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Approach for a Holistic Predictive Maintenance Strategy by Incorporating a Digital Twin

Andreas Werner[a*], Nikolas Zimmermann[b], Joachim Lentes[b]

[a] *University of Stuttgart IAT, Institute of Human Factors and Technology Management, Nobelstraße 12, 70569 Stuttgart, Germany*
[b] *Fraunhofer IAO, Fraunhofer Institute for Industrial Engineering IAO, Nobelstraße 12, 70569 Stuttgart, Germany*

Abstract

Determination of the right time for machine maintenance is a major challenge for many industrial companies. Currently, most companies react on occurring breakdowns (reactive maintenance) or maintenance is carried out in scheduled time intervals (preventive maintenance). These results in either unexpected production stops, or a waste of machine working hours, because components are switched too early. Consequently, predictive maintenance strategies offer a big potential. An essential part of predictive maintenance is the estimation of the Remaining Useful Life (RUL) of machine assets. RUL estimation approaches are based on statistical methods and derived algorithms. Thus, a lot of data is needed for a good estimation. Additionally, data can be generated by means of simulation to improve the RUL estimation. However, companies hardly have an overview of available data and according modules, which are needed for a holistic predictive maintenance strategy. This paper shows an approach for a predictive maintenance strategy dealing with acquisition, processing, and analysis of historical field data as well as the generation of respective simulation data. A structured process map with a derived systematic strategy will give companies an idea of how they can integrate predictive maintenance into existing processes. By incorporating the concept of a digital twin of a production machine, the interaction of measured and estimated as well as generated data by means of simulation, are shown. The digital twin could deliver results to retrofit data-driven prediction models, in order to improve the estimation of the RUL.

Keywords: Predictive Maintenance; Remaining Useful Life; Data continuity; Process map; Digital Twin

* Andreas Werner. Tel.: +49 711 970 2298.
E-mail address: andreas.werner@iat.uni-stuttgart.de

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1. Introduction

1.1. Initial situation

The importance of predictive maintenance (recording the conditions of machines and additional use of data to make predictions) becomes clear in a study of the management consultancy Staufen AG for the "German Industrie 4.0 Index 2017" with 394 participants [1]. Figure 1 shows the percentage of companies surveyed attaching great to very great importance to predictive maintenance. The automotive industry in particular is expected to offer great potential in terms of production, whereas the importance of predictive maintenance in the automobile itself is estimated to be relatively low.

In a study conducted between 2004 and 2005 by the Laboratory for Machine Tools and Production Engineering WZL at RWTH

