PROPHESY

Platform for rapid deployment of self-configuring and optimized predictive maintenance services

DELIVERABLE

D4.3 – Machines and Tools Models v1

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Executive Summary

- The objectives of WP4 are: the implementation of a framework for data integration; the specification of physical models of machines and tools that contributes to providing insight and better understanding of the system; the specification and implementation of effective predictive analytics techniques for predictive maintenance as well as the implementation of effective data analytics techniques which could be integrated in industrial practice based on CRISP-DM methodology. Finally, to offer a toolkit that can be used for PROPHESY-SOE and PROPHESY -CPS enabling data collection and analytics techniques.
- The deliverable provides insight about the machines, tools, physical modelling and lists some failure modes for systems in order to pave the way to physical modelling of the machines. It investigates a suggested use case which includes major parameters for physical modelling as a solid and practical example.
- General guidelines regarding the use of physical models in predictive data analytics are mentioned in the document.
- The physical model will be based on the possible failure mechanisms, which are presented in this deliverable.
- The deliverable describes the steps to a RUL prediction using a physical-based model simulation.

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Definitions, Acronyms and Abbreviations

Acronym/ Abbreviation	Title
ADC	Analog-Digital Converter
AR	Augmented Reality
ATC	Automatic Tool Changer
BL	Boundary Lubrication
CBM	Condition Based Monitoring
CMMS	Computerized Maintenance Management System
CNC	Computer Numerical Control
CPS	Cyber Physical System
CRISP-DM	Cross-Industry Standard Process for Data Mining
DAC	Digital-Analog Converter
DNC	Direct Numerical Control
ERP	Enterprise Resource Planning
FEM	Finite Element Model
FMECA	Failure Mode, Effects and Criticality Analysis
FTA	Fault Tree Analysis
HCF	High Cycle Fatigue
HCI	Human Computer Interface
HL	Hydrodynamic Lubrication
KPI	Key Performance Indicator
LCF	Low Cycle Fatigue
MES	Manufacturing Execution System
ML	Machine Learning
MLub	Mixed Lubrication
MTTR	Mean Time to Repair
NC	Numerical Control
PdM	Predictive Maintenance
PoF	Physics of Failure
RUL	Remaining Useful Life
SOE	Service Optimization Engine
TMF	Thermal Mechanical Fatigue

1 Introduction

1.1 The Prophesy Vision

Prophesy offers a platform which enables deployment of self-configuring and optimized predictive maintenance services. It comprises a cyber physical system where the collected data of current, as well as past status of the system, is accumulated. It is called PROPHESY-CPS which provides functionalities for real-time control and monitoring of manufacturing production processes and industrial assets.

The proposed architecture suggests the data is collected from the field and eventually put in data silos. This level is usually called the connection layer where sensor data and other indicators are collected as raw data under the term; condition-based monitoring (CBM).

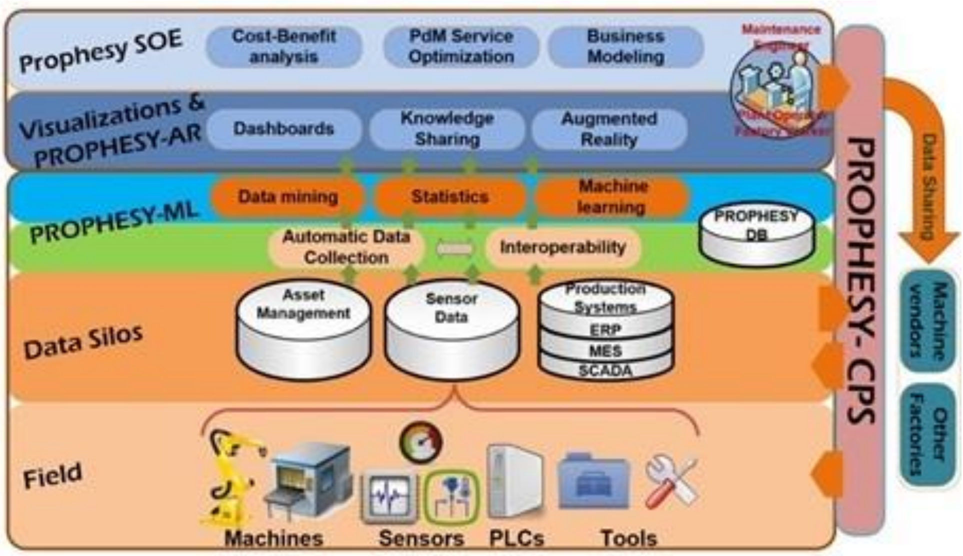

Figure 1: PROPHESY platform overview

The raw data need to be tuned and the features are to be selected. The step is called data-to-information conversion. This layer in the PROPHESY architecture is called PROPHESY-ML. It also contributes to the estimation of remaining useful life (RUL) and current health value of the systems based on developed algorithms and grants self-awareness to the systems.

The other layer above PROPHESY-ML is called Visualization and PROPHESY-AR. It provides dashboards, knowledge sharing and augmented reality where the system leverages the benefits of advanced training and visualization for maintenance, including increased efficiency and safety of human-in-the-loop processes.

The project will take advantage of an Augmented Reality (AR) platform. The AR platform will be customized for use in maintenance scenarios with a particular emphasis on remote maintenance. It will be also combined with a number of visualization technologies such as ergonomic dashboards, as a means of enhancing workers support and safety. The project's AR platform is conveniently called PROPHESY-AR.

There is one additional layer called PROPHESY-SOE. In order to develop and validate viable business models for predictive maintenance deployments, the project will explore optimal deployment of configurations of turn-key solutions, notably solutions that comprise multiple components and technologies of the PROHPESY project (e.g., data collection, data analytics, data visualization and AR components in an integrated solution). The project will provide the means for evaluating such configurations against various business and maintenance criteria, based on corresponding, relevant KPIs (Key Performance Indicators). PROPHESYs tools for developing and evaluating alternative deployment configurations form the project service optimization engine, which we call PROPHESY-SOE.

1.2 PdM Data Collection and Analytics Overview

The scope of activities within WP4 encompasses two layers in the PROPHESY architecture: data silos, and PROPHESY-ML. Specifically, PdM data collection and analytics aim to provide automatic data collection, physical modelling of systems and machines, statistical analysis development and fine-tuning, data mining techniques development and fine-tuning, and PROPHESY-ML toolbox integration.

On top of the collected datasets, PROPHESY will combine statistical methods for on-line monitoring (statistical process control) as well as predictive analytics on streaming data (data mining). Monitoring is an essential part of condition-based maintenance since monitoring the condition of systems allows for early identification of imminent failures. The statistical techniques focus on monitoring relevant parameters while correcting for external factors. The alarm thresholds are thus remotely adaptive, unlike customary static thresholds. Adaptive thresholds reduce the number of false alarms while at the same time increasing detection performance. The statistical approach complements data mining approaches because statistical modelling of failure times avoids the loss of information by treating the monitoring problem as a classification problem. Data mining techniques allow the generation of models for predicting the remaining useful life of components and discovering the root cause of failures. The data mining approach complements the statistical approach with algorithms for streaming data as well as model-free approaches to concept drift. Based on the PROPHESY-CPS platform, which allows collection of data from various production systems (e.g., ERP, MES), the scope of remote monitoring will be wider and will include quality-related information (such as workpiece tolerances, surface roughness, material properties and more). Data analytics will enable optimization of configuration and adaptation of production processes closing the loop in ERP systems. This work package will deliver the data services that will comprise the PROPHESY-ML toolkit. Its main objectives include:

- To implement a framework for integrating data from multiple (fragmented) data sources, in-line with PROPHESY-CPS data sharing and interoperability techniques.
- To specify physical models of machines and tools, as an invaluable input for specifying and implementing effective predictive analytics techniques for PdM.

- To devise and implement effective data analytics techniques that can be integrated in industrial practice based on the CRISP-DM methodology.
- To bundle data collection and data analytics assets in an integrated and reusable toolkit, which will be used in conjunction with PROPHESY-SOE and PROPHESY-CPS.

1.3 Physical Modelling Machines and Tools Overview

Physical modelling of machines and tools will add additional physical insights to the calculation of remaining useful life of systems. These insights will provide valuable knowledge for selecting and validating proper data analytics techniques in later tasks in WP4. The task will make an effort to provide more general guidelines that could be useful for predictive data analytics practitioners working on PdM. Physical models increases the knowledge of the system behaviour and helps to form a better understanding of data.

1.4 Introduction

Predictive maintenance is considered as a variant of preventive maintenance [1]. Preventive maintenance is a proactive method aiming to change or repair the system parts before the failure happens. This method is based on time and reduces the maintenance cost in comparison with run-to-failure method (corrective maintenance) and also avoids the breakdown of the system. Some components and parts of the system, in this case, are replaced with the new ones, however, they could continue for a while without any failure. The alternative to that is called predictive maintenance which aims to predict the time to failure. The method requires a thorough set of data, describing the status of the system, fingerprints which in case comprises the system history and algorithms to calculate the remaining useful life.

Prognostic approaches are used to determine the schedule for complete service life, based on the current condition and if possible also the assumed future usage and load of the system. It is also used to calculate the remaining useful life of the system based on the current status of the system. A sophisticated approach for basic prognostics is physical model-based prognostics.

According to classifications for fault detection and diagnosis methods, approaches based on physical models are categorized as a quantitative model-based method which is further divided into the detailed physical model and simplified physical model. Physical models are based on an a priori fundamental understanding of the physical principles governing the behaviour of the system. In a physical model, the behaviour of the system and the values of outputs are modelled for a given set of inputs and model parameters compared to measured performance or output [2]. As the term detailed physical model implies, it is based on detailed knowledge of the physical relation of the system while the simplified physical model employs a simpler approach such as lumped parameters which reduces the computational effort in solving numerically the differential equations of the physical model.

In a physical-based approach, a physical model of the components and its failure mechanism are used to simulate the degradation process of the system. Physical models have been extensively used for prognosis, in particular in the field of structural integrity and failure mechanisms [3] [4] [5] [6] [7] [8] [9]. Moreover, there are multiple studies in which several physical models are applied to predict the failures of bearings, gear tooth, electronic systems and a high power clutch system [10] [11] [12] [13] [14] [15] [16].

