Integrated planning and control of maintenance and production

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Abstract
Within the production planning phase, future maintenance activities are scheduled insufficiently. This leads to the possibility that immediate maintenance demands interrupt the production process. Consequently, the availability of the machine tool regarded is decreased and high costs of failure occur.

Hence, a novel approach is developed by the IFW, which enables to execute the production and maintenance planning and control simultaneously. The approach is based on condition-based maintenance and integrates the knowledge of load, wear and remaining service life time of tools and machine tool components in order to systematically schedule maintenance activities in production-free periods.

Keywords:
Condition-based maintenance, wear modeling, event-driven process chain simulation

1 INTRODUCTION
So far the areas of decision making in operational planning and control of production and maintenance have been regarded separately, even though they intertwine:

Stress during production processes causes wear of the components in the production systems. At a certain degree of wear, it is impossible to guarantee a stable and economic production process within the defined quality and safety specifications. The stability of these production processes can be kept up by means of specific maintenance measures. Due to these maintenance measures, the production process might be interrupted or at least affected [1].

The fact that these fields have been regarded separately is due to the different predictability and scheduling capability of planning tasks. In production planning the planning of quantities, schedules and capacities can be derived from a defined production program [2]. This high precision level, concerning parameters and regularities of the process organization in production, contrasts severely with the low precision level concerning wear and maintenance of machine tools. One of the reasons is that in the past, the possibilities of cost-effective analysis of the actual condition of the components by sensors have been very limited. That is why the interactions of application, wear and maintenance of the components were not considered. State of the art machine monitoring systems allow nowadays monitoring the actual condition of the components susceptible to wear while in operation. Based on these values, a prognosis for the remaining life span of the component can be given so that there is a planning lead time for maintenance [3, 4]. Based on that, maintenance measures can be considered during production planning and thus be scheduled in production-free periods.

At the Institute of Production Engineering and Machine Tools (IFW) a new approach is developed, which allows a simultaneous planning and control of maintenance and production. By means of simulation, the effects of production orders on the stress of the machine and tools can be illustrated and analyzed in a real application scenario. This also applies to the resulting wear, the required means of maintenance and their effects on the original production planning. Hereby, new decision-theoretic approaches for the integrated planning of production programs and maintenance measures can be generated. In doing so, the availability of machine tools can be increased in combination with a reduction of the respective maintenance and manufacturing costs.

2 MODELING OF BREAKDOWN AND WEAR BEHAVIOR OF MILLING TOOLS
The novel approach integrates the knowledge of condition-based maintenance in order to estimate the remaining life span of components and respective future maintenance measures. Therefore, it is essential to measure and analyze the actual breakdown and wear behavior of the components by means of field data collection in a real application scenario. The results can be formally described within the novel approach.

2.1 Field data collection of real breakdown and wear behavior of milling tools
The real application scenario includes a chipping interlinked flow production. The most expensive process within this production line is milling, due to high tool wear and the resulting maintenance costs. In addition to that, the milling tools have a great influence on the total productivity of the whole production line. For that reason, the breakdown and wear behavior of the tools used in milling has been analyzed.
The evaluation of the breakdown behavior of milling tools is illustrated in Figure 1. The distribution functions and their respective parameters, which best describe the actual data, were identified, based on the empirically determined data. The breakdown behavior of the tools of the milling machines were modeled by means of a 3-parameter Weibull distribution. The parameters identified were hence statistically ensured in different tests (Kolmogorov-Smirnov-test, χ²-test) [5]. In addition to the downtimes of the tools, data for the development of tool wear was taken. For this purpose, the progression of torque in two milling spindles – the roughing and the finishing spindle – was monitored and analyzed. The trend in Figure 2 shows the progression of torque of the milling spindle.