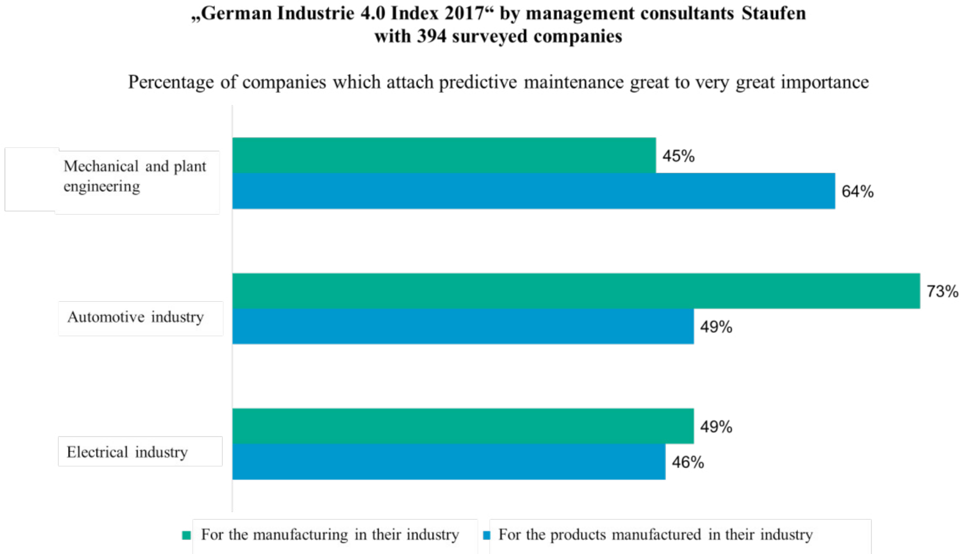

Fig. 1. Importance of predictive maintenance

Aachen University and the Fraunhofer Institute for Production Technology IPT [2], 83% of the 65 companies stated that they use preventive maintenance (maintenance in scheduled time intervals) in their companies. Reactive maintenance (react on occurring breakdowns) is used by 65% of the respondents (double entries were possible). The sectors represented were the automotive industry, mechanical and plant engineering and the food industry. Twelve years later, in 2017, a study about "Predictive Maintenance, service of the future – and where it really stands", conducted by Roland Berger GmbH and the German Engineering Federation VDMA [3] with 153 participants from the fields of power transmission and fluid technology, electrical automation or robotics, machine tools, manufacturing systems and software as well as digitalization, came to the following conclusion: 19% of the participants have not yet taken up the topic of predictive maintenance, while 81 % have given it intensive consideration. Another aspect of the survey was the availability of specific predictive maintenance "products". As the biggest obstacle to the introduction of predictive maintenance, the companies cite a lack of systematic approach in terms of a clear strategy. Thus, the need for action to develop an approach for a holistic predictive maintenance strategy is justified.

1.2. Objective and solution approach of this paper

The aim of this paper is to present a process-based strategy for predictive maintenance in production. The strategy is intended to simplify the introduction of predictive maintenance for manufacturing companies. Companies hardly have an overview of necessary modules required for predictive maintenance. Modules means, for example, software-based models. There is even greater uncertainty about how the individual modules can be combined in a targeted manner, or how the respective data can be used sensibly using suitable methods and software. The approach is to design a process map, which will create transparency about the complexity of predictive maintenance. Based on this, a systematic strategy is derived to support companies with the implementation of predictive maintenance. In this strategy, the incorporation of a digital twin is focused by hybridizing data-driven and physics-based modeling approaches to combine big data in production and physical, chemical etc. engineering laws.

2. Prognostics and Health Management

In this chapter, firstly the methods and techniques of Prognostics and Health Management (PHM) are classified by means of respective literature. Secondly, useful tools for predictive maintenance are assigned to the classes.

2.1. Classification of methods and techniques of PHM

Prognostics and Health Management (PHM) comprises methods, techniques and procedures for predicting connected with ensuring a defined condition (Health). This includes real-time condition assessment under current operating conditions, prediction future development based on updated data and estimating the RUL. [4]

Bailey et al. [5], Ahmadzadeh/Lundberg [6], Okoh et al. [7] and Ardakani [8] deal with a classification of the methods and techniques of PHM. In all works, a division into the following two existing paradigms to estimate the RUL becomes clear: data-driven and physics-based modeling. Furthermore, fusion approaches (hybridization of data-driven and physics-based modeling) are mentioned in respective literature. Data-driven approaches, on the one hand, mainly use statistical methods and/or algorithms of machine learning to develop a prediction model. After a certain training, the prediction model is able to make predictions and estimate the RUL. Physics-based approaches, on the other hand, require extensive theoretical knowledge about the systems and their components to be analyzed. This knowledge includes deductive and expert knowledge as well as empirical values.

2.2. Useful tools for predictive maintenance

Concerning the data-driven approach, there is no real agreement on the definition of the terms data mining and machine learning in literature. Data mining focuses on finding new patterns, while machine learning primarily recognizes known patterns in computer science in new data. Especially in Germany and Europe, machine learning and data mining are closely linked. In the USA, the development of machine learning methods was oriented towards statistics [9]. According to Riedel [10], both data mining and machine learning are technologies that combine traditional methods of data analysis with algorithms. They automatically extract useful information from data sets and follow a systematic process. Both were originally derived from statistics, in particular multivariate statistics, and are often only adapted in terms of complexity for the application in data mining. Machine learning is divided into three learning styles: supervised learning (classification and regression), unsupervised learning (clustering) and reinforcement learning [9]. Supervised learning trains a mathematical model using known input and output data. Exemplary algorithms for classification are Support Vector Machines, discriminant analysis, nearest neighbor etc. Exemplary algorithms for regression are linear regression, Support Vector Regression, ensemble methods etc. Unsupervised learning initially finds hidden patterns or internal structures within the input data and forms clusters. Exemplary algorithms for clustering are k-Means, k-Medoids, neural networks etc. [11]. Reinforcement learning uses the feedback of machines from their interaction with the environment to optimize future actions and minimize errors [9]. The reinforcement learning is not properly established yet, but the interest in it is growing. An example for a reinforcement algorithm is the Hidden-Markov-Model.

