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ORIGINAL ARTICLE

Condition-based tool management for small batch production

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Abstract This paper presents a novel tool management concept for cutting processes which integrates tool relevant information, such as distribution data, tool orders, tool condition, and allocation data, within a centralized information cycle. The developed tool management approach uses decentralized identification and storage technologies, enabling an autonomous cooperation of tools and machine tools within a production. The first part of the paper is focused on the assessment of tool condition in a flexible job shop production. A tool wear monitoring system based on cutting force coefficients is developed and demonstrated by an exemplary milling operation. Thereby, it is shown that cutting force coefficients are suitable for wear monitoring and prediction, even for varying cutting conditions. For the online assessment of the current tool condition and for the prediction of residual tool life, an empirical tool wear model is demonstrated. This is applied to a novel condition-based tool management strategy which enables the optimum exploitation of the life time and performance of the cutting tool. The developed condition-based tool management concept is finally demonstrated by a software demonstrator.

Keywords Cutting process · Tool wear · Tool management · Monitoring · Small batch production

1 Introduction

Complex manufacturing processes and innovations in terms of tool technology have led to an enormous increase in the diversity of cutting tools. For companies with small batch production and a wide range of product variants, in particular, the management of cutting tools has become a complex task. In the case of a flexible small batch production, up to 40 % of the tool costs are spent on handling, setup, reworking, and other tool management tasks within the tool cycle of the company. By ensuring the availability and utilization of cutting tools, the tool management system influences production performance significantly. For years, tool management systems have been the standard for the planning and control of the tool usage [1–3].

The main objectives of tool management systems are the exploitation of tool performance, the optimized tool selection, the reduction of idle time caused by the tools, and the management of tool logistics and procurement [1]. To maximize the tool performance and utilization, it is necessary to gain precise information about the tool condition from the shop floor. In an industrial job shop production, lack of information about tool wear often leads to a preventive tool exchange to avoid tool breakage and scrap production. In order to avoid tool breakage during machining, tools are not operated at the optimum cutting conditions which results in a loss of performance.

Tool condition monitoring (TCM) seems to be a promising approach to observe tool wear during the machining process [4]. Several TCM approaches have been developed so far. For the observation of the tool condition from the machining process, process signals have to be acquired by direct or indirect sensor technology. The existing TCM methods differ by their utilization of sensor technology, signal processing, and feature extraction for tool wear estimation. Force signals and motor currents are commonly used for tool wear monitoring of cutting processes [5]. Besides the estimation and observation of the tool condition, a reliable prediction of the remaining tool life is necessary for tool management. Therefore, artificial intelligence methods have been applied

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to predict remaining tool life based on the current tool condition. For example, neuronal networks (NN) are able to recognize implicit dependencies between various, indirect input signals and, thereby, have been successfully used for tool wear estimation [6, 7]. Neuronal networks have to be trained to the tool and process characteristics and, thus, are limited to constant process conditions [5]. A review of wear prediction methods is given in [8]. Due to the required training phase and the low flexibility of the existing prediction methods, their applications are limited to batch production. However, tool condition observation and prognosis is highly demanded in a flexible job shop production with small or single-batch production. There, cost-intensive workpieces can be damaged. For the observation and estimation of tool life in a flexible small batch production, process-independent wear indicators and characteristics for online monitoring have to be found in order to provide a reliable tool condition monitoring and prognosis.

Recent research in tool management systems (TMS) is primarily aimed at solving the job-tool allocation-problem especially in context of flexible manufacturing systems [9–12]. Different algorithms (simulated annealing, ant colony, etc.) have proven their capability, e.g., to minimize the makespan. Within these approaches, tool life is considered as a static value depending on the tool type that represents a constraint for the optimization algorithm. In real small batch manufacturing environment, tool life strongly depends on the cutting conditions and follows a random distribution. Therefore, Prickett et al. presents a promising approach that combines milling cutter monitoring with a TMS. The system focuses the monitoring of tool breakage and failure diagnosis [13].

In order to overcome the limitations of existing tool condition monitoring strategies in terms of flexibility and reliability, a flexible condition monitoring concept for milling tools is described and demonstrated in the following. The flexibility of the condition monitoring enables the application in a flexible job shop production, where various cutting conditions result in various tool conditions of individual tools over time. Additionally, manufacturing resources in a job shop production are highly distributed over time. To overcome this challenge, decentralized allocation technology, using radiofrequency identification (RFID), has been applied for tool management [14, 15].

In order to manage the information complexity generated by distribution and condition information and to profit from the high information availability, a novel condition-based tool management is described and demonstrated in the subsequent captions. The application of the condition-based tool management is pointed out by the improvement of process reliability, tool utilization, and the increasing of tool performance at the end of the paper.

2 Condition-based tool management concept

In order to provide current tool condition and allocation data for tool management, a centralized information structure was chosen for the condition-based tool management. Therefore, tool condition information are generated by online monitoring and are transmitted to a centralized tool management system. This enables an optimized tool assignment in a flexible small batch production in terms of process reliability and tool utilization (Fig. 1).

