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Wear Prediction of Woodworking Cutting Tools based on History Data

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Abstract

The tool lifespan is among the most contributing factors in machining economics. Accurate lifetime prediction maximizes the utilization of each tool and the machine tool. In order to predict the remaining tool life accurately the past has to be captured continuously. In this paper the capturing of tool usage data and its analysis is explained. With the captured data tool operation circumstances can be calculated. These are mainly responsible for tool wear. This circumstances data is captured by machine tool integration and combined with production planning data. The generated context of the machine tool information of the covered cutting path is combined with the material used. The combination results in specific tool wear. This cutting circumstances are logged in the tool history data. The cutting conditions are described with the material used, feed rate per tooth, cutting width, cutting speed, cutting path and number of revolutions. A model has been developed which describes the steps in detail. A forecast algorithm uses the history data to predict the occurring tool wear and end of life of the cutting tool. Input for the calculation are the cutting path, cutting circumstances, tool type and material type. With this information it is possible to forecast the remaining tool life by using a specifically tailored machine learning algorithm. The prediction will become more accurate after each learning cycle. In this paper the algorithm is explained and the generated characteristic diagram is displayed for each tool and its tool life.

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Keywords: Tool Wear; Wood Cutting; Prediction

1. Introduction and Motivation

The woodworking industry is undergoing drastic changes. The trend by the consumer market of demanding more individualized furniture [1] leads to mass customization of end products [2] which results in higher variances and smaller lot sizes.

In response to this demand the technological trends are a higher amount of engineered wood materials [3] and an increased number of cutting tool material with higher tool lifetime [4].

Both of these trends combined lead to higher combination possibilities between raw material and cutting material. Which creates the challenge of a higher planning uncertainty of the usage of cutting tools. Cutting tools can't be replaced preventive before the end-of-life due to the fact that tool lifespan is among the most contributing factors in machining economics. Accurate lifetime prediction maximizes the utilization of each tool and the machine tool. The existing scientific models have empirically studied the occurring wear at constant cutting conditions.

In applications such as the milling processes in a nesting operation cutting condition are not constant. Due to the planned geometry there are changes in direction the tool centre point. This direction changes leads to numerous decelerations and accelerations events. These planned events are executed differently depending on machine type on weight of raw material and tool and depending on manual operator interference in the process.

This results in different cutting conditions such as duration of the operation and smaller feed rated per tooth. The outcome of the process and the resulting wear are depending on theses cutting conditions.

This interrelation leads to different tool life depending on materials used, process parameters set and machine operated. A prediction of the remaining tool life has to consider these interrelation.

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2. State of the Art

The challenge in tool wear prediction is interdisciplinary. The start of the art is structured into the industry practice, the data acquisition and analytical solutions.

2.1. State of the Art in the Industry

Tool wear prediction is not done online during the operation. Some tool machine manufactures offer a function to track the sum of the tool centre point path. This function can't distinguish materials and can't differ between raw material present or not.

Common methods for tool wear estimation in series production is counting of the number of parts machined before tool life end is reached. This method works best with large lot sizes and similar variants.

2.2. Data Acquisition Methods

Tool wear can be measured direct or indirect. Direct methods are for example visual inspection or laser beams [5]. Indirect methods measure a second value which is interconnected to tool wear.

Indirect methods can be categorized into:

- *Feed and Spindle Measurements*: power, current, speed, position
- *Close to Process Measurements*: force, torque, strain , vibration, temperature, sound [6]

The data acquisition by built in-sensors into the machine tool is a combination of both categories.

2.3. Tool Wear Models

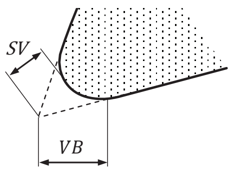

Fig. 1. Cutting Edge Offset Definition

Figure 1 shows the definition of the cutting edge offset (SV) and the flank-wear land width (VB) [7].

Tool Wear models have been derived from empirical test runs studies. Important work in this field was conducted by Kivimaa [8] and Fuß [9]. Each found correlations between certain parameter settings and resulting tool wear. The generalisation of the correlation was achieved by Fischer [10],[11]. His model explains the cause of the wear and also the wear progression.

By surpassing the line of equilibrate compression strength cutting material becomes loose from the cutting tool through abrasion. The loss of cutting material and the therefore connected loss of volume is correlating with constant cutting conditions. A comprehensive review of wood cutting tool wear literature was carried out by the University of California [12].

2.4. Gap

There is a lack of the combination of a machine learning algorithm with an extended wear model of the physical tool wear occurring in the woodworking domain. This combination would allow online prediction during the process.