Advantages of quantitative models include:

- Models are based on physical principles describing the governing behaviour.
- They provide the most accurate estimators of output when they are well formulated.
- Detailed models can model both normal and faulty operation.
- Physical models describe degradation indicators with a clear physical meaning as well as associated failures, which benefits more capacity and less uncertainty to predict failures.
- With explicit formulae at hand, a physical model eases estimation of state prediction and associated uncertainties.
- It is suitable for small data scenarios.
- Physical models lead to model-based control and decision analysis.

Disadvantages of the physical model or in general quantitative models include:

- They can be complicated models which require extensive computational effort.
- Their computation difficulty may appear in RUL prediction
- Model development requires significant effort.
- The model might need some specific inputs for which no available values exist.
- Extensive user input could lead to poor judgment and also errors which affects the result in a great deal.
- Physical models cannot be easily updated when new information is provided.
- Some parameters in physical models may not be observable while the observed machine still functions. For example crack in ball bearings.
- Model choice is subjective.

Using a physical model increases the knowledge of the system and its behaviour. The more knowledge about the system, the less uncertainty exists about the system relations. In a nutshell, the physical method does not rely on the huge failure data set. Having the physical model, knowledge of the material properties and local loads are enough to calculate the component service life. They also are not based on the historical data [1]. The quantitative relation between the usage and degradation predicts the future changes within the prognostic analysis. An explicit example of the advantages of using a physical model compared to using lifetime data only is given in [17], where also a general approach to use physical models is described.

2 Machine Concept and Structure

In order to provide insights into the physical models that drive operational life prediction for the machine tools, we provide an introduction to general concepts within the framework of machining in this chapter. Machining is the general term for describing material removal process from a workpiece. For this case, the milling machine MAG SPECHT 600 is used as a running example to illustrate general concepts. The MAG SPECHT 600 machine tool is the same machine tool which is observed in JLR demonstrator. The introduction is necessary as the potential failure cases for the linear motion system of the machine tool in MAG SPECHT are presented as a use case in section 3.3.

In machine tools, beds, bases, columns and box type housings are called structures that compose 70 – 90% of the total weight of the whole machine. Basic functions of machine tool structure include:

- Providing rigid support for the components to be mounted on.
- Providing housing for individual units like spindles, gearbox and linear motor.
- Supporting and moving the workpiece and tool like a rotary table, carriage, etc.

The following requirements should be fulfilled by the machine tool structures:

1. High degree of accuracy for all important mating surfaces of the structures.
2. Initial geometrical accuracy of the structure maintained during the whole service life of the machine.
3. Ensuring the working stress and deformation not exceeding specific limits while providing safe operation and maintenance by shape and size. The stress and deformation are due to mechanical and thermal loading.
4. Efficient thermal control on components and machine elements such as spindle, ball screw and etc.
5. Optimal and faster tool change system.
6. Very high traverse speed, cutting feed rate and positioning for increased metal removal.

Proper material selection and high static and dynamic stiffness are the two fundamental features for the fulfilment of the requirements above.

2.1 Machine Tools for Machining

Basic machine tools are turning machines, shapers and planers, drilling machines, milling machines, grinding machines, power saws and presses. As an example, the MAG SPECHT 600 milling machine is shown in Figure 2.

Figure 2: MAG SPECHT 600 Milling Machine

2.2 Basic Structure

The basic structure of a machine is shown in Figure 3. The structures of a machine tool are mounting and housing for spindle and gear trains as well as tool holders and movers. It comprises beams and bars in order to limit the deflection and to endure the bending and direct tension and torsion generated while the machine is functioning. The main parts of the machine are shown in Figure 3 including its feed drive and spindle drive.

Important material properties: Commonly used material for machine tools are steel and cast iron. The important material properties are module of elasticity, specific stiffness, damping, long-term dimensional stability, coolant resistance, wear rate frictional properties and thermal expansion coefficient.

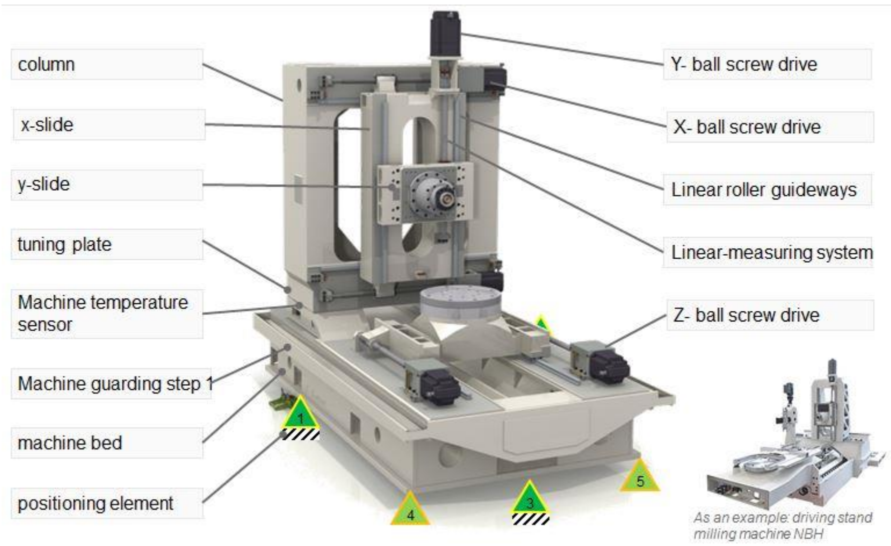

Figure 3: Basic structure for the SPECHT machine.

2.3 Machine Tool Drive, System and Mechanism

2.3.1 Electrical System

Voltage and current applied to a system are the quantities of external loads. The external loads are important parameters to consider calculating the remaining useful life due they influence the lifetime of the machine. In that sense and also on engineering level, electrical systems are analysed in terms of voltage and current in order to diagnose the electrical failure. The relation between voltage and current is Ohm's law;

$$\Delta V = IR \tag{1}$$

where R is the resistance of the component. Sources for loads are either generic as potential difference due to the distribution of charge over a body or specific which are different in the form of electric charge transformation or generation like in generators and solar cells.

For insulators, the internal electric load increases as the thickness of the insulating layer is reduced. The same approach holds for the electric current, as well. The local current density is the internal load parameter that governs failure. The current density is:

$$J = \frac{I}{A} \tag{2}$$

where A is the cross-sectional area of the wire. A current flowing in a thin wire will yield a much higher current density than the same current in a thicker wire. Hence, the thinner wire fails sooner than the thicker wire. The Ohm's law in terms of the internal load is as follows:

$$J = \sigma E \tag{3}$$

where σ is the connectivity or its reciprocal resistivity, ρ. The linear motion, spindle drive, lubrication system and etc. are examples of subsystems which fail when the electrical system fails. Hence, the electrical system requires more attention when it comes to functional status or condition monitoring.

2.3.2 Drives

There are many drives available in the machine tools as main drives and auxiliary drives. Machine tool drives provide motion to the moving bodies and are categorized into two main groups: spindle drive (main drive) and feed drive (auxiliary drive). Main drives, as well as auxiliary drives with the primary electrical drive, are shown in Figure 4.

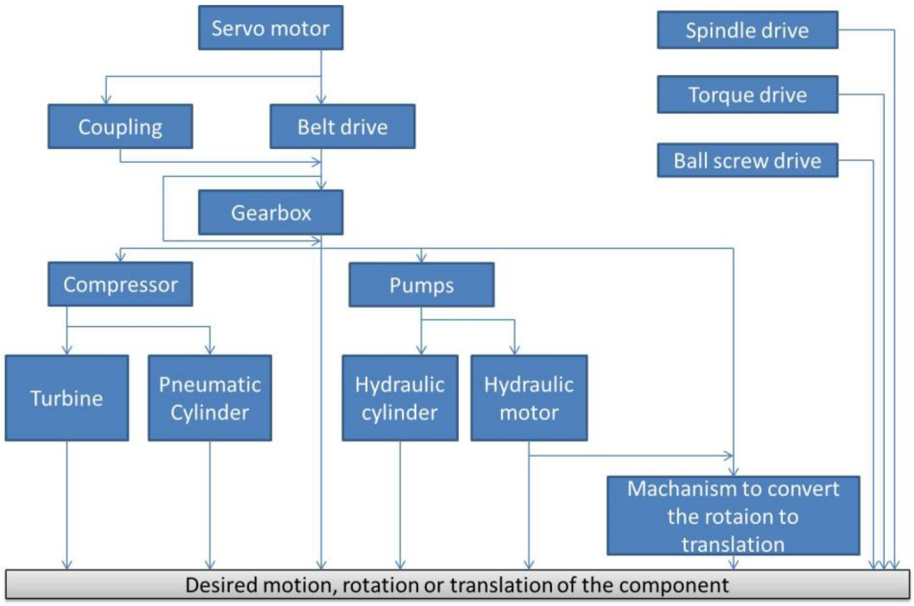

Figure 4: Various types of motion generators in main and auxiliary drives of machine tools with primary electrical drive [18].

2.3.3 Spindle Drive

Spindle drives are to rotate the cutting tools as in drilling, milling and grinding or to rotate the workpiece as in turning. The relative motion enables material removal operations. The common industrial spindle drive is shown in Figure 5.

The common spindle drive is available in three designs; belt drive, coupled drive and direct drive. The spindle shown in Figure 5 is a direct drive type spindle that holds a built-in motor, also known as the motor spindle. It requires no mechanical transmission elements so that it generates lower vibration. Built-in sensors in industrial spindles enable condition monitoring for the temperature of the motor stator, rotational speed, the temperature of the bearings, mechanical torque, the motor current and electrical power. However, available options by MAG SPECHT 600 are vibration sensors for bearing monitoring and tool system control in order to measure vibrations caused by imbalance as well as measuring stagnation pressure through pneumatic system control and sensors for tool abrasions and tool fracture.