Within the tool information cycle, a tool request is generated by the tool management system triggered by a manufacturing order and a process plan. Relevant tool information within the tool cycle is transferred to the central tool management system and is stored, connected to a unique tool identification number (ID). This allows a unique allocation of information to a single tool or tool component. In order to enable an autonomous cooperation of tools and machine tools, individual tool task information is stored decentralized on the tool, using inherent storage and transponder technology [16]. In order to realize a consistent and compatible information flow, a self-contained data format was developed. This format enables the connection of process data and tool data by its modular construction. On the semantic layer, the hierarchical Gentelligent markup language (GIML) provides a high scalability with respect to different use cases in the life cycle of a tool or tool component. As a basis for the textual representation of product and production-related information, GIML uses the extensible markup language (XML), which can be both easily human-read and at the same time machine-processed with a large inventory of preexisting software frameworks. The development and application of the GIML data model has been described in detail in [17]. It is applied here in order to provide a unique information model for tool information exchange in a job-shop production.

In order to acquire accurate tool condition inside a job shop production with less effort, a flexible tool monitoring method based on process-independent characteristics has been developed. Thereby, tool condition is automatically detected from process signals and is provided inside the tool information cycle enabling tool wear acquisition and prognosis in terms of process planning and control.

3 Monitoring of tool wear in end milling—investigation of process signals for wear monitoring

In order to provide an observation of tool wear during the manufacturing process, process signals have been investigated for the observation of tool wear. A common procedure for tool wear observation is the monitoring of process forces during the manufacturing operation [5]. Process forces can be captured within the flux of force of the machine tool during the

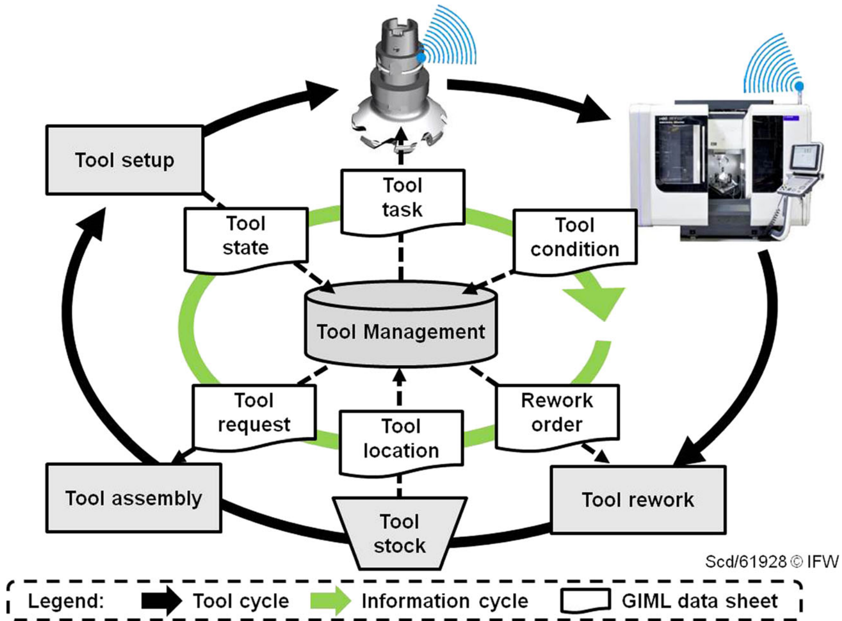


Fig. 1 Condition-based tool information cycle

machining operation. If force sensors like dynamometers are too expensive or insufficient for the application, a novel development of sensory fixture elements provide a comfortable and practical alternative for the observation of process forces even in industrial manufacturing processes [18].

An experimental milling process was performed in order to observe tool wear from measured process forces. Figure 2 shows the evolution of process force amplitudes and flank wear land *VB* over the course of the tool life for end milling of tempered steel (42CrMo4).

The average of the process force amplitudes (Fig. 2a) rises significantly up to 100 % (F_f) over the course of the tool life. Tool flank wear rises up to 200 μm after a tool life of 600 s (Fig. 2b). Therefore, a linear correlation could be assumed between the force amplitudes and tool flank wear. Hence, the monotonous rising characteristic of force amplitudes provides an indicator of tool wear for tool condition monitoring [19]. However, the increase of cutting force amplitudes is only applicable as a tool wear indicator in terms of constant process conditions. Cutting force changes due to changing engagement conditions can disturb that kind of wear indicator. In order to observe the tool wear from cutting forces, independent from process variations, the cutting force coefficients are taken into account.

