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A procedural approach for realizing prescriptive maintenance planning in manufacturing industries

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ABSTRACT

Prescriptive maintenance planning is an essential enabler of smart and highly flexible production processes. Due to increasing complexity, traditional maintenance strategies lack in fulfilling present-day production requirements. This paper proposes a novel procedural approach for prescriptive maintenance planning in manufacturing companies. Multivariate data analysis and simulation tools are utilized to analyse historical data (product quality data, machine failure data and production program data). Based on identified data correlations and incoming real-time machine data, system failures are predicted and prescriptive maintenance measures are proposed. Results from real implementations in the automotive manufacturing industry are presented to demonstrate the effectiveness of the proposed approach.

1. Introduction

Current developments in the field of smart manufacturing call for high machine availability, high quality of products and at the same time a high degree of flexibility of manufacturing processes [1]. One major challenge coming along with smart manufacturing is the increasing complexity of manufacturing systems, in terms of products, processes and systems. Recent investigations show that quality, maintenance and production planning strongly interact and jointly determine the achievement of the desired production performance, equipment availability and product quality [2,3]. The development toward predictive maintenance approaches in manufacturing industries can minimize maintenance costs up to 30% and eliminate breakdowns up to 75% in comparison to classical preventive maintenance [4].

However, with the digitization of the industry and the advancement of computing and visualization technologies, a new era is emerging in the fields of maintenance, the so-called prescriptive maintenance. The concept of prescriptive maintenance extends beyond the mere prediction of failures. Based on the analyses of historical data and incoming real time data, required maintenance measures are predicted by a system and a course of action is prescribed. Prescriptive maintenance means moving from planned preventive maintenance to proactive and smart maintenance planning [5]. One of the major challenges of realizing prescriptive maintenance is the collection and management of data [4]. The volume of available data for maintenance decisions has increased significantly with the growing popularity of condition monitoring, multisensory technologies and cloud computing. Therefore one major problem for developing data based prescriptive maintenance measures is the lack of formalized data structures [2,6].

In this paper a holistic, data based approach for prescriptive maintenance planning is presented. By steadily compiling and correlating relevant shop floor data (product quality data, PLC- and condition monitoring data, production program data) via "cause and effect" coherences, prescriptive maintenance measures are derived in order to avoid critical and unforeseen failures as well as to guarantee a high level of machine availability, product quality and process flexibility.

2. Data based maintenance approaches considering production planning and product quality

The interaction of production, quality control and maintenance has attracted much attention in the literature recently. Various models have been proposed to study the interactions between these three fundamental functions [7]. Current maintenance planning approaches mostly combine either production planning and maintenance [8–10] or align maintenance strategy planning with product quality [11]. Maintenance approaches which align all three fundamental functions are rarely available in the literature [7]. Colledani et al. [4] and Colledani and Tolio [12] investigated the interactions between these three functions and proposed a model which combines production planning and maintenance in order to control the quality of products.

The majority of quality oriented maintenance strategies focuses on the use of historical product and machine data to analyze possible coherence between product quality deviations and failure effects of certain machine components. Load oriented maintenance strategies statistically determine the remaining life time by using external measurement parameters, however, the dynamic aspect of

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deterioration is neglected [13]. In order to schedule maintenance intervals, machine- and process perspective are combined by linking the production program and failure effects of components [4,14,15].

The novelty of the proposed holistic, data based approach for prescriptive maintenance planning is the integration of these approaches based on historical data combined with real time condition monitoring data as well as load profiles of the machine that are calculated on the basis of PLC control data. This integration is significant for the novelty of the approach and in contrast to existing and already published approaches, system failures are predicted more precisely and prescriptive maintenance measures are proposed.

3. Methodology

The proposed procedural approach for realizing prescriptive maintenance planning consists of four main elements (see Fig. 1):

1. Data Acquisition and Pre-Processing
2. Data Analysis and Simulation
3. Reaction Model
4. Prescriptive Maintenance Decision Support System

In the first element maintenance relevant data are captured, classified and structured. The subsequent data analysis identifies correlations within the pre-structured data. A set of rules is defined and parameterized in the third element, which predicts condition based machine failures and reveals quality deviations on a real-time basis. Finally, the fourth element predicts system failures and suggests prescriptive maintenance measures based on this logic. But the final decision, whether the suggested maintenance activities should be carried out or rejected, is made by the operator. Therefore, the developed approach aims at a decision support system that allows operators to make the final decision.

The prescriptive maintenance planning approach was developed based on historical data resulting from a three-year observation period in a production plant and has been validated with real-time data. The following sections describe the approach in detail.