Useful methods for physics-based modeling in terms of predictive maintenance include computational life prediction, reliability methods (e.g. Failure Mode and Effects Analysis, FMEA) [12] and as a central component of a digital physics-based model approach, the actual modeling and simulation. According to VDI 3633-1 [13], modeling is the creation of a simplified reproduction of a planned or real existing original system and process in another conceptual or objective system. The model differs from the original with regard to investigation-relevant properties only within a tolerance range dependent on the objective of the investigation [13]. In this context, system refers to a defined arrangement of components (e.g. machine, human, work piece etc.) which are related to each other [13]. The models of the technical objects and system form the elementary basis for the expressiveness of a simulation. Simulation describes the emulation of a dynamic process in a system with the aid of an experimental model in order to gain knowledge that can be transferred to reality [14]. Simulation techniques can generally be divided into continuous and discrete systems. With discrete systems, a distinction must be made between time-discrete, integers and event-discrete simulation, whereby mixed forms are existing. The continuous simulation considers an infinite number of state changes per time interval by means of a numerical solution of the differential equations (e.g. simulation of an oscillatory motion) [15]. Both the Finite Element Method (FEM) and the Computational Fluid Dynamics (CFD) simulation are based on the continuous simulation. Discrete simulation techniques include a finite number of state changes per time interval (e.g. simulation of a traffic junction with different states of the traffic light circuit).

Visualization is used for both modeling approaches, albeit in different forms. Visualization in data analytics is mainly used for visualizing data by means of graphs and plots, while the visualization of physics-based models comes along with a 3D-simulation.

3. Process-based strategy by incorporating a digital twin

The following process map gives an overview over useful modules for predictive maintenance. The modules and the data continuity in between are described. Through the holistic consideration, a systematic strategy consisting of five steps can be derived.

3.1. Process map

The objective of this section is to explain the modular structure of the process in Figure 2 in order to gain a comprehensive overview of the complexity of predictive maintenance. In this section, the foundations to develop the derived strategy are established by means of a process map. The process map depicts relevant modules for predictive maintenance and shows how these can be combined with each other. In this paper, modules refer to both hard- and/or software-based systems as well as models, which are based on the tools shown in section 2.2.

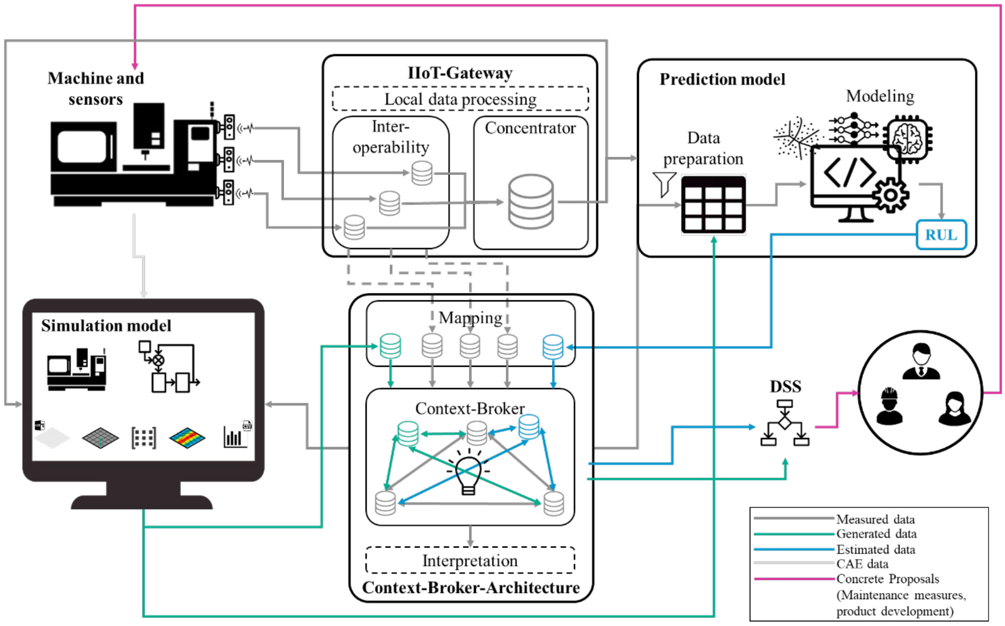

Fig. 2. Holistic process map with modules for predictive maintenance

3.1.1. Machines and sensors

The elementary foundations for the estimation of the RUL are the used machines with their components or subcomponents as well as the work pieces produced by them. Exemplary machine tools and equipment are forming, cutting and dismantling machine tools [16].