3. Approach

The approach for the challenge of planning uncertainty of cutting tool usage is the capturing of built-in sensor data. The as-is-process parameter are different from the planned parameter. Hence an online data capturing of the process is the preferred option instead of planned data.

An industrial learning method is a structured proceeding with recurring comparison of desired and achieved output [4].

The process data combined with context data and the physical measurement of the end-of-life point of the cutting tool enable such an industrial learning approach.

The basic idea is to use the built in sensors of the machine tool. These sensors which are used to control the motion can be tapped in and forwarded via an interface outside of the machine tool control.

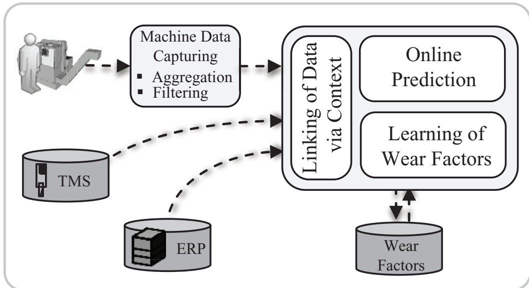

Fig. 2. Overview of the Approach

Figure 2 shows an overview of the approach. The machine tool control is one of the data sources used. The other data source are the Tool Management System and the Enterprise Resource Planning System.

The data sources can be combined to generate the necessary context. For instance it is important to know which tool was used for which operation in the NC-program and what production order was associated with this NC-program.

With this available information it is now possible to create a holistic tool history and calculate the tool wear cause by specific usage of this parameter settings and material combination. In the domain of woodworking the abrasive wear is the dominant wear type.

After sufficient learning cycles were carried out the system is enabled to predict the remaining tool life during the operation.

4. In-Situ / In-Process and Post Process Calculations

The calculation model is divided into the calculation performed during the process (in-situ) and the calculations which are performed after the process has taken place.

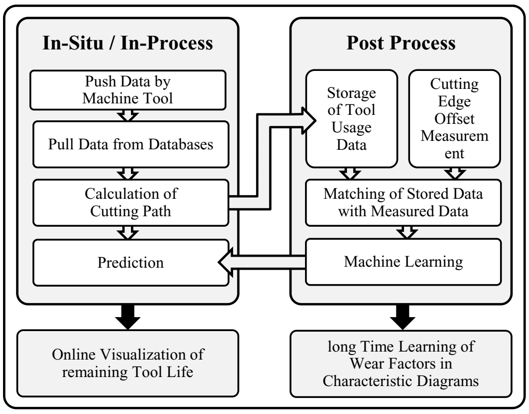

Fig. 3. Steps of the Data Flow

Figure 3 shows all the steps of the model. The two chains of calculation have different aims.

The in-situ calculations are using the wear factors, which were learned previously for this combination of cutting material and raw material, and state the predicated wear for these settings.

The post process calculation uses two data sets. The tool history data created by the in-situ calculation and the actual physical cutting edge offset measurements at the end-of-life of the cutting tool. The data sets are used with a tailored machine learning algorithm and the wear factors are stored. The wear factors represent the quantity of the influence of cutting circumstances on tool wear for each material combination.

4.1. In-Process Calculation

The frequency of this calculation should be in the range of less than 100 ms to achieve reasonable accuracy of the current tool position. The start of this calculation is triggered by a push message from the machine tool control. Depending on the settings of the interface the message interval is either a fixed time interval or a dynamic timespan after significant increment changes in one of the variables.

4.1.1. Push Data by Machine Tool

In order for the calculation of the cutting circumstances and to create a reasonable tool history the push message by the machine tool control has to cover Meta data, which is the timestamp and the machine-ID, and the values of the following variables.

- X/Y/Z- axis position in mm
- Number of revolution n in rpm
- NC-block as text
- Feed Rate v_c in mm/min

4.1.2. Pull Data by Databases

The data from the databases is requested upon necessity. The databases are the Tool Management System and the Enterprise Resource Planning System.

The Tool Management System is needed to access the tool-ID and tool geometry of the specific tool used for the current operation as stated in the NC-block

The Enterprise Resource Planning System is needed to retrieve the material type and material dimension specified in the production order.

4.1.3. Cutting Width Calculation

The machine tool itself does not know whether or not there is raw material present during the programed cutting operation. The machine is unaware of the exact position, size and shape of the raw material therefore cannot estimate the position of the tool in respect to the raw material.