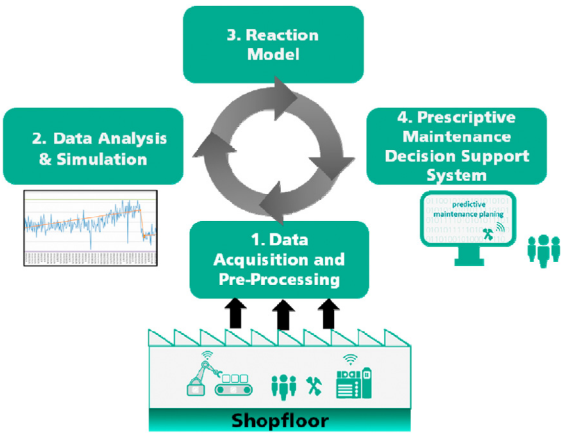

Fig. 1. Procedural approach for prescriptive maintenance planning.

3.1. Data acquisition and pre-processing

Capturing the necessary information required to predict machine failures and plan prescriptive maintenance activities is difficult due to the diversity of data [5]. According to several approaches to assess the diverse quality of data [16,17], this paper uses the three dimensions (i) data structure quality, (ii) information quality and (iii) veracity in order to describe and attain adequate data sets for the subsequent Sections 3.2–3.4. Failure protocols, product quality data (measurement protocols), PLC control and condition monitoring data as well as production program data serve as input data sets in the presented approach.

Failure protocols represent a collection of historic maintenance measures of a machine. Their data structure quality is, in its original form, due to a large proportion of free text passages, usually very low. Information quality and veracity is highly dependent on a companies' feedback culture, as these data are generated by the shop-floor operators themselves.

The incoming data set (see Table 1A) initializes a data structuring process, which aims at extracting metadata from the free text passages. Thus text mining algorithms, using the programming language R, were built to firstly clean free text passages from misspelling, used synonyms etc. and secondly extract metadata for the new categories: module, assembly and faulty part, which are meant to exactly describe the affected component of a maintenance action (see Table 1B). If the algorithm cannot identify metadata from a specific data set, this information has to be added manually in order to train the algorithm.

Table 1
Example of a failure protocol: original and target format.

(A) Original format

Time-stamp	Machine ID	Problem	Countermeasure	Employee ID
13.01.17 12:03:01	AC01	Untypical noise at Spindle 1	Observation of Spindle 1, leaking sealing air, Air hose of connection ventile C was exchanged	Mechanic 01d

(B) Target format

Time-stamp	Machine ID	Module	Assembly	Faulty part	Employee ID	Repair time
13.01.17 12:03:01	AC01	Spindle 1	Spindle seal air	Air hose C	Mechanic 01d	1.2 h

In contrast to failure protocols; product quality data, PLC control and condition monitoring data as well as production program data sets are usually generated automatically. Hence, a high data structure quality (large proportion of metadata) and information quality (high accuracy of data due to mainly numerical values) as well as a sufficient veracity are assumed for nowadays commonly used PLC-controls, ERP- or QM-systems. Similar to failure protocols, relevant information was extracted and re-structured from these data sets, leading to the following target formats (see Table 2).

All the target formats contain the metadata element "time-stamp", which serves as an unique key for the subsequent data analysis and simulation.

Table 2
Data target formats.

Quality data	Time-stamp	Product ID	Measuring point	Value	Machine ID
PLC control data	Time-stamp	Machine ID	Machine section	Error text	
CM data	Time-stamp	Machine ID	Sensor ID	Value	
Prod. program	Time-stamp	Machine ID	Product ID	#Pieces	

3.2. Data analysis and simulation

Within this element the pre-structured data sets are analyzed and correlated to detect (i) quality relevant cause and effect coherences and determine (ii) the remaining useful lifespan of a machine component.

For the detection of *quality relevant cause and effect coherences*, a two-dimensional "Quality Matrix", similar to the proven "house of quality", is designed. The matrix represents all possible failures on the horizontal axis and all product quality characteristics on the vertical axis (see Fig. 2).

Quality Matrix		Quality characteristics	roundness					flatness	positioning	
		Quality features	bearing bore					cutting surface	cutting surface	
		Related measuring point	201A	202A	204B	203A	203B	101A	102B	303B
Possible failures										
Modul	Assembly	Faulty part								
Spindel 1	Spindle cooling	flow controler	○	○	○	○	◔	○	◑	◕
		pressure regulator	◔	◔	◔	◔	○	◔	◕	◕
		nozzle	◔	○	◔	○	◕	◕	◑	◑
	Spindle seal air	air hose C	◕	◕	◕	◕	◕	○	◔	◔

Fig. 2. Quality matrix. (0.00 = no coherence; ±0.25 = low coherence; ±0.50 = medium coherence; ±0.75 = strong coherence; ±1.00 = ideal coherence.)