The installed sensors measure different kind of variables and transduce them into an electrical signal, mostly a voltage [17]. This signal can be transferred to an Industrial Internet of Things (IIoT)-Gateway via e.g. fieldbus.

3.1.2. Industrial Internet of Things Gateway

Generally, an ordinary IIoT-Gateway has three core functions: interoperability, aggregation and local data processing [18]. Which functions are actually used, depends on the respective application. Through interoperability, the interaction of different machines and devices is simplified. This is made possible by the variety of interfaces, protocols and standards both for local installation (Edge) and for remote data transmission via fixed and mobile networks [18]. In some cases, an aggregation of the sensor signals is needed. For this purpose, the IIoT-Gateway can interconnect the separate data sets to one single data stream. This leads to economic benefits, since only one expensive hardware module for communication is needed [18]. Depending on the application, however, it is expected that the sensor signals will be collected and stored separately in order to perform modular data analysis in the upcoming systems and models.

3.1.3. Context-Broker-Architecture

In the Context-Broker-Architecture, the separate data sets are contextualized to higher-value context information. Additionally, this information can be interpreted, if needed. This is made possible by the layer structure of the Context-Broker-Architecture. Among other things, this consists of a

- Mapping Layer to convert the proprietary signals and data into a uniform data format,
- Distribution Layer to make the information accessible via a central context-broker-system,
- Interpretation Layer (if needed) to interpret the contextualized high-value information by means of a representative knowledge base, a reasoning system for drawing logical conclusions and an Application Programming Interface API for integrating the knowledge base and the reasoning system and an
- Application Layer to make context-based use of the respective data. [19, 20]

In the process of figure 2, the final data are transferred to the data-driven prediction model and to the physics-based simulation model, which both are applications in terms of the Context-Broker-Architecture. Ethernet, W-LAN, Long Term Evolution (LTE) or EtherCAT are suitable ways of communication for this transfer [18].

3.1.4. Prediction and simulation model

In the prediction model, the data are prepared according to the algorithms of machine learning. Suitable formats as input for the prediction model are *.json or *.csv-files. For the data preparation there is a multitude of algorithms (e.g. filters, Principal Component Analysis to reduce complexity etc.) [21]. The output of the prediction model is the RUL. Depending on the data basis, the amount of generated data varies. The values can be standardized in the mapping layer of the Context-Broker-Architecture [19]. Subsequently, this data can also be integrated in the actual context broker in order to achieve even higher-value context information.

An essential input of the simulation model is the Computer Aided Engineering data. This include CAD data, simulation data from product development phases (if available) etc. Especially CAD data do not require real-time transmission. They are transferred once and adapted for correction purpose only. Just like the output of the prediction model, the generated data of the simulation model can also be converted into a uniform file format in order to be subsequently included in the contextualization. Possible outputs of the simulation model are stress peaks of a component in tabular form (e.g. *.csv format) [22]. If necessary, these can firstly be constituted in a uniform file format in the context-broker-architecture. It is important to note that the output of the simulation model can be directly transmitted to the prediction model to feed it with additional data for more meaningful predictions.

3.1.5. Decision Support System

Concrete solutions can be proposed as part of an automated or software-based solution using a Decision Support System (DSS). The DSS is supplied with the estimated data of the prediction model and/or with the generated data of the simulation model in order to provide rule-based, concrete solution proposals. Proposed solutions can include maintenance instructions for production workers and engineers, options to optimize costs for controlling and recommendations for optimized product or machine development in the future. If the modules (e.g. simulation model) are used to identify the exact causes of failure of a component, these findings can be used to develop the next generation of this component. The structure and logic of a DSS will not be discussed in this paper.

3.2. Strategic approach for predictive maintenance

Based on the process map in section 3.1 and its modules, the following five steps provide companies with an idea of how they can integrate predictive maintenance into existing processes.

