for predictive maintenance. He focuses on data analytics of the linear axes of industrial machine tools. Aggregated data comes from multiple disparate data sources, including double ball-bar circularity tests, maintenance management systems, and the machine tool controller. Bernard has applied and evaluated various data processing and machine learning methods. He has also performed an economic evaluation of the proposed approach.