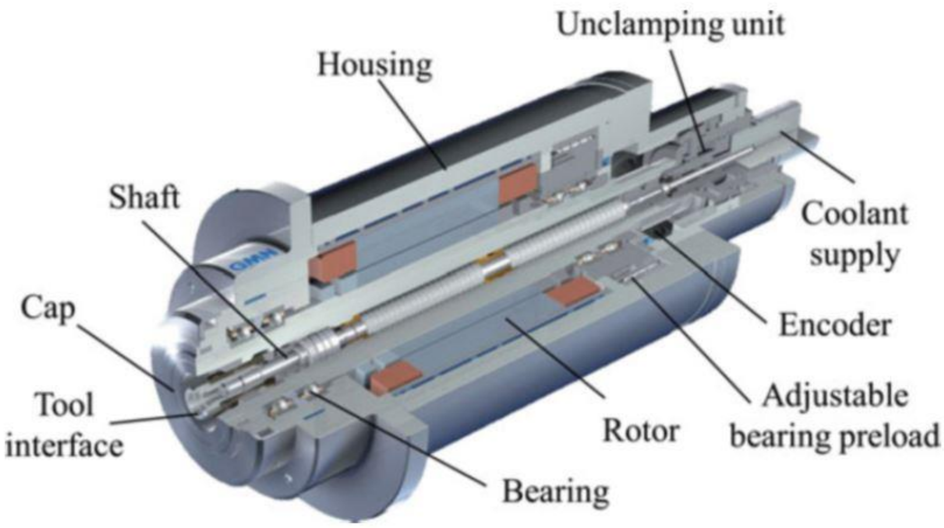

Figure 5: Common spindle drive [19].

2.3.4 Feed Drive

Cutting tools and workpieces mounted on the structure are moved to the desired location by the feed drive. Rails or guideways enable the movement. The speed and position accuracy play important roles in a feed drive, as they affect the product quality. There are several types of them including linear motors and rotary motors with ball screw or rack and pinion. A rotary motor is connected to the ball screw mechanism either directly or through gear reduction in order to enable torque amplification for large heavy-duty machine tools. In terms of control, the feed rate as an input to the Numerical Control (NC) program is combined with the acceleration and jerk limits of the feed drives. Then, discrete position commands are sent to feed drive by a real-time trajectory generation algorithm. Electrical signals (i.e. the converted corresponding digital velocity commands) are fed to the amplifier and motor of the drive. As mentioned earlier, guides are used to direct the motion. In light of positioning and motion, high accuracy is required. Good toughness, damping, load capacity and stiffness to withstand impacts and vibration are other requirements. Furthermore, they ought to possess wear resistance and low friction to avoid deterioration. Ball screws are typical mechanisms for feed drives as mentioned above. The mechanism is shown in Figure 6 schematically.

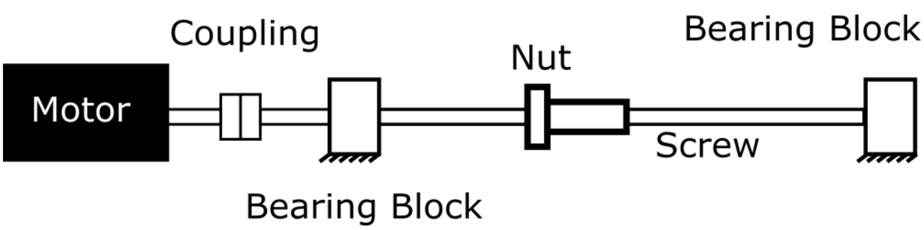

Figure 6: Schematic figure of ball screw drive.

Measuring System: As already mentioned, the linear systems for the feed drive consist of either a linear motor or a ball screw motor. The linear motor is an electric motor, which has a stator and a rotor unrolled so that it produces a linear force along its length and allows the translational motion. In this case, the system lacks the converter part, which exists in the ball screw motor that can also function as a measurement system. However, both systems possess a measurement scale, a measuring system that reads the position.

2.3.5 Numerical Controls

Numerical control in machine tools uses the coded instructions converted to signals in order to move the machine parts. In general, there are two types of control systems, direct numerical control (DNC) and computer numerical control (CNC). In the earlier form, a central computer is used to directly control all machine tools in the manufacturing floor, this implying the risk that all machines go down when the DNC stops. In the latter form, a microprocessor or microcomputer is integrated in the control system which provides each individual machine tool to operate independently. In addition to the two types, distributed numerical control benefits from both forms. Therefore, in complex modern manufacturing systems, a central computer is used to coordinate individual CNC machine tools.

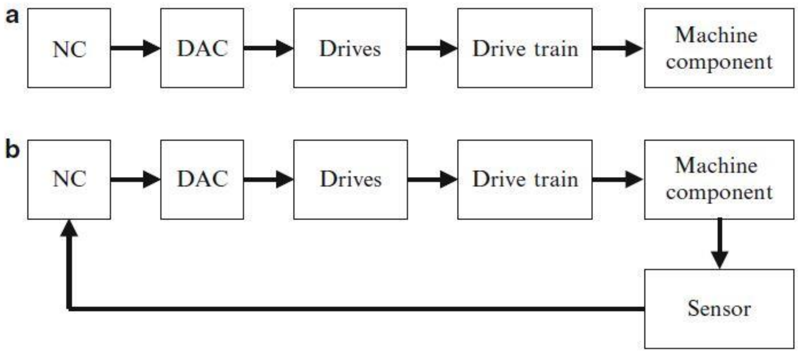

Figure 7: Scheme for a) open-loop b) closed-loop numerical control [19].

Motion control in condition monitoring is possible via NC machines through an open-loop or closed-loop system, as shown in Figure 7. In the open-loop case, signals are delivered to drives by controllers where the controllers receive no feedback of position or motion. On the other hand, in closed-loop systems, machine tool's status is fed to the controller. A digital-to-analog converter (DAC) is used to interface the controller with the drives.

There are also two types of NC systems, point-to-point, and continuous path. With point-to-point (or positioning) systems, the path from one point to another is not considered and the workpiece or cutting tool is moved to the programmed position as in drilling. The machine accelerates initially to maximum velocity and decelerates when it reaches the position. With continuous path (or contouring), the component follows the prescribed path. Therefore, the controller needs accurate position data and a synchronization of velocities as in milling and turning.

2.3.6 Hydraulic and Pneumatic System

Hydraulic and pneumatic systems are used to generate, control and transmit power. Hydraulic systems use liquids as operating resource, whereas pneumatic systems use gases. Pneumatic systems are powered by compressed air or inert gases. A pneumatic system in the machine tool, depending on components and design, is typically distributed throughout the machine as shown in Figure 8 for the MAG SPECHT 600. The MAG SPECHT also has an individual hydraulic unit which empowers the clamping function for the spindle, rotary table and automatic tool changer (ATC). The hydraulic circuit is depicted in Figure 9.

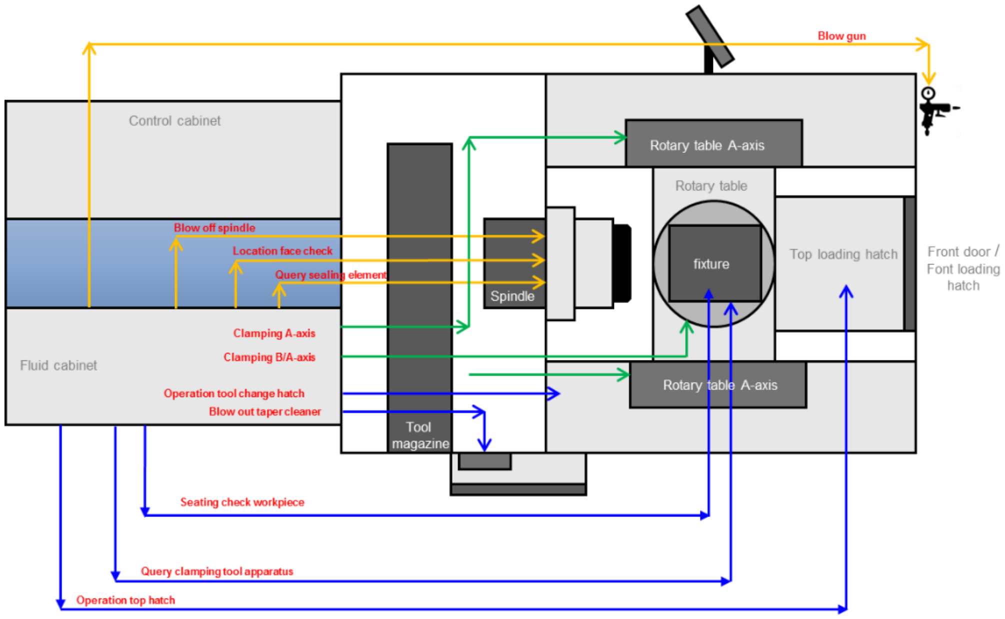

Figure 8: Pneumatic system distribution plan for MAG SPECHT.

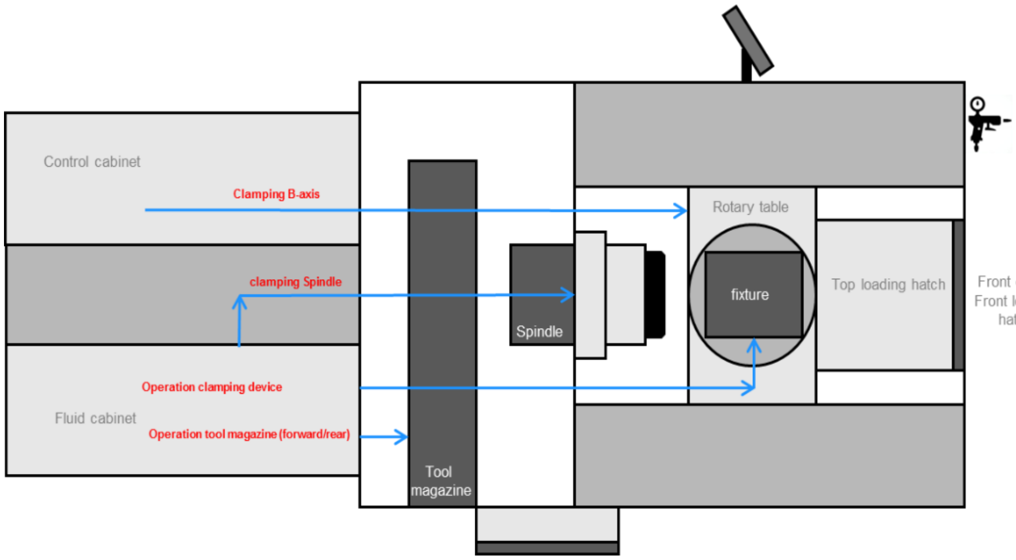

Figure 9: Hydraulic distribution plan for MAG SPECHT.