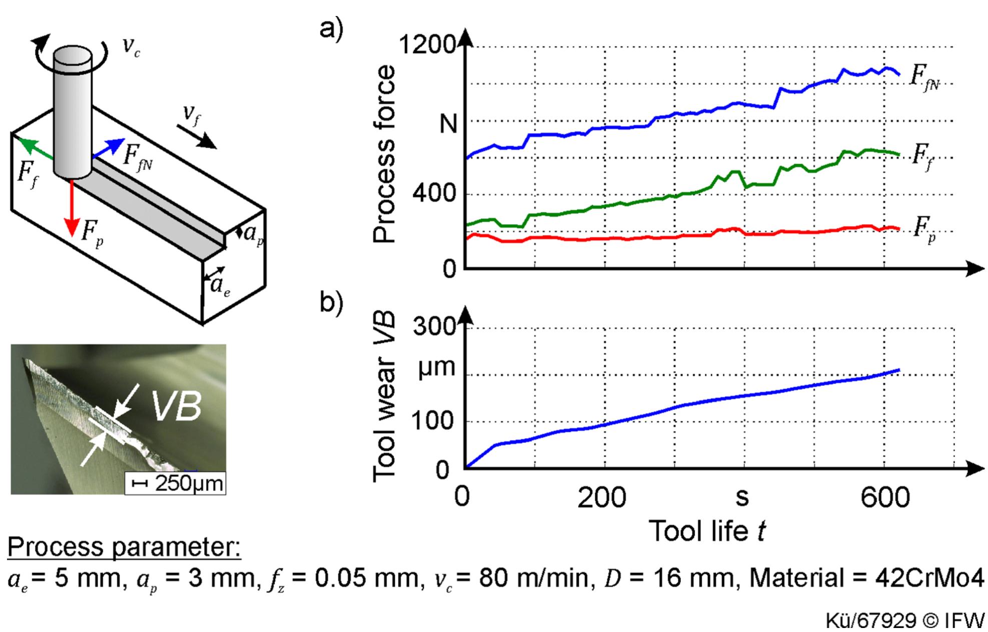


Fig. 2 Evolution of process force amplitudes (**a**) and flank wear land (**b**)

3.1 Calculation of cutting force coefficients

In order to provide a wear indicator even for changing engagement conditions, the cutting force coefficients are taken into account for tool condition monitoring. The cutting force of a milling process can be described as a function of the uncut chip geometry and the cutting force coefficients [20]. The cutting force function can be written in a matrix formulation as follows:

$$\mathbf{F}(\varphi) = \mathbf{K}\cdot\mathbf{G}^T(\varphi) \quad (1)$$

$$\mathbf{F}(\varphi) = \begin{bmatrix} F_t(\varphi) \\ F_r(\varphi) \\ F_a(\varphi) \end{bmatrix} \quad (2)$$

$$\mathbf{G}(\varphi) = \begin{bmatrix} A(\varphi) & b(\varphi) & 0 & 0 & 0 & 0 \\ 0 & 0 & A(\varphi) & b(\varphi) & 0 & 0 \\ 0 & 0 & 0 & 0 & A(\varphi) & b(\varphi) \end{bmatrix} \quad (3)$$

$$\mathbf{K} = \begin{bmatrix} k_{tc} & k_{te} & k_{rc} & k_{re} & k_{ac} & k_{ae} \end{bmatrix} \quad (4)$$

where F_t, F_r, F_a are the process force components, $\mathbf{F}$ is the resultant process force vector in the tool coordinate system, $\mathbf{G}$ is the geometry matrix, including the cross-section of the undeformed chip $A(\varphi)$ and the width of undeformed chip $b(\varphi)$, and $\mathbf{K}$ being the coefficient matrix, including the cutting coefficients k_{tc}, k_{rc}, and k_{ac} and the edge coefficients k_{te}, k_{re}, and k_{ae}. The geometry matrix $\mathbf{G}$ has to be calculated based on the given process parameters, using a cutting force simulation (see [21]).

For determining the cutting force coefficients from given process forces from a milling process, Eq. 1 has to be solved for the coefficient matrix $\mathbf{K}$:

$$\mathbf{K} = \mathbf{F}(\varphi) \Big/ \mathbf{G}^T(\varphi) \quad (5)$$

Due to the scale and complexity of force and geometry matrix, Eq. 5 has to be solved numerically by determining the coefficient vector $\mathbf{K}$ over a range of rotation angle positions φ. The cutting force coefficients incorporate the nature of the cutting process and are highly sensitive to changes in the tool and workpiece behavior, the coolant, the temperature, the cutting edge condition (in terms of wear or breakage), as well as many other influences.

In order to provide a robust wear indicator even for varying process parameters, their influence on cutting coefficients has to be determined. Consequently, the sensitivity of the cutting force coefficients has been evaluated over a variation of process parameters over several cutting experiments based on the process shown in Fig. 2. Table 1 quantifies the maximum variation of each coefficient for different cutting conditions.

Based on the theoretical background of semiempirical cutting force models, the cutting force coefficients have to be independent from changes in the engagement parameters. The identified variations of the cutting force coefficients for the process parameters indicate the accuracy of the proposed method for calculation of force coefficients described above. Even if the influence of tool wear is more sensitive than the variation of the force coefficients (c.f. Table 1, <33 %), the cutting force coefficients can be used to indicate tool wear for varying process parameters.