The integrals of the torque of the spindle are proportional to the wear of the milling tools and therefore allow making predictions about the progression of wear [6]. This trend is close to linear and describes the frequently encountered appearance of wear known from practice [7]. Besides the linear progression of wear, a normally distributed scattering of the increase along the trend of the slope was detected.

### 2.2 Selection of a method for modeling breakdown and wear behavior

To be able to map the real breakdown and wear behavior of tools and selected components measured in a simulation model, it is essential to first identify an adequate modeling method. Table 1 shows a selection of possible modeling methods.

**Table 1: Methods for modeling breakdown and wear behavior**

<table>
<thead>
<tr>
<th>Methods</th>
<th>Focus</th>
<th>Parameterability</th>
<th>Formal description</th>
<th>Flexibility</th>
<th>Efficiency</th>
<th>Popularity</th>
<th>Sources</th>
</tr>
</thead>
<tbody>
<tr>
<td>Deterministic methods</td>
<td>S-curve (DIN 31051)</td>
<td>W</td>
<td>□</td>
<td>□</td>
<td>□</td>
<td>□</td>
<td>[8]</td>
</tr>
<tr>
<td>Stress collective</td>
<td>Stress integral</td>
<td>W / B</td>
<td>□</td>
<td>□</td>
<td>□</td>
<td>□</td>
<td>[9]</td>
</tr>
<tr>
<td></td>
<td>L_(10) method</td>
<td>B</td>
<td>□</td>
<td>□</td>
<td>□</td>
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<td>[10]</td>
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<tr>
<td></td>
<td>Wöhler curve</td>
<td>B</td>
<td>□</td>
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<td>□</td>
<td>□</td>
<td>[11]</td>
</tr>
<tr>
<td></td>
<td>Linear cumulative damage</td>
<td>B</td>
<td>□</td>
<td>□</td>
<td>□</td>
<td>□</td>
<td>[12]</td>
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<tr>
<td>Heuristic methods</td>
<td>Genetic algorithm</td>
<td>B</td>
<td>□</td>
<td>□</td>
<td>□</td>
<td>□</td>
<td>[13] [14]</td>
</tr>
<tr>
<td></td>
<td>Neural network</td>
<td>W / B</td>
<td>□</td>
<td>□</td>
<td>□</td>
<td>□</td>
<td>[15] [16]</td>
</tr>
<tr>
<td>Stochastic methods</td>
<td>Markov model</td>
<td>W</td>
<td>□</td>
<td>□</td>
<td>□</td>
<td>□</td>
<td>[17] [18]</td>
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<tr>
<td></td>
<td>Wiener process (Brownian motion)</td>
<td>W</td>
<td>□</td>
<td>□</td>
<td>□</td>
<td>□</td>
<td>[19]</td>
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<tr>
<td></td>
<td>Poisson process</td>
<td>W</td>
<td>□</td>
<td>□</td>
<td>□</td>
<td>□</td>
<td>[19]</td>
</tr>
<tr>
<td>Stochastic distribution / models</td>
<td>Model Birnbaum &amp; Saunders</td>
<td>B</td>
<td>□</td>
<td>□</td>
<td>□</td>
<td>□</td>
<td>[20]</td>
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<tr>
<td></td>
<td>Life prediction model</td>
<td>B</td>
<td>□</td>
<td>□</td>
<td>□</td>
<td>□</td>
<td>[21]</td>
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<tr>
<td></td>
<td>Distribution functions (e. g. Weibull)</td>
<td>B</td>
<td>□</td>
<td>□</td>
<td>□</td>
<td>□</td>
<td>[22] [23]</td>
</tr>
<tr>
<td>Expert systems</td>
<td>Fuzzy logic</td>
<td>W</td>
<td>□</td>
<td>□</td>
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<td>□</td>
<td>[24] [25]</td>
</tr>
<tr>
<td>Mathematical methods</td>
<td>Splines</td>
<td>W</td>
<td>□</td>
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<td>[26]</td>
</tr>
</tbody>
</table>
The methods were analyzed and evaluated regarding the present case by means of six criterions. These evaluation criterions are weighted (decreasing from left to right) and have the following meaning:

- **Focus:** Describes the object which is modeled: Either the wear behavior, the breakdown behavior or both can be modeled with this method.
- **Parameterability:** Classifies the parameterization accuracy of the data for the given breakdown and/or wear behavior analyzed.
- **Formal description:** Indicates if the methods are fully described by formulas or if only qualitative processes for the breakdown and wear behavior are given.
- **Flexibility:** Describes the transferability of the methods for different machine components.
- **Efficiency:** Evaluates the amount of data records and measured values required for parameterization of the process.
- **Popularity:** Displays the popularity and application respectively of the method for the breakdown and wear behavior modeling.

To keep the subjective influence on the evaluation as low as possible, different values (high, medium, low, non-existent) were defined, which can be proven by quantitative characteristic values.

It is obvious, that many methods, which are commonly used in science (popularity), are severely simplified and only map the real breakdown and wear behavior inaccurately (parameterability).

Stochastic methods are especially effective for the modeling of wear, because they illustrate real wear progresses far more accurately than other methods (parameterability). Furthermore these methods are not exclusively suitable for certain components, but can also be adapted for any characteristic progress (flexibility).

The breakdown behavior can be modeled best using stochastic distributions, which are characterized by high accuracy (parameterability) and easy applicability (formal description, efficiency).

### 2.3 Modeling of real breakdown and wear behavior of milling tools

The modeling of breakdown and wear behavior by means of the combination of two methods, Wiener process and 3-parameter Weibull distribution, are described in the following. The Weibull distribution illustrates the distribution of the tool failures documented over time. The Wiener process however models the wear progression during the machining of an increasing number of work pieces.

The Wiener process (also called Brownian motion) is the most important method among the stochastic methods. It is a process that has an initial value of zero, as well as independent, normally distributed, stationary growths. The Wiener process (WP) \( W(t), \ t \in [0, T] \) is formally described as [27]:

\[
\text{P}(W(0) = 0) = 1
\]  

\[
W(t_1) - W(t_0) \sim N(0, t - s), \text{ with } 0 \leq s < t
\]  

(c) The growths follow a normal distribution with a variance that equals the difference of the arguments,

\[
W(t) - W(s) \sim N(0, t - s), \text{ with } 0 \leq s < t
\]  

The modeling of breakdown and wear behavior is subject to certain exceptions. They can be derived from the measurements and also illustrate generally accepted connections in the field of strength of materials:

- The value of the wear allowance of a tool \( A_w \) at the beginning of its application (number of workpieces machine \( s = 0 \)) is 100% and can be described as \( A_w(s = 0) = 100 \% \).

- During the application of the tool, the wear allowance decreases continuously until it reaches the predefined limit \( G_w \). The tool should hence be replaced.

- At a wear allowance of zero the tool is not functional.

- Measuring the wear process of the milling tools used, a linear progression was detected (compare 2.1). In a linear model of wear, the slope \( VP_w \) of a wear gradient of the tool \( w \) is decisive for the point of time \( T_w \) at which the tool will fail. This point of time can be calculated as follows:

\[
T_w = \frac{100 - G_w}{VP_w}
\]

- It is assumed, that the wear level of the milling cutter changes after the machining of a work piece is fully completed. The wear really occurs from the time of the first contact of the milling cutter with the work piece, so that the wear progression should actually be infinitesimally small. In the required simulation of wear of each single milling tool this would lead to an enormous calculation complexity.

- The breakdown behavior of the milling tool is being illustrated by means of a 3-parameter Weibull distribution \( \text{Wei}(\alpha, \beta, t_0) \). The parameters of \( \alpha, \beta \) and \( t_0 \) of the Weibull distribution have been determined in the field data collection.

The modeling of breakdown and wear behavior of the milling tools is illustrated in Figure 3.