2.3.7 Rotary Table

The rotary table is used for fast positioning of the processed component. The desired component or part is mounted on the table and is held fixed by the clamping system, which provides a 70 bar hydraulic pressure. The rotary table enables a rotation of the component around two axes, A and B. The axes, A and B are the rotation axes around x and y, respectively. The swing angle is unlimited.

2.3.8 Automatic Tool Changer (ATC) - Tool Magazine

Magazines in machine tools store tools for machining. They are available in two main types, drum and chain, which are selected depending on the machine tool design. The drum type ACT also known as disk tool magazine enables a faster tool selection process as the number of mounted tools on a disk is smaller than the one of the chain type.

The chain type requires more time as there is a wider range of options for tools. The typical shape designs for a chain type automatic tool changer are top O-chain, side O-chain and L shape. There are several options available including drill breakage monitoring and tool taper cleaning.

The tool loading mechanism has an ergonomic loading height, an optional control panel and a tool codification. It grabs the tool from the tool magazine and sets it up on the spindle. The whole set has an impact on productive time as it lessens the unproductive time to a large extent. It can help to lift and to hold heavy and large tools as well.

2.3.9 Machine Cooling and Lubrication-Machining Coolant

Machine cooling and lubrication are the processes to cool down the components in the machine and to reduce the friction. High temperature and high friction are the two common phenomena of many that can cause failure as discussed in Chapter 3. Machine cooling is done either by the cooling media circuit or by the primary fans and air circulation system within the machine tools. The medium is mostly water, which is reserved in the tank and is pumped into the circuit. The lubrication system pumps either oil or grease mostly in the regions where two relative motions are taking place in order to reduce friction. For a MAG SPECHT, two methods are responsible for lubrication: (1) central lubrication, which takes place every 8 hours and (2) lifetime lubrication.

3 Failure Mode

3.1 Introduction

In this chapter, various failure mechanisms are presented. The failures are put into mathematical relations; however, not all failure mechanisms are able to capture the real physical failure of parts. The term failure is meant to be a state that the system cannot fulfil its intended function.

With the failure models, one can observe and investigate the degradation of systems considering the parameters. However, some parameters cannot be observed or measured for the machine whilst it runs.

3.1.1 Static Overload

The static strength is a property of materials, which shows the load-carrying capacity of the system. Static overload happens when the applied load exceeds the static strength. The strength at which the plastic deformation starts is called yield strength that is temperature dependent. For most materials, the yield strength decreases when the temperature increases. It is important to consider the static strength while designing a structure or a system so that the active load level is lower than the strength of the material. As clearly stated, it is a design issue that relates to design improvement methods classified under aggressive maintenance.

Working conditions can affect the lifetime of a machine or component. For example, the effects of high temperature on the material strength as mentioned above or rotational speed which is given as an example later. Considering the parameters, failure models can be built.

Static overload generates voids that eventually lead to fracture. Dimples on material surface suggest the existence of voids. Figure 10 shows that the voids start to nucleate around impurity in material and grow bigger. They join and generate fracture. In this fashion, damage happens due to static over-load.

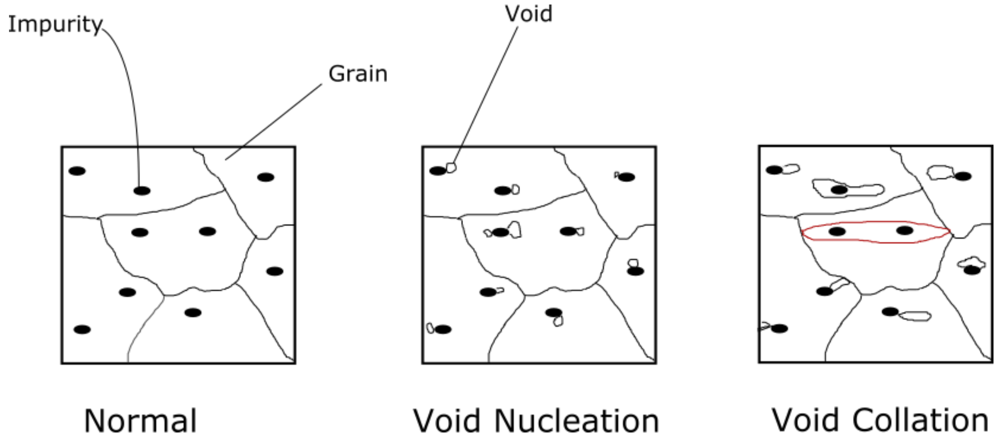

Figure 10: Static overload and void nucleation.

The local stress is calculated as follows:

$$\sigma(r) = \frac{F_{exerted}}{A_{surface}} \tag{4}$$

where F is the exerted force on an area, A. The calculated stress should be less than the material strength. For example, in order to calculate the fracture of a nut in a ball screw, due to overload, considering the centrifugal force exerted on the nut, the stress is calculated as follows:

$$\sigma(r) = \frac{\rho\omega^2}{2} R_{shaft}^2 \tag{5}$$

It shows that the nut receives the amount of stress depending on threaded shaft's radius (R) and the rotation speed, ω.

3.1.2 Deformation

Deformation of a part, component is also a cause of mechanism's failure. For example, for the machine tools, the stand can bend and cause plastic deformation because of the heavy load, its own mass, thermal expansion of the material which can result in quality loss of the product as the machine loses its precision. A machine tool is schematically shown in Figure 11 that the stand is bearing the load and the moment.

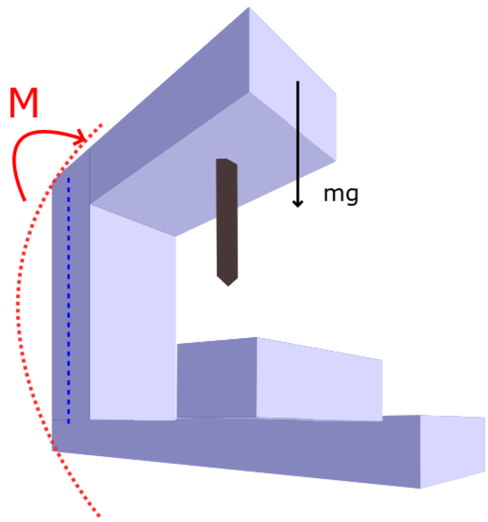

Figure 11: Schematic figure of a machine tool which the stand may deform due to acting bending moment.

It is also important to note that temperature affects material properties like elastic modulus, which affects both elastic and plastic deformation. However the stress and temperature levels are taken into account in design, whereas unexpected operating conditions are the main failure sources. In order to measure the deformation, having the stress calculated, the strain can be determined using Hooke's law:

$$\sigma(r) = E\varepsilon(r) \tag{6}$$

With the strain at hand, elongation is consequently measured as follows:

$$\Delta L = \int_{R_1}^{R_2} \varepsilon(r) dr \tag{7}$$

The deformation of the nut, according to the stress calculated with Eq. 7 is determined as follows:

$$\Delta L = \frac{-\rho\omega^2 R_{shaft}^2}{2E}(R_2 - R_1) \tag{8}$$

The stress should be negative as it is of compression form for the nut.

3.1.3 Fatigue

As mentioned in Section 3.1.1, static overload plays an important role in design. Nevertheless, fatigue should not be neglected. It comes into play when a repetitive load is applied to a component. For example, Figure 12 shows an acting stress in cycles both in tension and compression form. In this case, material failure would happen even below the material strength. Material failure depends on the magnitude of the applied cyclic load and the material fatigue strength. Materials typically run to failure after 10^3-10^7 cycles [1]. Cyclic loads could depend on component rotations and vibrations. Robust design usually solves the issue; however, it is still a big problem in industries which thin structures are expected in order to lessen the body's weight.

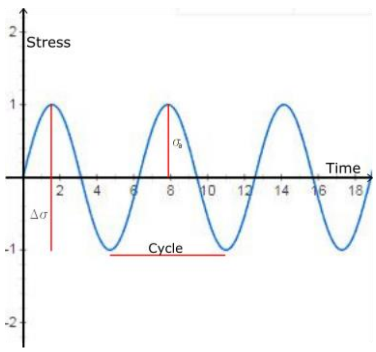

Figure 12: Periodic load acting as fatigue in material.

As mentioned, fatigue is caused by a cyclic or repeatedly applied load, which results in material weakening and eventually failure. The load is designated with stress magnitude $\sigma_a$and its range, Δσ. There are three types of fatigue mechanism, low cycle fatigue (LCF), high cycle fatigue (HCF) and thermal mechanical fatigue (TMF). One way to distinguish the two types of low and high cycle fatigue is to consider the transition between LCF and HCF that is in most cases at 10^6 cycles. When the maximum stress during cycles never exceeds the material yield where the deformation is fully elastic, it is called high cycle fatigue. In case, some plastic strain develops during the process, it is called low cycle fatigue. Thermal Mechanical Fatigue is when thermal expansion and contraction happens because of large temperature changes. It causes significant strain in parts and components like turbine blades, vanes and other hot components. The strain caused by TMF combines with other associated mechanical strains and causes material degradation [20].

An S-N curve or Wöhler curve is used to determine the number of cycles to failure (N_f) for constant amplitude loads. The relation between stress amplitude S and N_f is shown in Figure 13.

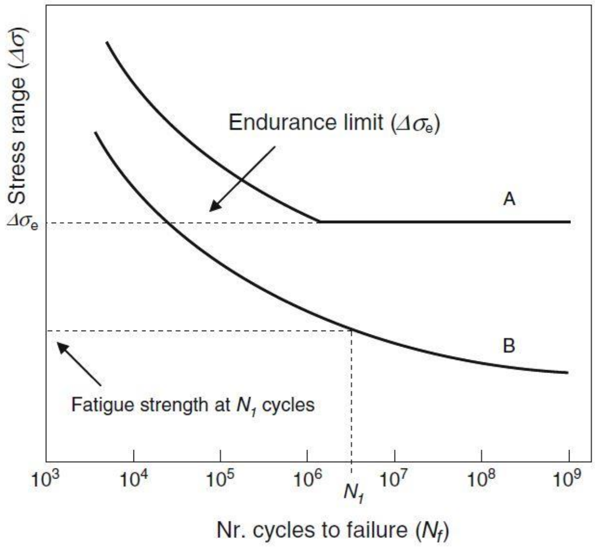

Figure 13: Wöhler curve [1].