3.2 Observation of cutting force coefficients

In order to identify the tool condition based on process forces, the cutting forces coefficients were observed and evaluated over the course of tool life. Desfosses et al. proposed a tool wear estimation based on the cutting force coefficients [22, 23]. By tracking the cutting force coefficients over tool life, they have found that the edge coefficients correspond systematically to the tool wear. Thus, a tool wear observation can be performed even for changing process conditions. In order to improve the robustness of the coefficient based tool wear monitoring for a wider range of process conditions, the whole coefficient spectrum (cutting and edge coefficients) is analyzed in the following to identify wear sensitive signal features.

Based on the measured process forces from the obtained machining process (see Fig. 2), the cutting force coefficients can be solved by Eq. (5). Figure 3 presents the development of the coefficients over the course of tool life. The influence of tool wear on the force coefficients can be indicated by a significant drift over tool life.

The development of tool wear can be clearly correlated to the continuous change of the cutting force coefficients. In particular, the edge coefficients (k_{te}, k_{re}, and k_{ae}) rise linearly

Table 1 Variation of the cutting force coefficients for changing cutting velocity, engagement widths, and engagement depths for process given in Fig. 2

	Cutting velocity v_c=100–200 m/min	Engag. width a_e=1–10 mm	Engag. depth a_p=1–5 mm
k_{tc}	5 %	19 %	5 %
k_{te}	14 %	30 %	15 %
k_{rc}	10 %	29 %	12 %
k_{re}	20 %	33 %	20 %
k_{ac}	15 %	22 %	10 %
k_{ae}	5 %	21 %	20 %

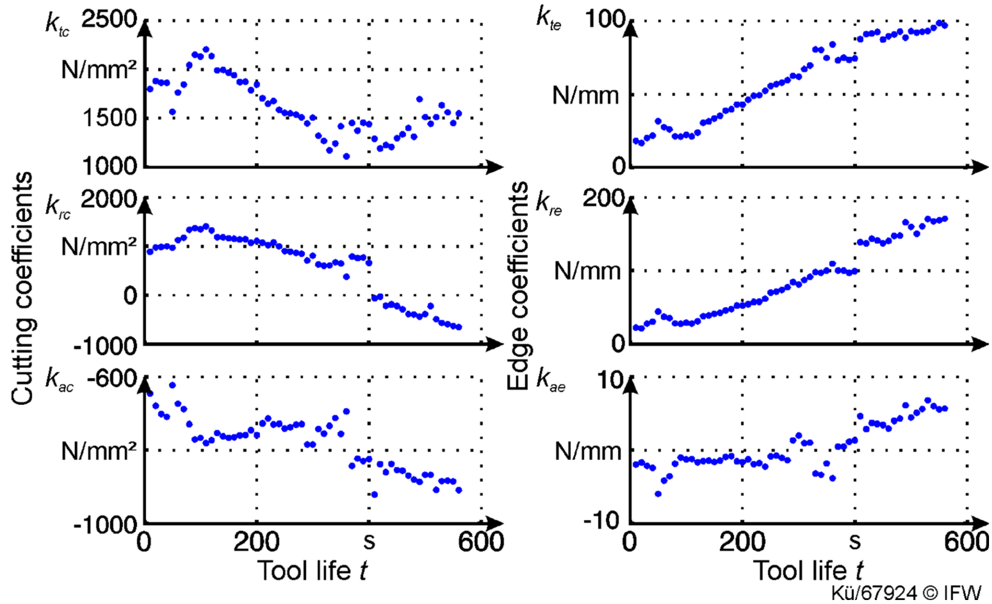


Fig. 3 Evolution of cutting force coefficients over tool life

over the course of tool life. In order to qualify the cutting force coefficients for tool wear observation and prognosis, the repeatability of this observation value has to be verified. Therefore, the tool wear observation was evaluated statistically over seven tool observations. The correlation of the cutting coefficients and the tool wear is presented in Fig. 4.

This dataset was generated by performing identical cutting tests with seven endmills and by capturing the cutting coefficient seven times per second. The confidence bounds of the dataset for 96, 50, and 20 % are shown as gray areas. The correlation data was evaluated in order to identify general functional relations for an empirical wear indicator. In order to qualify coefficients for a tool wear indicator, the sensitivity, the correlation index, and the distribution has been quantified. Table 2 shows the sensitivity S of the cutting force coefficients calculated by a linear approximation of the data from Fig. 4. The confidence range was calculated by a Student's t distribution [24] from seven observations. The correlation coefficient is drawn in order to evaluate the significance of tool wear in the development of coefficients.

The edge coefficients (k_{te}, k_{re}, and k_{ae}) show high sensitivity and correlation (R>0,8) and thereby are qualified for the application of wear observation. Regarding the cutting force coefficients, solely the axial cutting coefficient k_{ae} exhibits a linear correlation over tool wear.

