A procedural approach for realizing prescriptive maintenance planning in manufacturing industries

Kurt Matyas a, Tanja Nemeth a,b,*, Klaudia Kovacs a,b, Robert Glawar a,b

a Institute of Management Science, Vienna University of Technology, Theresianumgasse 27, 1040 Vienna, Austria
b Fraunhofer Austria Research GmbH, Division of Production and Logistics Management, Theresianumgasse 7, 1040 Vienna, Austria

ARTICLE INFO

Article history:
Submitted by Wilfried Sihn (1), Vienna, Austria

Keywords:
Maintenance
Predictive Model
Production quality

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.

© 2017 Published by Elsevier Ltd on behalf of CIRP.

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]. Collledani et al. [4] and Collledani and Toloio [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 deterioration is neglected [13]. In order to schedule maintenance

Please cite this article in press as: Matyas K, et al. A procedural approach for realizing prescriptive maintenance planning in manufacturing industries. CIRP Annals - Manufacturing Technology (2017), http://dx.doi.org/10.1016/j.cirp.2017.04.007
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.

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>
<thead>
<tr>
<th>Table 1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Example of a failure protocol: original and target format.</td>
</tr>
</tbody>
</table>

(A) Original format

<table>
<thead>
<tr>
<th>Time-stamp</th>
<th>Machine ID</th>
<th>Problem</th>
<th>Countermeasure</th>
<th>Employee ID</th>
</tr>
</thead>
<tbody>
<tr>
<td>13.01.17 12:03:01</td>
<td>AC01</td>
<td>Untypical noise at Spindle 1</td>
<td>Observation of Spindle 1, leaking sealing air, Air hose of connection ventile C was exchanged</td>
<td>Mechanic 01d</td>
</tr>
</tbody>
</table>

(B) Target format

<table>
<thead>
<tr>
<th>Time-stamp</th>
<th>Machine ID</th>
<th>Module</th>
<th>Assembly</th>
<th>Faulty part</th>
<th>Employee ID</th>
<th>Repair time</th>
</tr>
</thead>
<tbody>
<tr>
<td>13.01.17 12:03:01</td>
<td>AC01</td>
<td>Spindle 1</td>
<td>Spindle seal air</td>
<td>Air hose C</td>
<td>Mechanic 01d</td>
<td>1.2h</td>
</tr>
</tbody>
</table>

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>
<thead>
<tr>
<th>Table 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Data target formats.</td>
</tr>
</tbody>
</table>

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

---

دریافت فوری
متن کامل مقاله

امکان دانلود نسخه تمام متن مقالات انگلیسی
امکان دانلود نسخه ترجمه شده مقالات
پذیرش سفارش ترجمه تخصصی
امکان جستجو در آرشیو جامعی از صدها موضوع و هزاران مقاله
امکان دانلود رایگان ۲ صفحه اول هر مقاله
امکان پرداخت اینترنتی با کلیه کارت های عضو شتاب
دانلود فوری مقاله پس از پرداخت آنلاین
پشتیبانی کامل خرید با بهره مندی از سیستم هوشمند رهگیری سفارشات