3.2.1. Step 1: State analysis and definition of objectives

To integrate a predictive maintenance strategy into existing processes, the current maintenance strategy of a company has to be clarified. Depending on the prevailing maintenance strategy, the respective benefit of predictive maintenance for a specific company can be derived. Particular attention must be paid to companies that are already using data-driven and/or physics-based approaches, but do not know how to use the approaches in order to estimate the RUL. An example would be a company that has already installed sensors at a machine, but do not know how to analyze the occurring data. Furthermore, an essential part of the state analysis is the identification of critical components, i.e. which components (parts, tools, machine etc.) are exposed to wear out and recurring failures.

3.2.2. Step 2: Checking the availability of data, information and knowledge

This step is justified by the growing trend to analyze or simulate systems in production when they are already in use. So far, simulation, especially FEM simulation, has been regarded as a tool in the product development. The originated knowledge in a product development process must be used and integrated into the development of the process for predictive maintenance. In order to avoid missing data and information for calculations, analytics or simulation, the availability of these has to be checked in an early phase. In practice, questions frequently arise regarding data protection and confidentiality. With the exception of Original Equipment

Manufacturer, the machines used to produce parts/products are often manufactured by another company – the machine manufacturers. The result is a lack of information between the development or production phases of the machines and the production phases of the parts. There is a need for research in this area, especially regarding legal issues.

3.2.3. Step 3: Integration of data-driven modeling

In principle, data-driven modeling can be divided into three phases, the acquisition, the processing and the analysis of data. The measures to be taken in these sub-steps are described in more detail below.

According to DIN 19222, data acquisition is defined as obtaining analog or digital data by measuring or counting and, if necessary, by signal conversion [23]. In terms of digitalization of production, sensors become an appropriate aid to measure and obtain analog and digital data. After choosing suitable sensors or measuring principles, the sensors have to be integrated mechanically [24]. Mechanical integration means both sensor positioning for determining the measured variable and the sensor housing integration. Additionally, the sensors have to be protected mechanically and the energy transmission of the sensor must be ensured. To gather all occurring sensor signals or data, an IIoT-Gateway must be chosen. Among others, possible selection criteria might be:

- Support of the respective bus protocols in the Edge,
- Conversion into suitable format for connectivity,
- Maximum number of connected devices (number of connections),
- Possibility of processing third-party software etc. [18]

In data processing, a distinction can be made between the design of the processing respectively the provision of the processed sensor data and the actual logic of generation of information from the sensor data. The former means influencing factors on the required power to process data and potential locations for processing as well as the display and provision of generated information and data. Furthermore, access rights to sensor data are regulated, for example with the aid of an Industrial Data Space-Connector, which is a specific trusted IIoT-Gateway [25]. This answers the question of how and where the gathered data are collected and subsequently processed. The logic of generation of information is used both in data processing and in data analysis. Generation of information within data processing defines steps for generating and understanding data. Additionally, methods for preprocessing the sensor data are determined. This includes methods of signal processing (transformation of data, e.g. conversion from time to frequency domain by means of Fourier transformation) or methods for filtering the data (e.g. bandpass filter, noise suppression). Generation of information within data analysis describes the actual modeling using statistical methods and machine learning algorithms. [24]

As already indicated in section 3.1.4 on data preparation, data analysis uses statistical methods and/or machine learning algorithms to model a relationship within the data. Thus, after training the model and achieving a certain maturity, a mathematical predictive model is generated, which estimates predictions. This means that patterns with the ability to extrapolate a known trend in the measured historical data are detected within the data set. The details of the individual algorithms will not be discussed in this paper. Which algorithm is most suitable for the corresponding data set poses challenges even for experienced data scientists. Data scientists often try multiple algorithms. *MATLAB* provides a function that checks in advance which algorithm fits best. It should be noted, however, that the algorithm with the most accurate results does not necessarily have to be selected. Other criteria must be taken into account. Therefore, the selection of suitable algorithms for the respective data set represents an important point in the data analysis.

3.2.4. Step 4: Integration of physics-based modeling

For physics-based modeling, the object to be simulated is first analyzed, and then reliability methods (e.g. FMEA) as well as potential pre-dimensioning information from previous machine development phases (if available) are integrated. After selecting suitable simulation software, the actual simulation process is carried out depending on the simulation technique. Up to the required simulation technique, different simulation software have to be used. Depending on the required granularity of the simulation model, the introduction of Reduced Order Models can be useful to reduce computation speed of the simulation.