![Figure 3: Modeling of breakdown and wear behavior of the milling tools](image)

At the beginning of the application of each milling cutter a random number \( LD_w \sim \text{Wei}(\alpha, \beta, t_0) \) is produced out of the respective Weibull distribution, which will predict the expected life span of the tool. Hence the slope \( VP_w \) of the wear gradient is being calculated:
The slope equals the speed of the progression of wear of a tool. In a purely deterministic model the time of tool failure can be calculated using the following formula:

\[ T_w = L D_w \cdot \frac{100 - G_w}{100} \]  

(7)

If the limit \( G_w \) is defined as zero, the time of tool failure equates to the life span \( L D_w \).

With this process, though, the purely physical wear progress cannot be modeled. It rather illustrates all influencing factors that have produced the wear level measured at a certain point of time. The Wiener process is parameterized by means of the detected data as follows.

As mentioned before, the wear allowance of a new milling cutter is 100%. According to the increasing number of work pieces machined with the tool, the wear allowance of the tool decreases:

\[ A_W(s) = A_W(s-1) - SP(s) \]  

(8)

The decrease of the wear after the machining of a workpiece is defined by the variable \( SP \), which is normally distributed \( SP(s) \sim N(\mu_s, \sigma^2_s) \). The parameter \( \mu \) in the model of the slope conforms to \( V P_w \) of the linear wear path and therefore depends directly on the Weibull distributed life span of the tool. The standard deviation \( \sigma \), though, has been determined based on the knowledge from the data evaluation.

The results of the modeling of three different milling cutters are shown in Figure 4. The scattering of the normally distributed wear increases can lead to deviations of the life span resulting from the model and the life span \( L D_w \) measured in the Weibull distribution. The reason for this deviation is of stochastic nature. To evaluate the effects of the phenomenon, a simulation has been made, in which the wear of the milling cutters progresses according to the previously presented stochastic model. Hence, the distribution function of the life span of the simulation was compared to the distribution function of the Weibull distribution, with which the life span \( L D_w \) was generated.

![Figure 4: modeling of breakdown and wear behavior of milling cutters](image)

The Kolmogorov-Smirnov-test carried out on that purpose revealed that no significant differences between these two distributions could be detected. Thus, the approach described can be evaluated as an adequate means for illustrating the breakdown and wear behavior of machine components in a simulation model.

3 MODEL-BASED COORDINATION OF OPERATIONAL PLANNING AND CONTROL OF PRODUCTION AND MAINTENANCE

3.1 Approaches to the coordination of the two planning fields

As mentioned before, a novel approach is developed at the IFW, which enables to execute the operational production and maintenance planning and control simultaneously. This approach comprises the following coordination mechanisms.

Scheduling of maintenance measures at optimal costs

In the past, mostly preventive maintenance means could be considered during production planning. In the future, condition-based maintenance will make it possible to predict necessary maintenance measures for selected machine components. Therefore, an algorithm is developed, which considers the total production costs and determines the optimal point of time for maintenance.

![Figure 5: Systematic scheduling of maintenance measures at favorable points of time](image)

The algorithm shall, based on the actual status of the production, evaluate alternative points of time concerning their respective economic impacts. Depending on the degree of utilization of the machine tool, as well as the imminent failure and consequential costs, it shall be evaluated whether it is reasonable to schedule maintenance means in times of production breaks (e. g. during times of setting-up, Figure 5), or if a stop of the machine would be more favorable. Thereby, aspects such as the required maintenance times and the available maintenance personnel are considered.

Load dependent machine scheduling and sequence planning

This coordination mechanism is based on the assumption that the production of different component variants (e. g. different geometries, different material) causes different stress for the tools and machine components.