Equation (9) shows the relation between the stress amplitude and the number of the cycles [21].

$$\frac{\Delta\sigma}{2} = A(2N_f)^2 \tag{9}$$

In case of cyclic and constant stress, the number of cycles to failure is determined by the use of the Smith diagram shown in Figure 14 [1]. Stress close to holes needs a stress concentration factor K_t to give the real value of stress.

$$\sigma = \mathrm{K_t}\sigma_{\mathrm{nom}} \tag{10}$$

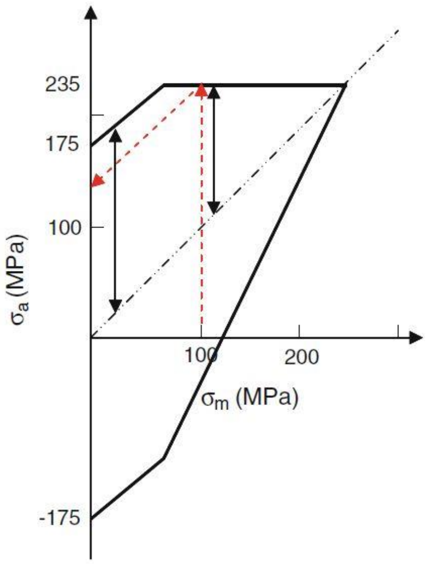

Figure 14: Smith diagram for a typical steel alloy [1]. The mean value as well as alternating stress can be calculated with finite element.

Fatigue is dependent on the size and surface quality of the component. The bigger the component, the higher the chance is that more irregularities exist in the material, which affects the service life prediction. Moreover, the defect surface enhances crack initiation process. This is also expressed using a correction factor, R_a. The manufacturer considers these factors in the design process. Variable amplitude loads in fatigue are taken into account with the cumulative damage rule [22] [23].

$$D = \frac{n}{N} \tag{11}$$

where *D* is the fatigue damage after n cycles at a constant stress σ assuming that failure happens after *N* cycles. Thus for a variable amplitude load consisting of *p* blocks of $n_i(1 < i < p)$ constant amplitude cycles to failure N_i, the cumulative fatigue damage is:

$$D = \sum_{i=1}^{p} \frac{n_i}{N_i} \tag{12}$$

The total service life is calculated as follows:

$$L = \frac{1}{D_T} T \tag{13}$$

where *T* is the duration of some load sequence, which generated damage D_T. In case of complexity and large numbers, Spectrum loading, Counting Methods, Mean Crossing Peak Method, Level Crossing Count Methods, Range Pair Count Methods (Rain Flow Count) can be used to reduce the amount of data [1].

3.1.4 Fracture Mechanics

In some structures where crack initiation is inevitable, it is important to know where the crack happens, what maximum stress the component is allowed to endure and how fast the crack grows. Having the intensity factor which is dependent on crack mode (tensile, sliding and tearing), the stress can be determined using the Eq.14.

$$\sigma_{i,j}(r,\theta) = \frac{K}{\sqrt{2\pi r}} f_{i,j}(\theta) + \text{higher orders} \tag{14}$$

where K is the intensity factor and f, a dimensionless factor dependent on the geometry and the load.

$$K = BS\sqrt{\pi a} \tag{15}$$

In general K (also known as Fracture Toughness) is in the form of Equation (15), S is the far field stress and B accounts for the shape of specimen and the geometry of the crack. The plastic zone in front of a crack tip is calculated as follows:

$$r_p = \frac{1}{2\pi}\left(\frac{K}{2\sigma_y}\right)^2, \text{plane stress} \tag{16}$$

$$r_p = \frac{1}{6\pi}\left(\frac{K}{2\sigma_y}\right)^2, \text{plane strain} \tag{17}$$

Fatigue can affect the crack propagation and the Paris-Erdogan equation, Equation (17) is the mostly accepted form of fatigue crack propagation expression [12].

$$\frac{da}{dN} = C(\Delta K)^m \tag{18}$$

where C and m are material constants and $\Delta K = K_{max} - K_{min}$ is the stress intensity factor range. If the remaining cross section of the structure is unable to carry the load due the crack front has grown (overload) or if the crack has caused impair of the structure like leak-age in a fuel tank (functional impair) or the stress intensity factor exceeds the fracture toughness of the material, the crack leads to failure. According to Equation (15), critical crack length is calculated as below:

$$a_{critical} = \frac{1}{\pi}\left(\frac{K_{Ic}}{BS}\right) \tag{19}$$

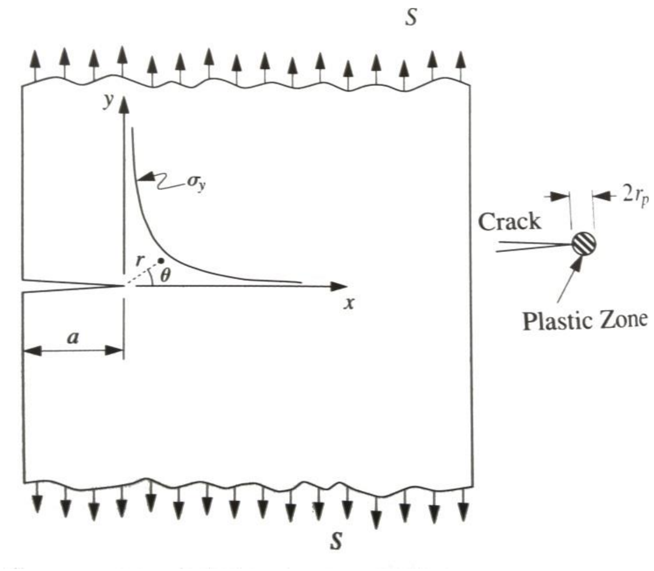

Figure 15: Crack on a sample under tension [24].

Thin sheets are more crack tolerant than thick sections which means a mixed mode K_I/K_{III} happens that K_c is higher than fracture toughness, K_{Ic}.

3.1.5 Creep, wear and Friction

Creep: Creep in material causes inelastic deformation, which is not intended, especially in the machine tool case; if creep happens, a loss of accuracy and eventually a loss of product quality is inevitable. Temperature and applied stress affect this parameter. The Norton creep law [25] is as follows:

$$\dot{\varepsilon_{cr}} = AT^n\sigma^m \tag{20}$$

where A, n and m are material constants derived from experiments. With the applied stress and temperature at hand, creep strain rate is calculated via Eq. 25. This is an approximation for many applications to make life assessments. There are many models available that can predict the crack behaviour in all regimes. The Larson-Miller parameter [26] shows the combination of stress and temperature in one curve.

$$P_{LM} = T(C + \log t) \tag{21}$$

where t is the time to rupture and T is the temperature [26].

Wear: In case of relative motion of two or more parts, loss of material is caused by physical contact that is called wear. For example with linear motion mechanisms (linear drives in a machine tool), a huge effort is put to reduce the friction and eventually wear by periodic and continuous lubrication. Friction happens at interfaces of two contacting objects. The mechanism is also used to stop motions, i.e. by braking. The friction force is calculated as follows:

$$F_f = \mu F_n \tag{22}$$

where μ is the friction coefficient, and F_n is the normal force on the sliding body. The surface roughness and the material toughness play an important role in friction. The toughness mechanism is used for ploughing if the relative roughness between the two materials is more than 20%, one with more toughness penetrates in the softer one. Milling is based on this concept. For instance, the balls in ball bearings are subject to direct contact to the runways in the threads that is associated with relatively large penetration depths. The friction coefficient is calculated as follows:

$$\mu = \frac{\sigma}{p}\frac{A_f}{A_r} \tag{23}$$

where A_f is the frontal area and A_r is the contact area. The parameters p and σ are pressure and stress at frontal surface, respectively. Figure 16 shows a sliding ball representing ploughing friction. Two-body wear is divided into four wear mechanisms; Adhesive wear, Abrasive wear, Corrosive wear and Surface fatigue. Erosion is also a wear cause as well as single-body wear, which occurs when a specific medium (gas or fluid) is present. There is one general relation for life assessment, which is applied widely to all types of wear. The Archard [27] relation is as follows:

$$V = kF_n\Delta s \tag{24}$$

Equation (24) also known as the Archard law that is rather a phenomenological relation shows that the volume loss V is proportional to the normal load F_n and the distance the part travels under the load. K is the specific wear rate.

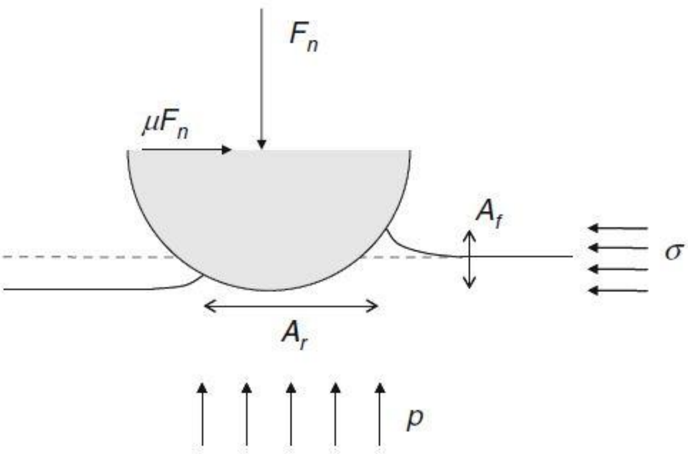

Figure 16: A spherical intender representing ploughing friction [1] .

Melting and Thermal Degradation: Depending on the heat capacity c_p of the material, the temperature increases in some parts, which can cause thermal failure. Melting is not often the case, however, high temperature in general can gradually lead the system or part to deterioration. Mechanical properties as well as electrical properties are in this case prone to degradation.

Lubrication: Considering friction and wear, lubrication is of high importance. Lubrication in a sense increases the lifetime of parts and systems. Three regimes, boundary lubrication (BL), hydrodynamic lubrication (HL) and mixed lubrication (MLub) exist in sliding or rolling elements. Wear rate in BL is 0.1 while for HL has a wear rate of 0.01. If a lubricant is present in a contact between two parts while the load is being transferred by them, it is called BL. On the other hand, when the contact of two materials is prevented as in ball and journal bearings, it is called HL. The Stribeck curve [28] shows the relation between the speed and the resulting friction coefficient that the designer can use to determine which regime is active and eventually give insight about critical film thickness. It is a fundamental concept in the field of tribology which shows that the friction in fluid-lubricated contacts is a non-linear function of the contact load, the lubricant viscosity and the lubricant entrainment speed. As lubricants flow in most regions where parts are in contact, they can help detect wear in the system. The lubricants as well as the lubricant filters can be investigated for wear particles as a parameter for condition monitoring.