By correlating each historical failure event with the quality control chart of each measuring point over a certain time-period, coherences between a specific measuring point and failure event can be identified and visualized within the matrix. The Quality Matrix can be interpreted using the following example: The roundness of the bearing bore measuring point 201A is strongly influenced by a failure of air hose C of the spindle seal air of Spindle 1.

To determine *the remaining useful lifespan of a machine component*, the machine is systematically structured into the three categories: module, assembly and machine part (following Table 1) and then integrated as 3D multi-body model in the software CHECKitB4. The current wear condition for each relevant part is estimated based on information regarding spare parts replacements, machine age and wear measurements. The calculation assumes that the analyzed machine is used for similar production process steps and that a fixed use of machine tools is given. From the pre-processed PLC control, condition monitoring and production program data sets, load profiles (such as rotation speed, speed, acceleration profiles) for each machine part per NC-program are determined analytically.

CAD-data of the workpiece combined with the NC-code (machine instructions, tools, switch commands) for the machine tool form the basis for the incremental wear calculation (see Fig. 3). Firstly, the feed path and the ablation volume is calculated by the simulation software CHECKitB4. An archive file containing all relevant technological data of the PLC control is pre-loaded in the software to define the production environment and the NC-programs. The following simulation delivers the exact feed path of the process. The simulator then delivers the axis motion data, the chip volume as well as the switch commands needed for the dynamic computation. Drive and guidance loads are calculated using an analytical multi-body model during dynamic computation. These calculations build the input for the subsequent wearout calculation. Depending on the type of component, three different wearout calculations can be distinguished: lifetime calculations according to DIN ISO 3408, DIN ISO 281 and DIN ISO 14728 (e.g. rolling bearings), number of switch commands (e.g. valves) or duty cycle times (cooling sensors). Future wear progress, caused by every single produced part, is then predicted based on the wearout calculation, incoming condition monitoring data and the future production program.

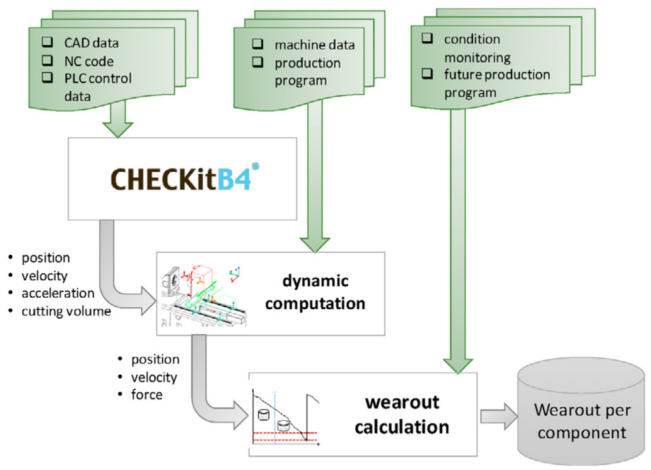

Fig. 3. Approach for wearout calculation of a machine component [14].

3.3. Reaction model

As a result individually parametrizable rules are derived for each machine component, based on the *prognoses of the wear reserve for machine components, condition based monitoring* and *variations in product quality*. Each rule is represented by a mathematical function. In case of rule violations, specific maintenance measures in the subsequent prescriptive maintenance decision support system are triggered.

Rules based on variations in product quality and condition based monitoring: These rules are based on the identified quality relevant cause and effect coherences and incoming condition monitoring data and aim at identifying statistical significant data variations and trends. An example of such a rule is defined as the following: If the arithmetical mean value $\bar{y}$ of a certain amount of quality characteristic measurements exceeds or falls below a default value t_1,

$$\bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i < / > t_1 \tag{1}$$

and the slope of the regression line b exceeds or falls below a default value t_2, the rule is violated and a specific reaction (maintenance measure) is triggered.

$$b = \frac{\sum_{i=1}^{n}(x_i - \bar{x}) * (y_i - \bar{y})/(n-1)}{1/(n-1)\sum_{i=1}^{n}(x_i - \bar{x})^2} \tag{2}$$

wherein n is the number of measurement values; y_i is the observed values; x_i is the 1,. . .,n (represents the dates of the measurements); $\bar{x}$ is the arithmetical mean value of x_i.

Fig. 4 shows the violation of the described rule above parameterized for the component air hose C (Assembly: spindle seal air; Module: Spindle 1).

Herein the number of measured values is 25 (n = 25), the arithmetical mean value should not exceed 123.4 ($\bar{y}$ < 123.4) and the slope of the regression line should be between 9.00 × 10^{-5} and 9.05 × 10^{-5}.

Rules based on prognoses of the wear reserve for machine components: These rules are triggered if the wear reserve w_r of a machine component drops below a pre-defined stock value w_s:

$$w_r \leq w_s \tag{3}$$

The stock value is defined for each machine component according to DIN 31051.