To analyze the object, which has to be simulated, all necessary information have to be gathered. In the FEM simulation, for example, the information can be divided into categories of geometry (e.g. CAD models in *.stp-format), material (e.g. modulus of elasticity) [12] and process data (e.g. feed rate of a moved component within the machine). All the information required for pre-dimensioning in earlier development phases can be used in the course of the simulations. In addition, computer-aided simulation makes use of reliability methods (e.g. FMEA). The benefit of computer-aided simulations becomes clear, since any conceivable error (identified in the FMEA) can be simulated without significant costs. The most important criterion for the selection of simulation software is the required simulation technique. Depending on the defined components (component, machine, factory etc.), there is a multitude of simulation software that meets the requirements of the different simulation techniques. As soon as a simulation technique has been chosen, further criteria have to be established. Exemplary criteria for the selection of a simulation software would be acquisition and/or license costs, necessary programming knowledge, usability, type of import as well as export of data and interfaces with other software (CAD, Analytics etc.).

3.2.5. Step 5: Hybridization of modeling approaches

Once both data-driven and physics-based modeling have been successfully integrated into processes, the two approaches will be combined. This opens up two essential possibilities, which are described in the following. The individual models will not be described further, but rather the interface and the possibilities offered by hybridization of the two modeling approaches will be discussed.

If no sensor data is transferred to the simulation model or at least used from a historic database (see figure 3 top), the simulation only reproduces theoretical calculation results. With the help of empirical values, the simulation model can be approximated relatively close to the real system. It then serves as a good comparison between the sensor measurements and the respective data analysis of the prediction model as well as the physical, chemical etc. theory. Nevertheless, these theoretical data can be fed into the prediction model and treated as a further data set. Many simulation tools offer the possibility to present the simulation results in a structured way in the form of a *.csv-file for example. The corresponding new data set as output can be used for prediction in the prediction model. In general, a simulation always offers the benefit of generating data that does not occur in the real field, e.g. failure modes that could not be measured in the past. Furthermore, a simulation is often associated with a 3D-visualization, which can contribute to a general understanding of the behavior of the machine for respective workers.

When field data are used or transferred to the simulation model, a realistic digital image is created (see figure 3 bottom). Both the simple validation and the retrofitting of the predictive model are performed with realistic data. The simulation model then learns from actual experiences and events in reality. Thus, the simulation model is no longer a simple theoretical calculation, but reproduces the real behavior of the machine or individual components almost identically. This fusion of real and digital systems creates a digital twin.

The hybrid modeling approach with the transfer of sensor data to the simulation model can also be extended by real-time operations. Both the prediction model and the simulation model are then supplied synchronously with data from the IIoT-Gateway. This shows the great benefit of the hybridization of both modeling approaches. The prediction model is supplied directly and in real time with historical real data and additionally enriched with the realistic data generated in the simulation model – also in real time. This high-performance interaction of the two models creates a data basis prepared for many eventualities to enable an overall system that monitors, controls and optimizes itself [26]. Only in this case a production control is suitable.