3.1.6 Electric Failure

Electronic components and devices are key parts of machines and systems and their failures result in operation shutdown, quality loss and etc. By nature, the electrical systems are more complex in comparison to mechanical systems. Hence, deducting the service lifetime depending on the applied load is not as in mechanical systems. In a sense, predicting failures in electronic systems is random [1].

Current overload: one major failure in electric systems is due to excessive electric current. It does not directly cause the failure, however generates thermal load due to parts resistance.

$$\mathrm{P} = \mathrm{I}^2\mathrm{R} \tag{25}$$

Considering the heat generated by the resistance of the parts, Eq. 30 is put in local quantities below which shows the heat generated per unit volume. In such systems, cooling capacity helps to remove generated heat from the parts.

$$P = J^2 \rho l A \tag{26}$$

where J is the current density and ρ is the resistivity of the part. Thus, the cooling capacity is proportional to the cross-sectional area of the component. A thin wire generates less heat in comparison with a thick one.

Intrinsic Breakdown The insulating material in the systems may breakdown due to high electric fields. In a specific scope, insulating capacity fails when large numbers of electrons are excited in conduction band. Electric insulators have very high resistance and are used to support and separate electrical conductors without allowing current flowing through themselves. This failure is called intrinsic breakdown or dielectric breakdown. Dielectric capacities of some materials are presented in Table 1. The most common degradations are Thermal aging, Partial discharge, Electric Treeing, Water Treeing, surface discharge process and Interface discharge.

Table 1: Dielectric constants and strength for some dielectric materials [29].

Number	Material	Dielectric constant ε_r	Dielectric strength (V/mm)
1	Titanate ceramics	15-10,000	2,000-12,000
2	Mica	5.4-8.7	40,000-80,000
3	Steatite (MgO-SiSo2)	5.5-7.5	8,000-14,000
4	Soda-lime glass	6.9	10,000
5	Porcelain	6.0	1,600-16,000
6	Fused silica	3.8	10,000
7	Phenol-formaldehyde	4.8	12,000-16,000
8	Nylon 6,6	3.6	16,000
9	Polystyrene	2.6	20,000-28,000
10	Polyethylene	2.3	18,000-20,000
11	Polytetrafluoroethylene	2.1	16,000-20,000

Breakdown in Gas and Vacuum It happens when vacuum or gas fails to separate the conductors. The distance for the two individual conductors and the gas pressure is determined by Paschen's law [30] following below;

$$V_{bd} = \frac{Apd}{\ln(pd) + B} \tag{27}$$

where A and B are constants dependent on the gas and d shows the distance between the electrodes and p shows the gas pressure.

Electrostatic Discharge and Electromigration Electrostatic discharge can cause failures. For instance, the electrostatic electricity, which is present on human body during assembly or maintenance. Electromigration is a typical failure for integrated circuits and its effect increases when the size of the structure decreases. Momentum transfer between conducting electrons and diffusing metal atoms cause gradual movement of the ions in conductors, which results in material transport. The phenomenological relation for mean time to failure (MTTF) due to electromigration is called Black's law [31];

$$\mathrm{MTTF} = \mathrm{AJ}^{-n} e^{\left(\frac{E_a}{KT}\right)} \tag{28}$$

where A is a constant based on the cross-sectional area of the interconnect, E_a is an activation energy i.e. material constant, k is Boltzmann's constant and n a scaling factor.

Life assessment of electric systems is based on historical lifetime data only and is often expressed as mean time between failures (MTBF). The drawback of using historical data is that it extrapolates to predict the future. A physical model for the failure mechanism would eliminate this drawback. Nevertheless, the large number of individual components for electrical systems makes this approach infeasible. Hence, both methods, experienced-base and model-based together seem to be the best solution in this case. They can be achieved by the application of phenomenological models. These models are based on certain amount of failure data rather than mathematical failure mechanism. They relate the mean time between failures of the system to the governing loads. The Black's law related to Electromigration is one of the examples. The Eyring-Peck model for printed circuit board (PCB) and the Power law model for intrinsic breakdown of insulators are two other examples of such models. Common failure of PCB is corrosion of the plastic package. It increases short circuits due to metallization process [1] [32].

The Eyring-Peck model reads as follows:

$$t = t_{ref}(\frac{85}{H})^3 \exp\left[-\frac{\Delta E}{k}(\frac{1}{T}-\frac{1}{358.1})\right] \tag{29}$$

It is related to the life time at reference condition, which is 85% relative humidity (H), and 85°C. ΔE is the activation energy of the corrosion process and k is the Boltzmann constant is mentioned earlier. The Power law model for insulating material degradation is;

$$T = \frac{C_{bd}}{E^n} \tag{30}$$

where C_{bd} and n are material constants. In order to calculate the service life for a component, which experiences several field strengths, it can be cumulatively considered. C_{bd} is considered as the maximum allowable amount of damage and the combinations of service time periods t_i at field strength E_i can be accumulated as follows:

$$\sum_i t_i E_i^n \leq C_{bd} \qquad t_A = t_B\left(\frac{E_B}{E_A}\right)^n \tag{31}$$

which means that t_A at field strength E_A is equivalent in terms of life consumption to another period t_B at E_B.

3.2 Failure Analysis

General failure modes are failure during operation, failure to operate at a prescribed time, failure to cease operation at a prescribed time and premature (spurious) operation. They may be classified according to failure causes, time of failure, detectability and degree of failure [33]. There are two classifications of methods at hand to analyse failures in a system [1]. One group applies when the failure has not happened yet; the other type of method applies when the system has already run to failure. Some of the many available methods are

Failure Mode Effect Analysis (FMEA), Fault Tree Analysis (FTA), Pareto and Degrader Analysis, Root Cause Analysis (RCA), Common Cause Failure, Sneak Circuit, Energy Trace and Fault Hazard [34].

The steps to failure analysis are:

1. Problem definition
2. Fault Tree Analysis
3. Determine Priorities in Failure Mode
4. Determine Failure Mechanism
5. Determine Loads, Usage and Their Relations
6. Solution Search

The process can be used for real world problems. However, the following conclusions have been achieved by case studies and recent researches [1];

- Details about the failures of the system might not be available in information systems like computerized maintenance management system (CMMS).
- In case of shortage of information, experts and their experiences are the best way to obtain required information.
- Human errors compose a significant fraction of the total system failure. Investments on instructions and training courses can enhance the system’s operation. It requires, however, a detailed analysis and root cause analysis of the system.

3.3 Use case ball screw

Linear motion plays an important role in providing the final quality of workpiece for machine tools. Hence, they are listed as important parts or systems when it comes to machine tool maintenance or for whatever systems, which utilize a ball screw mechanism. The ball screw mechanism is suggested as the key part in the machine, therefore an introduction to its major design terms and criteria is helpful which is given in this section as a use case.

The ball nut moves in an axial direction when it rotates around its axis. This is possible when the helical form grooves are designed and available on the screw. Screw is a mechanism, which converts a rotational motion into a translational motion or vice versa. The steel balls in the ball screw facilitate the rotation of the nut generating a rolling friction between the steel balls and the grooves. The rolling friction requires far less force in comparison with the sliding type. Therefore, the steel balls should be able to recirculate within a path to ease the motion. In this case, a return tube provides the desired path so the series of steel balls are redirected and recirculated.

The lead or pitch has been defined and the relation between lead, lead angle and the screw diameter is as follows;

$$\text{Lead angle} = \arctan\left(\frac{1}{\pi d_m}\right) \tag{32}$$

where d_m is the mean diameter of the screw. The lead is classified into two groups, high helix lead, which travels a longer distance per rotation of the shaft and is suited for high-speed operation, and the fine pitch lead that travels a shorter distance per one rotation of the shaft.

Some issues with ball screws are accuracy, preload and rigidity of the ball screw. Inaccuracy can be caused by lead error or its grade as well as mounting. Figure 17 presents the possible errors including their causes for a ball screw. However, a lead error is the nut travel accuracy when the nut rotates. It is completely dependent on manufacturing accuracy of the ball grooves in their feed direction. The largest travel variation in lead errors over any 300-mm interval within the effective travel length is called accuracy grade according to the ball screw manuals. There is also an issue regarding inappropriate installation, the clearance and looseness can cause vibration, noise and reduced service life. Improper montage can also cause the inaccuracy for positioning or excessive current use by the motor coupled with the ball screw. Preload provide the ball screw the required rigidity. Providing an axial load, the required elastic deformation is created in steel balls and the ball grooves in the nut and the screw shaft. It reduces the backlash or the axial play and the elastic deformation caused by external force. Dynamic torque is the rotation force multiplied by the rotation centre distance, required to move the nut in axial direction. The relation between the preload and dynamic torque is as follows;

$$\mathrm{T} = \mathrm{k}\frac{\mathrm{F_{a0}.l}}{2\pi} \tag{33}$$

where T is the dynamic preload torque (N.cm), F (N) is the preload and l is the lead in cm. Rigidity is the resistance to its deformation when an external load acts on a ball screw. Axial rigidity of a ball screw is calculated as follows;

$$\frac{1}{\mathrm{K_t}} = \frac{1}{\mathrm{K_s}} + \frac{1}{\mathrm{K_n}} + \frac{1}{\mathrm{K_b}} + \frac{1}{\mathrm{K_h}} \tag{34}$$

where;

$K_t: Axial\ rigidity\ of\ the\ ball\ screw\ system,$

$K_s: Axial\ rigidity\ of\ the\ ball\ screw\ shaft,$

$K_n: Axial\ rigidity\ of\ the\ nut,$

$K_b: Axial\ rigidity\ of\ the\ support\ bearing$

$K_b: Axial\ rigidity\ of\ the\ housing\ for\ the\ nut\ and\ the\ support\ bearing.$

The rigidity unit is (N/μ). The relation between rigidity and preload is as follows;

$$\text{Rigidity of ball screw} \propto \text{Preload}^{\frac{1}{3}} \tag{35}$$

which means rigidity increases by only 1.26 when the preload force is doubled.