3.3 Empirical tool wear indicator

In order to provide a robust wear indicator for the estimation and prognosis of tool life, the linear behavior of several cutting

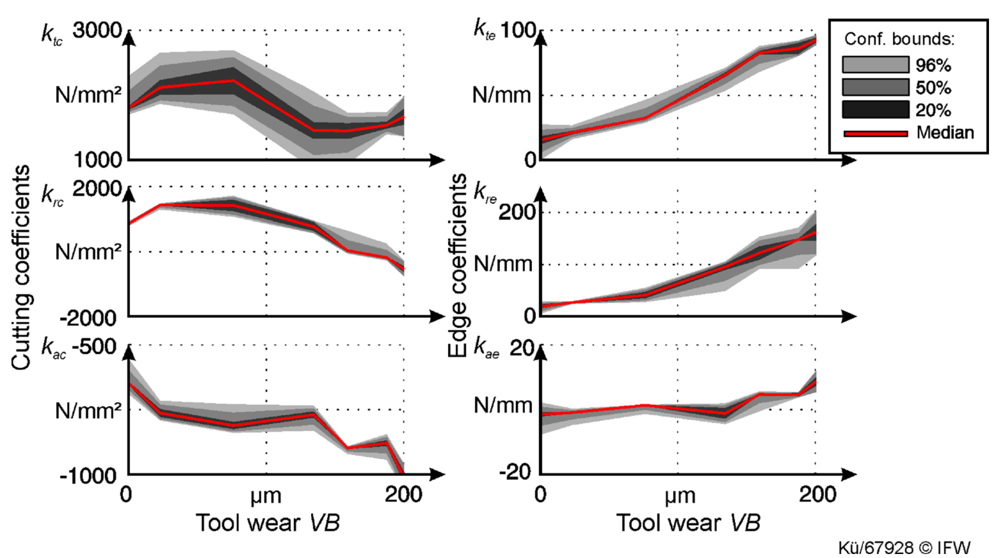


Fig. 4 Distribution of correlated cutting force coefficients over tool wear land

Table 2 Sensitivity, standard deviation, and correlation coefficient of cutting force coefficients

	Sensitivity S	95 % Confidence range	Correlation coefficient R
k_{tc}	Non-linear	780 N/mm^2	0.67
k_{te}	0.45 N/mm μm	21 N/mm	−0.85
k_{rc}	Non-linear	610 N/mm^2	−0.29
k_{re}	0.9 N/mm μm	70 N/mm	0.957
k_{ac}	−2.3 N/mm^2 μm	293 N/mm^2	−0.82
k_{ae}	0.05 N/mm μm	8 N/mm	0.831

force coefficients was merged into a nominal tool wear indicator. The tool wear indicator is based on the assumption that the tool wear exhibits a linear trend and can be reproduced within a small confidence range. In order to provide a robust indicator, a multicriteria method is used, merging a couple of independent signal features.

The tool wear estimation is based on an empirical database, which stores linear wear function parameters and confidence ranges of the observations. The end of tool life has to be defined manually for the first observations. Afterwards, the observed process can be indicated by comparing the observed value to the empirical wear function.

In the first step, the empirical model has to be generated from the observed processes. In order to get an equally scaled parameter range, the observed coefficients are normalized over tool life.

$$\overline{k(t)} = \frac{k(t)}{k(t_{end})} \tag{6}$$

The normalized coefficients were weighted according to their linear correlation coefficients, taken from Table 2, and afterwards summed up to get a linear tool wear indicator $I_{VB}(t)$:

$$I_{VB}(t) = \overline{\boldsymbol{K}} \cdot \boldsymbol{W}^T \tag{7}$$

$$\boldsymbol{W} = \begin{bmatrix} w_{tc} & w_{te} & w_{rc} & w_{te} & w_{ac} & w_{ae} \end{bmatrix} \tag{8}$$

$$\overline{\boldsymbol{K}} = \begin{bmatrix} \overline{k_{tc}(t)} & \overline{k_{te}(t)} & \overline{k_{rc}(t)} & \overline{k_{re}(t)} & \overline{k_{ac}(t)} & \overline{k_{ae}(t)} \end{bmatrix} \tag{9}$$

The weights were chosen, in order to generate a linear wear indicator (R>0.8), by means of high sensitivity and a low confidence range. The combination of redundant signals provides a robust indication of tool wear. Due to their low significance (R<0.8, c.f. Table 2), the cutting coefficients k_{tc} and k_{rc} were rated by w=0 (Table 3).

Table 3 Normalized weight coefficients

	w_{tc}	w_{te}	w_{rc}	w_{re}	w_{ac}	w_{ae}
Value	0	1/3	0	1/3	1/6	1/6

The tool wear indicator $I_{VB}(t)$ quantifies the tool condition by means of a ratio between 0 and 1, where 0 describes a new and 1 a worn tool. The empirical tool wear model is build up by the parameters of the linear tool wear function and the confidence level of observations. By every observation refining the confidence level of the Student's t distribution, the model is improved continuously. The following empirical function has been generated from the tool wear observations from seven milling experiments.