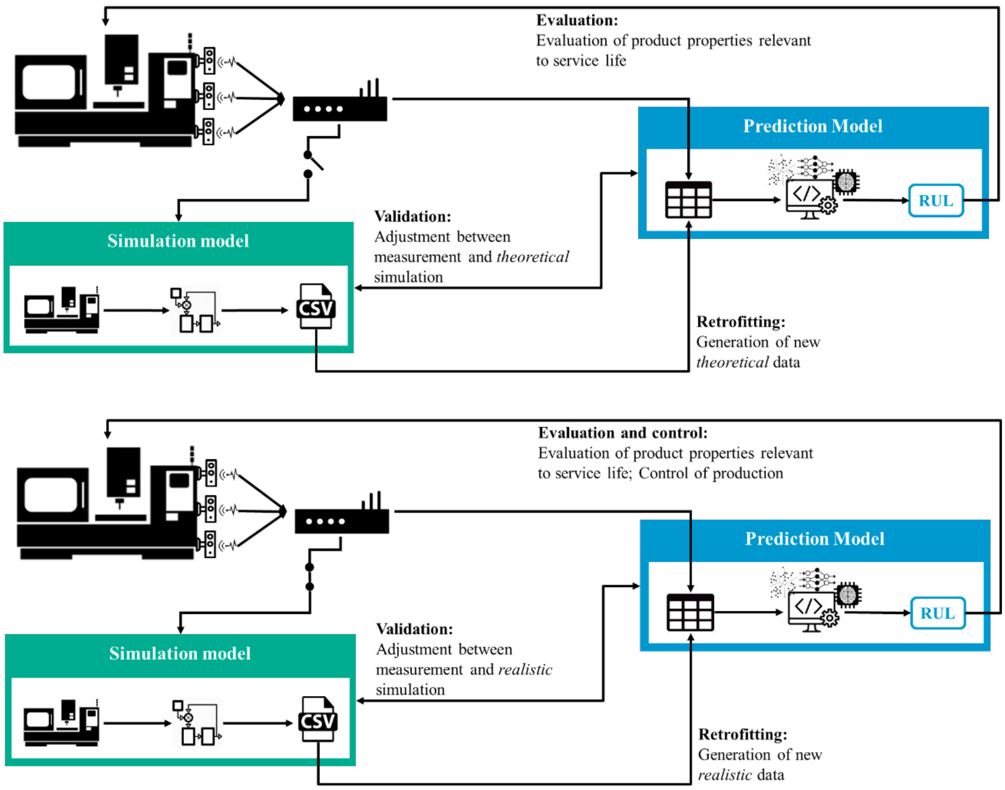

Fig. 3. Hybrid approach without (top) and with (bottom) sensor data transfer to simulation model

4. Summary and outlook

4.1. Summary

Despite the great to very great importance of predictive maintenance as stated by companies, reactive and/or preventative maintenance are still the most commonly used maintenance strategies. Companies indicate a lack of systematic approach in the sense of a clear strategy as the biggest obstacle to the introduction of predictive maintenance. The objective of this paper was therefore to develop an approach for a holistic predictive maintenance strategy. By incorporating a digital twin, a hybrid approach by combining data-driven and physics-based modeling to estimate the RUL was shown. To achieve this objective, a process map that structures and explains useful modules serves as the basis for the derived systematic strategy for predictive maintenance in manufacturing. In particular, the combination and interaction of the individual modules were shown. The derived systematic strategy supports manufacturing companies in integrating predictive maintenance into processes. In the first step (state analysis and definition of objectives), the benefits of a predictive maintenance strategy compared to the current one in a company will be identified. After checking the availability of data, information and knowledge, data-driven and physics-based modeling are integrated to calculate the Remaining Useful Life. Data-driven modeling is based on data acquisition, processing and analysis. Physics-based modeling mainly means simulation according to physical, chemical etc. engineering laws. The hybridization of the two modeling approaches combines them to an integrated overall solution. A distinction is made between an existing and a non-existing sensor data transfer to the simulation model. With existing sensor data transmission (in real time), a digital twin can be created that monitors, controls and optimizes itself.

4.2. Outlook

Based on this work, the process of data modeling and physics-based simulation must be implemented in follow-up work. The mathematical models as well as the interfaces shown for data transmission must be validated and verified with the help of practical examples. Especially for hybrid modelling approaches, integrated software solutions are not yet optimally equipped. If no expensive standard solution can be purchased, the interfaces must be developed independently. Companies often lack the necessary capacity for this. As far as simulation software tools are concerned, there is still no solution that has a so-called multiscale capability. An overall solution is required, which enables both continuous and discrete event simulation techniques in one environment. In addition, the adaptability of the simulation software tools to real conditions of production assets is not yet fully developed. However, conceptual solutions are currently being developed on the market.

Nomenclature

CAD	Computer Aided Design
CFD	Computational Fluid Dynamics
CSV	Comma-separated values
DIN	Deutsches Institut für Normung
DSS	Decision Support System
EtherCAT	Ethernet for Control Automation Technology
FMEA	Failure Mode and Effects Analysis
FEM	Finite Element Method
IIoT	Industrial Internet of Things
JSON	JavaScript Object Notation
LTE	Long Term Evolution
PHM	Prognostics and Health Management
RUL	Remaining Useful Life
ST(E)P	Standard for the exchange of product model data
VDI	Verbund Deutscher Ingenieure
W-LAN	Wireless Local Area Network

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