Ball screws generate heat while operating which can cause shafts to elongate with respect to their expansion rate and consequently lead to inaccurate positioning. An elongation of 12µm per meter is expected to take place for 1°C temperature rise.

Allowable axial load for a ball screw is the limit of tensile or compression load which is applied to the screw shaft. Any load more than the limit would cause plastic deformation. Moreover, the ball screw fails if the applying load goes beyond the allowable axial load.

Basic static load rating (Coa) is an axial load that causes the sum of deformations between the balls and the groove to exceed 0.01% of the diameter of that steel ball. An allowable load rating (P_0) against permanent deformation is as follows:

$$P_0 = \frac{\mathrm{Coa}}{\mathrm{fs}} \tag{36}$$

where $f_s$is the static allowable load coefficient, which is a safety factor. For regular operation is 1 to 2, and if there is vibration or impact, the safety factor is 1.5 to 3. Considering fatigue life (L) for a ball screw requires parameters determining axial load, and basic dynamic load rating (Ca). Basic dynamic load rating is a value listed in catalogues published by manufacturers, which indicates the axial load applying on a group of identical ball screws rotated individually under identical conditions so that 90% will successfully achieve one million (10^6) rotations without any flaking. Fatigue life is:

$$\mathrm{L} \propto \left(\frac{\mathrm{Ca}}{\mathrm{Fa}}\right)^3 \tag{37}$$

A machine will fail due to its critical component failure. Considering a ball screw as a machine, its key components are the bearings, since it is through the bearing that machine forces are transmitted. Manufacturers provide ways to calculate bearing life. Bearing life is the number of operating hours at a given speed, which the bearing is capable of enduring before the first sign of metal spalling or fatigue happens on the rolling element or the raceway of the inner or outer ring. Basic rating life denoted as $L_{10}$is the fatigue life that 90% of a sufficiently large group of apparently identical bearings, operating under identical operating conditions, can be expected to attain or exceed.

Basic rating life:

$$\mathrm{L_{10}} = \left(\frac{\mathrm{C}}{\mathrm{P}}\right)^{\mathrm{p}} \tag{38}$$

If speed is constant, then life in operating hours is:

$$\mathrm{L_{10h}} = \frac{10^6}{60\ \mathrm{n}} \mathrm{L_{10}} \tag{39}$$

where C is the basic dynamic load rating and P is the equivalent dynamic bearing load. The exponential value, p is 3 for ball bearings and 10/3 for roller bearings. Rotational speed, n [rpm] is the rotational speed. The life equation was formulated using Weibull probability theory of fatigue

As mentioned, these expressions are design parameters and basic rating life is influenced by the operating conditions. For instance, the equivalent dynamic bearing load is the hypothetical load, constant in magnitude and direction, which acts radially and axially and centrically on thrust bearings. It has the same influence on bearing life as the actual loads to which the bearing is subjected. Hence, in case of machine deterioration or impeding problems, the machine will start to vibrate and this vibration engenders other forces. The P value increases and results in less life duration as designed. Furthermore, doubling the rotation speed cuts the bearing life into half. However, some other factors like lubrication, lubricant contaminant and damage from improper storage or installation are not taken into account.

3.3.1 Relationship among ball screw and nut parameters

Design parameters are interconnected and changing one can have a major effect on another or on overall functionality. Some parameters are presented in Table 2. For example, the critical speed as well as system stiffness increases while increasing mounting rigidity or the preload of the nut, the position accuracy would increase as well as the drag torque.

Table 2: Design parameter effects for ball screw and nut.

Number	Parameter adjustment	Parameter effect
1	Increasing screw length	Decreases critical speed
2	Increasing screw diameter	Increases critical speed as well as, stiffness, load capacity, inertia, spring rate and column load.
3	Decreasing lead	Decreases torque input, load capacity as well as steel ball diameter. Increases angular velocity as well as position accuracy
4	Increasing angular velocity	Decreases critical speed
5	Increasing number of ball bearings	Increases system stiffness and its load capacity
6	Decreasing load	Increases life of system
7	Decreasing ball diameter	Decreases life, system stiffness and load capacity

There are also other parameters involved, for example, in order to increase load capacity and stiffness of the system, one may increase the nut length. The interconnection among the parameters sets the boundaries of design. However, design issues are taken care of by manufacturers. Parameters like load for instance can be important considering the life of the system or degradation process. Linear motion system in the milling machine tool, MAG

SPECHT, is designed to run 20000 hrs and holds for workpieces of aluminium material; however, this limit drops drastically when the workpiece is of steel material.

3.3.2 Cause and Effect List

Some issues regarding linear motion system in the MAG SPECHT machine tool have been listed in Figure 17 describing the possible errors or causes and the respective effect.

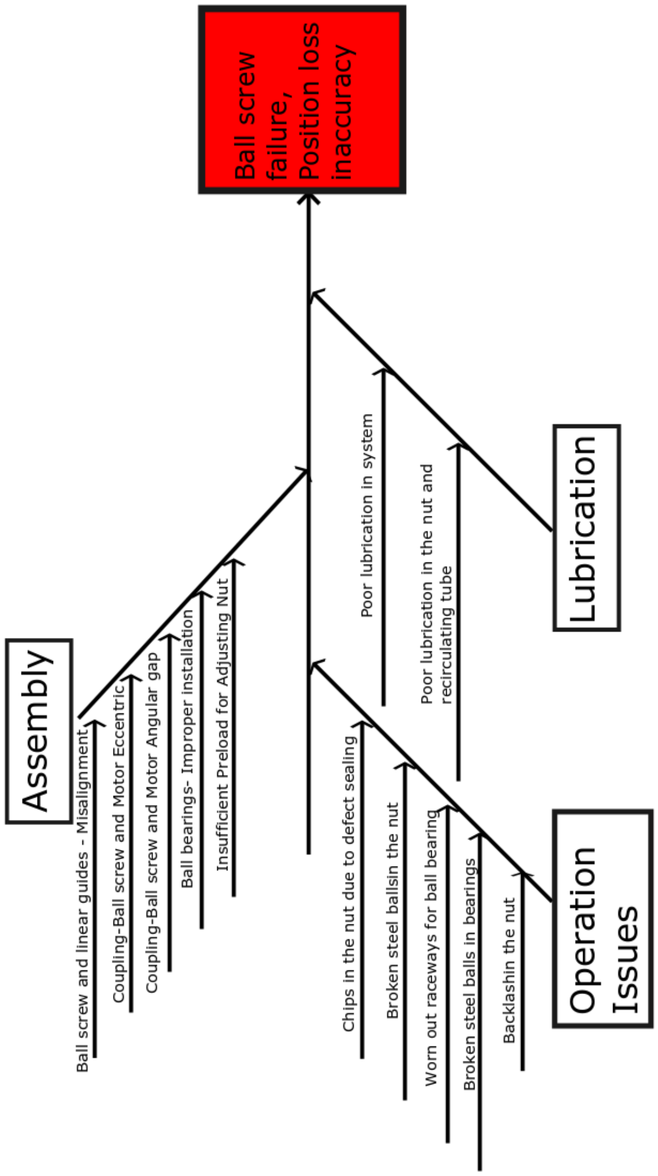

Figure 17: Ishikawa diagram for ball screw

4 Physical models for RUL Prediction

Prognostics, in a sense is the prediction of the system's life time and corresponds to the last level of the classification of damage detection methods [35]. It is also a way to quantify the chance that a machine operates without a fault or failure up to some future time. International Organization for Standardization suggests: "the estimation of time to failure and risk for one or more existing and future failure modes" [36]. It follows to predict the remaining useful life (RUL) before the failure happens based on current status of the system and its history.

As mentioned, the remaining useful life of an asset, a machine or a system is the expected life before it runs to failure or the usage time remaining before the machine requires repair or replacement. The term life time is the life of a machine defined in terms of quantity used to measure the system life including distance travelled, the fuel consumption or time since the start of the machine.

Remaining useful life of a system can be estimated based on the developed model which can perform the estimation based upon the time evolution of a condition indicator values, such as;

- A time evolution model of a condition indicator which predicts its remaining time before the threshold value of a fault condition is met.
- A time evolution comparative model of a condition indicator which measures or simulates the time series from systems running to failure.

It is important to note that a model-based condition indicator is a quantity derived from fitting system data to a model and performing further process using the model. Condition indicators could be model parameters (coefficients of a linear fit), statistical properties of model parameters (variance), dynamic properties (system state values) and quantities derived from simulation of a dynamic model. The models above provide probability distribution of the RUL of the test machine. Predictions from the models are statistical estimates with associated uncertainty [37].

4.1 RUL estimators

RUL estimation models are divided into three subcategories [37], similarity models, degradation models and survival models. RUL estimation models provide methods in order to train the model and use it to predict the remaining useful life. The training is based on historical data.

4.1.1 Similarity Model

It bases the RUL prediction on known behaviour of similar machines from historical database. They are useful when the run-to-failure data from similar systems are available. Furthermore, the run-to-failure data shows similar degradation behaviour. The similarity models in this fashion are used to obtain the degradation profile, which represents the evolution of one or more condition indicators for each component as the system transitions from healthy state to a faulty state.

4.1.2 Degradation Model

In order to predict the future condition of a system, a degradation model is needed for extrapolation from the past behaviour. This type of RUL calculation fits a model to the degradation profile of a condition indicator. Then it uses the degradation profile to statistically compute the remaining time until the indicator reaches a threshold. These models are most useful when there is a known value of your condition indicator that indicates failure.

Degradation models work only with a single condition indicator. In this case, principle-component analysis or other fusion techniques are useful to combine condition indicators that incorporate information from more than one condition indicator. Complex systems may encounter multiple degradation processes. These processes are affected by randomly changing covariates, such as temperature, humidity and voltage. There are two types of approaches to assess the degradation or extent of deviation from the expected performance: data-driven and model-based approach.

Data-driven approach: This approach uses real data in order to approximate the degradation of components and predicts its future status. It is categorized into statistical and artificial intelligence techniques. The approach is considered as a block box approach as they do not need the system models or systems specific knowledge to start the prognostics [38]. The historical data as well as monitored data are used to learn how the system behaves and to calculate the remaining useful life. The main advantage of the data-driven approach is that the underlying algorithms are quicker to implement and computationally more efficient.