At the beginning of tool life t<100 s, the index is not sensitive. However, within the tool life t=100–600 s, a linear function can be approximated from the observations. For the indication of tool wear for a current observation, the current index $I_{VB}(t)$ indicates the absolute condition of the observed tool. For a tool life prognosis, the linear approximation of the tool wear model is used to extrapolate the end of tool life t_{end} based on the current index location (c.f. Fig. 5). The failure probability of tool life can be estimated based on the predicted end of tool life and the empirical failure distribution at the end of tool life $I_{VB}(t)$=1.

Due to the robust behavior of the cutting force coefficients for the varying process parameters (c.f. Table 1), the tool wear index can be indicated even for changing process conditions. For the prognosis of tool life, the empirical tool wear function has to be generated from the past observations. The end of tool life can be predicted by the extrapolation of the linear tool wear function. Therefore, a tool database is required which stores tool-specific wear models. By linking several wear models to their process specifications, given by the process parameters, machine tool, coolant, and workpiece information, the tool wear monitoring could asses and predict tool wear even under changing process conditions. This enables a tool wear monitoring and prediction even for a complex and individual single-batch production. The application of tool

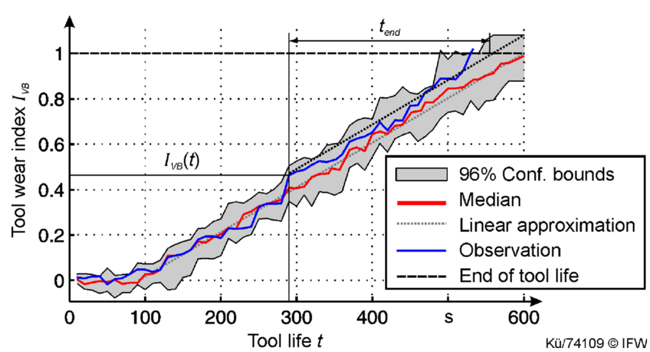


Fig. 5 Tool wear indicator, confidence range, and observation

condition monitoring for tool management are demonstrated in the next chapter.

4 Strategy for condition-based tool management

Common tool management strategies are based on empirical data from the shop floor based on manual observations of tool life, which have to be generated by extensive experimental tests. Thereby, the statistical probability of the end of tool life is determined and can be used to calculate the probable tool life for manufacturing operations. However, as the shop floor usually does not provide any feedback on the tool condition, the true end of tool life cannot be determined accurately. Thus, an effective tool is often exchanged preventively in order to ensure the stability of production.

In order to optimize the manufacturing resource utilization and thereby reduce tool and manufacturing costs for a flexible job shop production, a novel condition-based tool management strategy was developed (Fig. 6). As described above, the residual tool life is calculated from the monitored process signals by means of an empirical tool wear model separately for every single tool. The GIML format provides a consistent data structure for both centralized systems (e.g., TMS) and decentralized systems (e.g., tool inherent data storage) and enables a direct communication of single tools (e.g., via RFID) and legacy systems.

If the identified tool wear index I_{VB} exceeds the empirical threshold value, which is generated by the confidence level of the empirical end of tool life, the residual tool life t_{end} is compared with the operation time $t_{Operation}$ specified in the process plan. If the remaining operation time exceeds the predicted tool life, the cutting parameters (e.g., the cutting velocity [25]) can be reduced in order to avoid either an additional tool exchange or a higher risk of tool breakage. In order to gain empirical data for the tool wear prediction, the tool wear model is updated continuously by the practiced tool