3.4. Prescriptive maintenance decision support system

Within this element a prescriptive maintenance decision support system is developed. Based on the previously identified

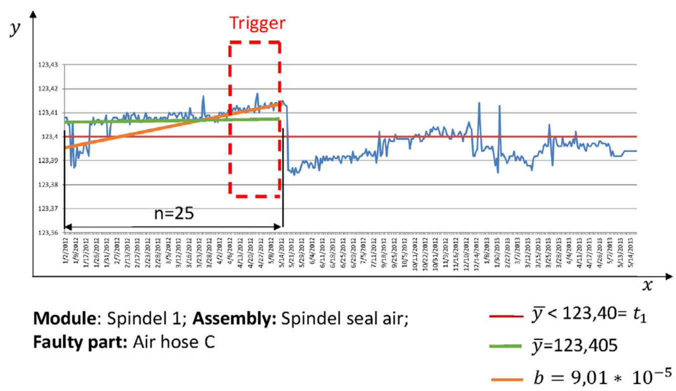

Fig. 4. Quality control chart (measuring point 201A_X1_D).

data correlations, incoming real-time machine data and the rules defined in the reaction model, this support system visualizes and predicts machine conditions and quality deviations and suggests anticipative maintenance measures.

These maintenance measures are automatically bundled if they affect the same machine and become due within a defined timespan of two weeks. The bundling has positive effects on the repair time and therefore availability of the machine. Finally, the maintenance operators have to accept or reject the suggested measures – their implicit experiential knowledge is necessary to decide context-dependent in a highly flexible production environment. The information regarding the acceptance or rejection of the suggested measure is processed and analyzed as feedback information to continuously improve the defined rules and measures.

4. Application

The proposed approach has been applied on triaxial machining centers of an automotive manufacturer in Austria. Fig. 5 shows the developed decision support system applied on the manufacturer's machines. It consists of four main modules: (i) overview, (ii) machine condition prediction, (iii) planning support and (iv) KPI-board. Within module (i) each machine, its status as well as the production layout can be overviewed. If a machine failure is expected the status will turn orange. In order to get further details about the expected failure, module (ii) needs to be opened. Within this module the operator is able to get information about the predicted machine status. If a rule is violated a window pops up, identifying the violated rule and its reason.

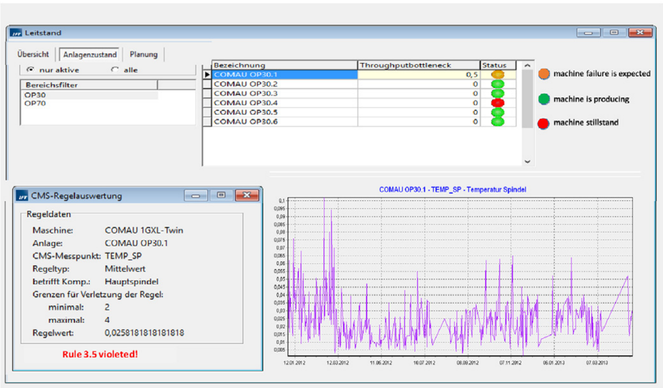

Fig. 5. Decision support system – module (ii).

Module (iii) then suggests prescriptive maintenance measures according to Table 3. Maintenance relevant key performance indicators are finally reported in module (iv).

Although random failures can occur at any time in the lifecycle of a machine component, results show that 43% of unplanned machine breakdowns caused by mechanical failures can be predicted. This effect leads to a higher quality in maintenance planning–time savings of 20% for carrying out maintenance activities (time for realizing, analysing, assessing and carrying out an activity), maintenance cost reductions of 30% (due to the avoidance of direct and indirect failure correction costs) and an increased equipment availability of 12% could be realized within the described application.

Table 3
Examples of a prescriptive maintenance measure.

Date	Trigger	Machine ID	Measure	Repair time	Due date
23.12.16	Wear	AC01	Critical wear reserve – Spindle 1 – spindle seal air	1.2 h	20.1.17
26.12.16	Quality	AC01	MP 201A: Scattering > 20% → Control of spindle seal air	0.75 h	22.1.17

5. Conclusion and outlook

This paper presents a novel procedural approach for realizing prescriptive maintenance planning by building conclusions based on the interaction between real-time PLC-, condition monitoring- and production program data from the short- and medium-term planning as well as historical quality- and machine failure data.

A real production environment was used to collect the necessary data and to develop the proposed approach. The approach was tested and validated in a case study based on triaxial machining centers of an automotive manufacturer. The results point to a successful implementation. However, future work is required to automatically adapt the proposed set of rules to a dynamic production environment, which is currently done on a periodic basis. Furthermore, the design of the used 3D multi body model (see Section 3.2), at present, requires substantial time and efforts.

Therefore, a modular design of this model, for easily applying it to different machine types and guaranteeing a broad applicability of the proposed approach, is another field for further research.

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