Model-based approach: Earlier, a brief introduction to the model-based approaches has been given. The model-based methods assume that an accurate mathematical model is available or can be constructed from the first principle. For instance, the failure mechanism is considered by describing the degradation process in a physics-based approach. The failure behaviour of the system is quantitatively described using physics laws. Overviews of such approaches can be found in the overview papers [38] and [41], as well as in the monographs [39] and [40]. Many physics-based degradation models consider the physics of failure (PoF) models such as Arrhenius, Eyring and Inverse Power models. The Arrhenius model is used when the temperature is the acceleration variable. The Eyring model is used in case of incorporation between temperature and stress as in Eq.34. The Inverse Power model is used to estimate the RUL of electronic devices when dealing with non-thermal variables. Paris Erdogan crack growth is also one of the commonly used models for structural elements which is represented in Equation (18).

Popularity of physics-based models relies on their ability to capture the physical phenomena. The bias in the measured data is handled better in this method in comparison with data-driven models. Some methods to estimate model parameters are Kalman filter; extended Kalman filter and particle filter methods [40].

4.1.3 Survival Models

Survival analysis is a large collection of statistical methods which is used to model time-to-event data. The term survival analysis is mostly used in medical contexts, while reliability theory is the common term in industrial contexts. Survival models can handle situations when there is no complete run-to-failure history (censored data) and the available data limits to data about the life span of the similar components as well as some other variable data (covariates) which correlates with the RUL. The information about the manufacturing batch, the component provider and the regimes in which the component was used is called environmental or explanatory variables also known as covariates.

4.2 Simulation Approach

Simulation approaches are commonly applied to estimation of the RUL based on physical models. The approach for the RUL calculation using model simulation is described in section 4.2.3. Regarding the physical model, one should consider following remarks:

- Physical models could be too complicated to be analysed and require extensive computational time. Estimating the time left to system failure is a difficult inverse problem.
- Direct prediction based on physical models is much easier.
- Physical models have uncertainties that need statistical data and description.

4.2.1 FEM Models in physical-based model simulation for RUL prediction

Using Finite Element Method (FEM) in order to be able to model the remaining useful life is a technique that has been used for several years in mechanical engineering problems. Basically, the FEM is a powerful technique originally developed for a numerical solution of complex problems in structural mechanics, and it remains the method of choice for complex systems. In the FEM, the structural system is modelled by a set of appropriate finite elements interconnected at discrete points called nodes. Elements may have physical properties such as thickness, coefficient of thermal expansion, density, Young's modulus, shear modulus and Poisson's ratio. This kind of model is called physical model, and is widely used in order to analyse the behaviour of the structure. Using Finite Element Analysis (FEA) and Modal Analysis, vibration data from the structure can be introduced in the model, and using model updating methods [41], it is possible to know how damaged the structure is, and even to locate the crack within the structure. Other approaches rely on strain and stress data [42] [43]; in these cases, strain and stress data is recovered, and several cracks are modelled using the FEM model; with the information of the stress and strain, and the different FEM models, FEA is used in order to detect how large the crack is. Finally, other works use a model updating [44] for predicting and changing the way the crack propagates [45].

Taking all into account, FEM can provide accurate solutions with controllable numerical error to deterministic partial differential equations. Simulating a FEM model, the state of the model can be observed and measured. However, the prediction of time-to-failure, remaining useful life of the model needs further techniques.

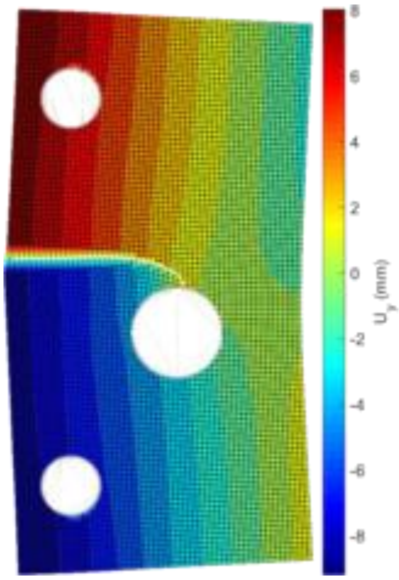

Figure 18: Crack Propagation based on FEM [45] .

4.2.2 Digital Twins

A digital twin is a representative of the real world simulating the behaviour of an asset. ”It is an integrated Multiphysics, multiscale simulation of a vehicle or system that uses the best physical models, sensor updates, fleet history, etc., to mirror life of its corresponding flying twin.” [46]. The accumulated knowledge and information (e.g. 3D-models or physical models) about an asset forms its virtual representation. It includes both static and dynamic information. Static information stays unchanged with time like geometry dimensions, bill of materials and the process, however, dynamic information (e. g. temperature) undergoes changes. The digital twins dealing with information are able to call on their information and make decision about their future. In a sense, digital twins are a part of smart asset. Issues related to creating a digital twin are [47]:

- Identification: Linking each physical asset to its digital representation.
- Data management: A data collection can grow so big that it can lead to problems with data storage and analysis
- Digital Twin Models Interoperability: Since there are different types of models for one asset, for example concerning system level, functional models, 3D geometry or Multiphysics, manufacturing and usage models, it is crucial to make these models work together.
- Digital Twin Information, predicting the asset’s future uses big data generated during the whole life of cycle of the real asset. (cf. Data Management)
- Human Computer Interface; represent information and data from digital twins visually for certain users.
- Communication: Within an ecosystem of cyber-physical systems, all components must (potentially) be able to communicate with each other, e.g. data storages with HCIs, or digital twins with sensors.

In order to be able to use the models between systems, the methodology sketch in Figure 19 can be used. In this context, a digital twin uses available models that were created during the creation/engineering of the asset (e.g. blueprints, physical models or simulation models). In a PdM aware engineering additional models are developed that especially support maintenance tasks and are transferred to the digital twin. With the digital twin in the play, other systems are able to read and process the data for PdM purposes thus enabling typical maintenance scenarios like monitoring assets and predicting RUL, and supporting augmented and virtual reality.

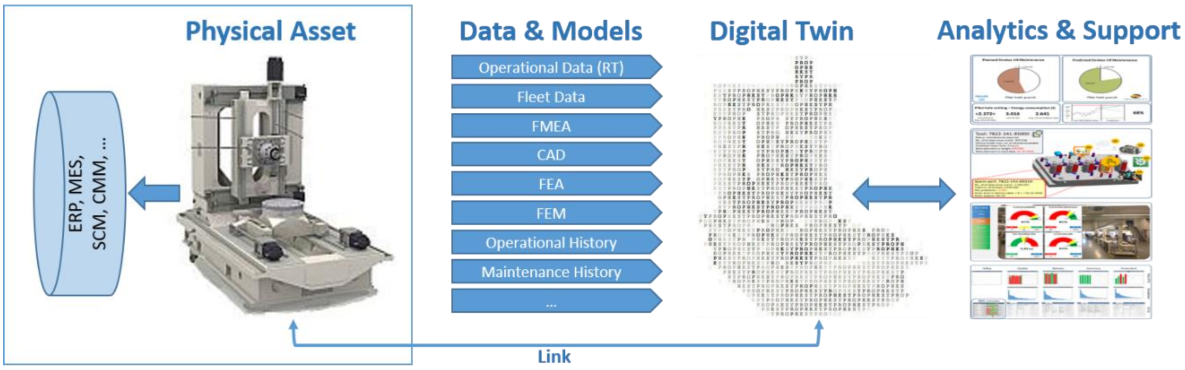

Figure 19: Methodology layout sketch for Digital Twin's application.

4.2.3 A RUL Calculation Approach Based on Physical-based Simulation Models

The model-based (physically-based) RUL prediction addresses sufficient monitoring data collection in order to capture the degradation process and predicting a reasonable RUL. The RUL calculation based on machine component physical-based models simulation requires data both from the controller and the virtual sensors. A virtual sensor is a software that estimates what a physical sensor output should be from the available information. A virtual sensor is needed when the use of a physical sensor is not possible due to the hazardous and aggressive environment, sensor's price or when it could not be reliable. The virtual sensor learns the governing relationship between the different variables, inputs and outputs during the Training phase. The simulation model can be updated based on these data in order to hold it in accordance with the real one. The fusion of simulation results, reliability parameters of the machines and the monitored data helps to calculate the RUL.

In order to build a path to a successful online calculation of the machines' RUL during their operations, four steps are required [48]:

1. Advanced physical modelling of the machines
2. Synchronous simulation tuning of the physical-based model
3. Simulation of the machines' functionality
4. RUL calculation

Within the first step, a model should be made that represents the behaviour of the machines based on mechanical, electrical, hydraulic and other functions considering the computational time needed for simulation. The virtual sensors are used here to collect data from the physical-based model during the simulation. Furthermore, the modelling parameters should be defined in order to update the model based on the data collected from the controller and the sensors. In the second step, the aim is to achieve the digital twins of the real behaviour. The relevant data from sources, the sensors and the controller is translated into information which is used to update the model. Parameter selection here also deals with computational time for model updates as some parameters do not need to be updated continuously. Once all the steps till here are already taken, the model is simulated with the same tasks as the real one and the output is combined with the monitored data for the RUL calculation.

5 Conclusions

Physical modelling of machines and tools attempts to provide physical insight about the machines and mechanisms as well as how the machine vendors anticipate the anticipating useful life.

Condition based predictive maintenance is an alternative to reactive and preventive maintenance that uses embedded diagnostics and prognostics to determine system's health. The advances in model-based design and its integration enabled diagnosis and prognosis of system, which is possible with an accurate simulation model. Physical models can provide knowledge for making predictions about physical systems and explaining their behaviour. The model is simplified description of the real world system, which represents it via mathematical relations. Hence, the more complicated is the real world is, the more difficult gets the system modelling (abstraction). A realistic model includes more details and corresponds more directly to the real world. Nevertheless, a more realistic model is not necessarily better as it requires more computational effort. In any case, models help to understand fault to error characteristics. The model-based approach is applicable if accurate mathematical models can be constructed from first principles.

The document presents a brief and general introduction about the machine to give an idea and shape an understanding of the machine tool. Furthermore, different failure modes are depicted and explained which are considered in the design of tools, machines and systems. Considerations on failure analysis as well as a ball screw use case wraps the topic up. Physical modelling is explained to be used for RUL prediction. Finite Element Models and Digital Twins are examples for possible contributions to RUL prediction and are described in short.

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