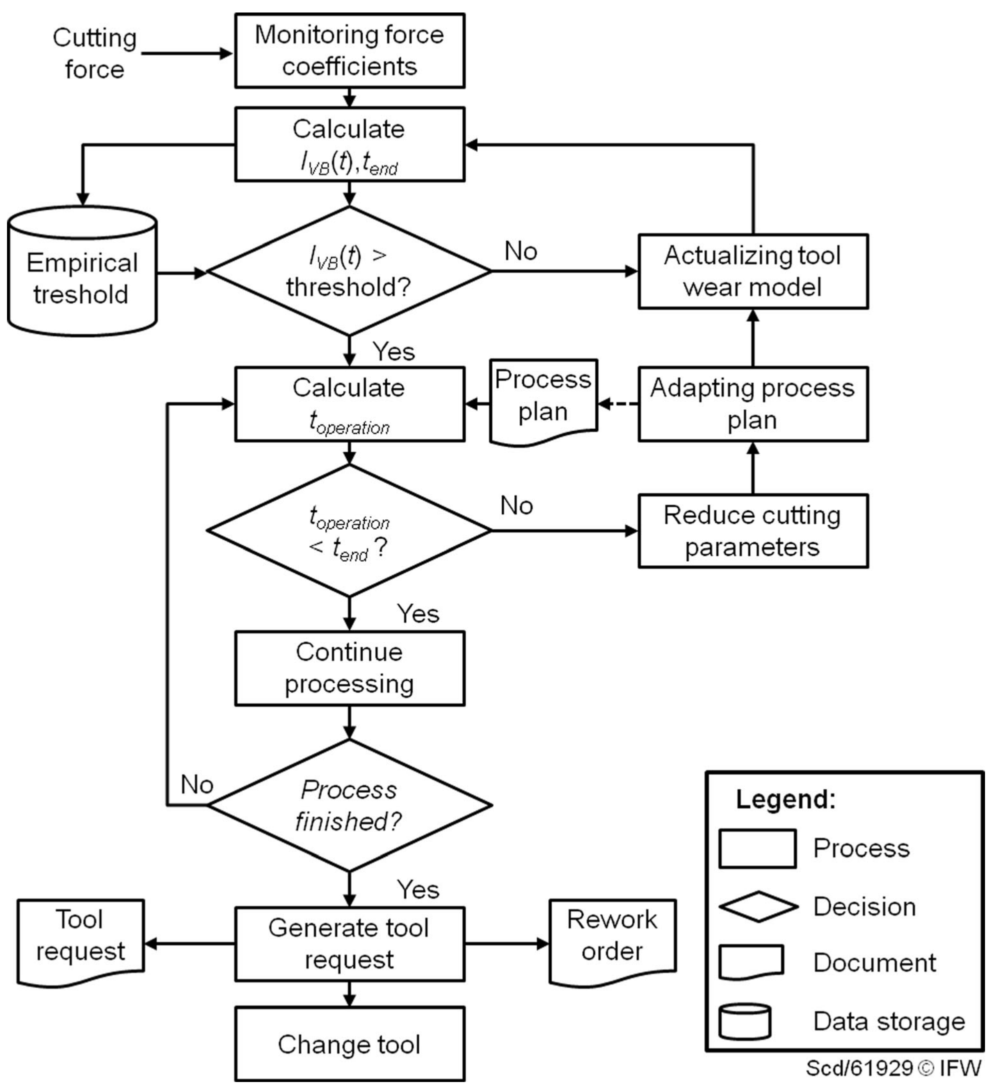


Fig. 6 Condition-based tool management strategy

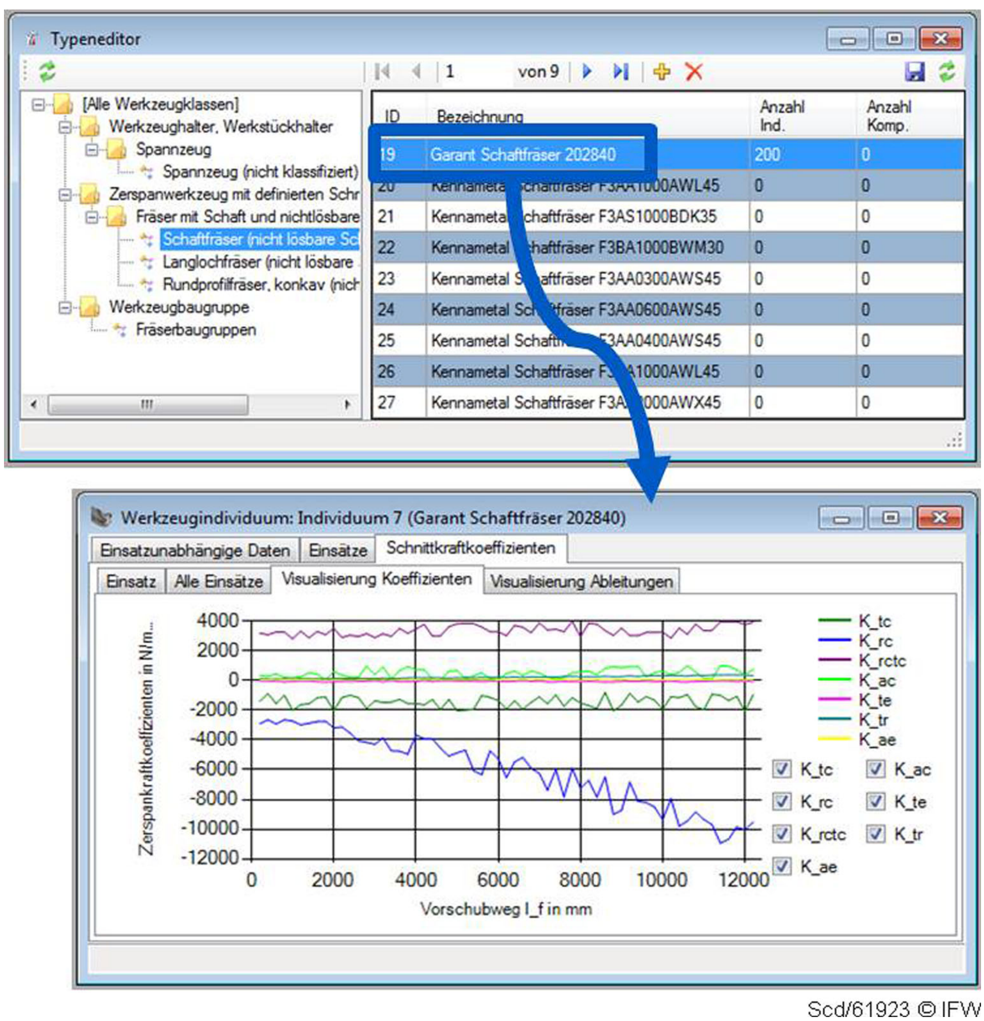
life time and by the conducted process parameters. If exceeding the tool life cannot be avoided, the systems stops the cutting process in order to avoid tool breakage. The permanent monitoring of single cutting tools and the continuous comparison of the current tool condition with empirical data in every phase of the tool life enable a sustainable exploitation of single cutting tools considering their special operational history in unique cutting processes. In combination with a very high process reliability, the strategy meets the demands of small batch production. After finishing the cutting process, a tool request and a rework order is generated to ensure the efficient regrinding of the tool and the secure tool supply for following cutting processes.