The aim is to schedule necessary maintenance measures for the time slots in which the machine is not running. This approach implies an upgrade of the coordination mechanism presented before, considering an adjustment of the original production plan in addition to the rescheduling of the maintenance orders. Therefore, the machine scheduling and sequence planning are considered (compare Figure 6).
useful to choose process parameters that guarantee a stable process and compliance of the work piece quality if within the defined range of process parameters that guarantee a positive outcome. Depending on the utilization, it could be necessary to adjust the process parameters so that smaller batches, or those that put less stress on the components, are brought forward. Hence, necessary maintenance measures do not affect or interrupt the production process. This coordination mechanism, though, requires a certain flexibility concerning the delivery times of the customer orders.

Load dependent adjustment of process parameters

It is assumed, that for certain process steps, there is a defined range of process parameters that guarantee a stable process and compliance of the work piece quality at the same time. Depending on the utilization, it could be useful to choose process parameters that guarantee a longer life span of the tools / components on the one hand and require a longer primary process time on the other (Figure 6). This strategy should be chosen if the production losses due to reduced process parameters are less important than the advantages resulting from the rescheduling of the maintenance measures to the time slots in which the machine is not running.

For this purpose an algorithm is developed, that contrasts the positive (longer life span, lower energy costs,...) and negative effects (longer primary process time, costs for additional shifts,...) and makes it possible to determine cost-effective process parameters considering the interactions of the interlinked machines.

**Figure 6: Load dependent machine scheduling and sequence planning**

3.2 Development of an event-driven simulation model

The development of an event-driven simulation model of a real production is the basis for the analysis of the coordination mechanisms described. An interlinked chipping flow production of a company applying the method is taken as an application example. Different work piece variants that are machined from the raw part to its final geometries run through a multi-level process chain.

For different analytic, statistic and numeric methods it is often required (due to performance issues) to make simplified assumptions so that the adequacy of these approaches for supporting the decision making in today's complex production systems are limited. Furthermore, these methods quickly meet their limits when it comes to implementing time dynamics of production processes in the calculation. These disadvantages are reduced by using an event-driven simulation. The software Plant Simulation® enables the simulation and optimization of production and logistic processes. By those means even complex production systems and structures can be modeled so they are easy to analyze [28].

Currently, production structures and processes of real application scenarios are modeled. The models illustrate the relevant production schedules, work piece variants, cycle times of the machine, speed and capacity of the line, algorithms of material flow control and other factors. The implementation of breakdown and wear behavior of the tools and components is especially important for the modeling (compare 2.3). In doing so, it is possible to estimate the remaining life time of the component, based on the knowledge about the current wear allowance and the prospective stress resulting from the machining of the work piece. This is necessary to evaluate the coordination mechanisms described.

In future research work, a detailed verification and validation of the simulation model will be carried out. Moreover, the advantages (maintenance costs, manufacturing costs, availability of machine tools) of different coordination approaches (compare 3.1) in comparison to the conventional way of regarding the planning areas independently shall be proved (initially offline). In addition, the simulation model shall be used online to support the simultaneous planning and control of maintenance and production. Different development scenarios of production can be simulated for a short-term planning horizon, based on the current actual state of the production (current degree of wear, buffer filling, utilization of machine tools,...). Hence, instructions for the matching of production and maintenance can be derived.

4 SUMMARY

In research and praxis, the areas of decision making in operational planning and control of production and maintenance are predominantly regarded separately. As a consequence, high costs of maintenance and a decrease of the availability of machine tools occur as maintenance measures are not systematically scheduled for the time the machine tools are not running and therefore often interrupt the production process.

In this paper, a novel approach is presented, which enables to execute the production and maintenance planning and control simultaneously. This approach integrates the knowledge of the condition-based maintenance by regarding the actual condition and the remaining service life time of machine tool components. In doing so, a planning lead time for the maintenance occurs which is used to systematically schedule mainte-
nance activities in production-free periods. Therefore, different coordination mechanisms are analyzed and evaluated using the event-driven simulation.

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6 REFERENCES