By combination of wear monitoring, decentralized data acquisition, and centralized wear prognosis, the proposed method of condition-based tool management offers several advantages for an industrial production scenario.

- Avoidance of tool breakage and resulting interruptions
- Optimal exploitation of the tool performance
- Analysis of former tool applications
- Increasing performance through optimized cutting conditions
- Reduction of tool management efforts by a central organization
- Reduced process failure probability by process monitoring

For the tracking of tool wear and the allocation of tool life time information, it is essential to realize a novel perception of tool data administration. Instead of a tool type oriented approach, an individual tool component specific data administration is required, as the current condition can vary between different tools of the same type. Therefore, a database for the condition-based administration of individual tool components and their dynamic condition data was developed and realized in an SQL-based prototype in connection with a tool information interface programmed in .net framework (Fig. 7). On the left, a general classification of tools and tool components is shown. In the associated list of tool individuals (on the right), single components can be chosen to display the dynamic progress of wear (below).

Fig. 7 Administration of tool-specific wear data



Within the database, the development of cutting force coefficients, the wear indicator, and the residual tool life time is tracked related to the instant of time. This enables the on-time tool exchange as well as the avoidance of manufacturing disturbances and product quality failures due to probable tool breakage. The collection of life time data from the shop floor also serves as an experience basis for the evaluation and optimization of the subsequent processes and tool selections.

In order to estimate the added value of the condition-based tool management strategy, a testing case on a milling tool has been examined. For the exemplary milling process (Fig. 2), the predefined tool life was set at 470 s. Within a testing case, milling tools of the same type were examined in extensive wear investigations within a standardized testing procedure until breakdown. In the testing case, 50 % of the tools reached actually a tool life of 600 s (Fig. 5). Regarding the fact that 50 % of the tools reached even a longer tool life, the median corresponds to the average tool life applying the condition-based strategy. Thus, an increase of approximately 130 s in tool life within the testing case can be realized which represents a benefit of about 26 %. With respect to the tool costs in small-batch machining, the condition-based tool management strategy promises a significant saving of variable operating costs.

5 Conclusion

The paper provides an approach for online tool wear estimation and condition-based tool management. The proposed integrated tool management strategy provides several advantages for a job shop production as follows:

- The combination of decentralized cooperation of tools and machine tools in combination with a centralized data collection and analysis enables an efficient tool management, especially for companies with small batch production and a large variety of processes, tools, and products.
- The cutting forces from a milling process were analyzed in order to observe an indicator for flank wear, which is a dominant wear effect in metal cutting. A significant rise of cutting forces was detected from milling experiments over the course of tool life.
- In order to provide a wear indicator independent from changing process conditions, the cutting force coefficients were taken into account. It was found that coefficients show a small variance over cutting speed (<20 %), engagement width (<30 %), and engagement depth (<20 %, c.f. Table 1).
- The cutting force coefficients were found to be high sensitive to wear land (>300 %) over the course of the tool life of an endmill. A linear correlation was determined between the cutting force coefficients and tool wear.
- The tool condition during the machining process was observed by means of tool wear monitoring approach. By merging the normalized coefficient matrix over tool life, a linear tool wear indicator was created. Based on an empirical tool wear model, the wear indicator enables the assessment and prognosis of tool life, even for changing process conditions.
- Based on the obtained tool condition, a strategy for condition-based tool management was developed. This allows an on-time exchange of tools to realize a maximum exploitation of cutting tools in terms of life time and cutting performance, while reducing the risk of tool breakage and scrap production.
- Within an experimental test case, the utilization of tools can be enhanced by 26 % by the proposed method for condition-based tool management. This can be provided in parallel to an improved process reliability until the actual end of tool life.
- A condition-based tool database and decentralized data transmission using the unified GIML data format enables a single component-specific and condition-based administration of tool data as well as a maximum of data consistency between information systems in manufacturing (e.g., CAM, MES).

Future research focuses on the analysis of wear information to improve process planning. The collected data offers a great opportunity to learn from already finished cutting processes for the planning of future processes, especially in terms of tool selection and setting of cutting conditions.

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