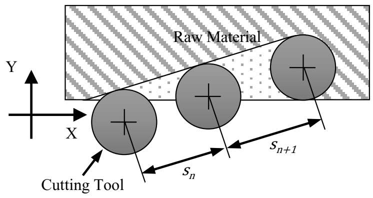

Fig. 4. Tool Path Line Segments with different Cutting Widths

To tackle this challenge the references points on the machining table, such as bolts, are used for the placement of the raw material. In the woodworking industry engineered wood panels are used. These panels have a simple shape of a rectangle and the dimensions are known through the production order. Once the dimension and placement is known the calculation is initialized. The calculation of the current cutting width is performed per line segment. Three exemplary placement of the cutting tool and two line segments are illustrated in Figure 4. The left placement has a small cutting width. The middle placement has more than the tool radius and the right placement the cutting width of the full tool diameter.

The procedure of the calculation of the value of the cutting width is shown in Figure 5. Inputs are:

- Contour point with radius correction
- The current raw material
- Tool geometry of the current tool in operation

The first check is whether or not the contour point lies within the defined raw material. If this is not the case the cutting width is zero. If this is the case the length of the line segment from the contour point to the point where the raw material ends and lies on a line from the contour point through the middle of the tool diameter. This point is defined as P_{ae}. If this line is bigger than the tool diameter the cutting width is exactly the diameter. This is the case in full section cutting. If the length is smaller than the diameter, the line segment length is equal to the cutting width.

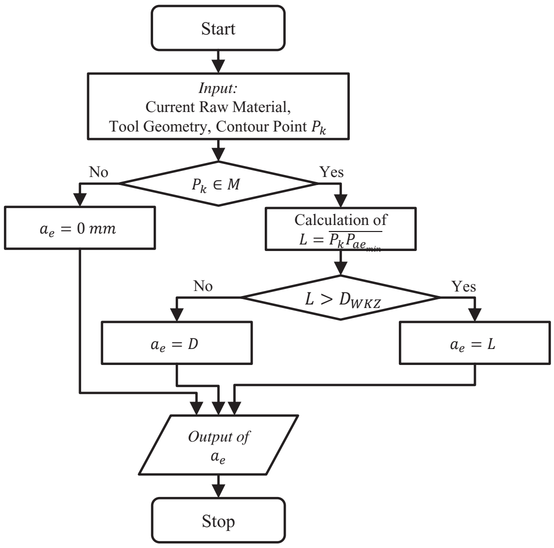

Fig. 5. Cutting Width Calculation Flow Chart

After the calculation is complete the raw material is updated with the information of the now updated new material contour. This procedure is illustrated in Figure 6.

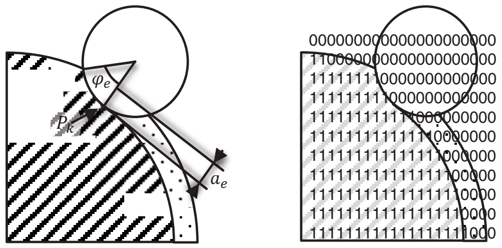

Fig. 6. Dynamic Online Raw Material Update

This recurrent updated digital twin of the material on the machine is the starting basis of the calculation of the proceeding contour path with the same of the next cutting tool in the NC-program.

4.1.4. Cutting Path Calculation

The overall cutting path per tool path segment can be calculated according to Equation 1.

$$l_{c\,tot} = \frac{D\ arccos\left(1-2\ \frac{a_e}{D}\right)\ l_f\ n\ z}{2000\,v_f} \quad (1)$$

The nomenclature German Standard DIN 6580 [13].

- $l_{c\,tot}$: total cutting path
- l_f: tool path
- v_f: feed rate

4.1.5. Integration function

To get the predicted cutting edge offset (SV) features have to be calculated. In total three features are used for the prediction:

- x_1: total cutting path (l_{c_tot})
- x_2: cutting speed (v_c)
- x_3: cutting speed over feed rate ($v_c/\ v_f$)

Feature 1 (x_1) is calculated in the previous step. Feature 2 (x_2) has to be calculated according to Equation 2. Feature 3 (x_3) is Feature 2 divided by the feed rate.

$$v_c = \pi\ d\ n \quad (2)$$

The features are inserted into the prediction function and the cutting edge offset for the duration of t is calculated (Equation3).

$$SV = \int_0^t \dot{f}\ (x_1, x_2, x_3)\ dt \quad (3)$$

4.2. Post Process Calculations

After the tool operation is complete the tool history data for this operation is stored. After the end-of-life of the cutting tool the cutting tool is send to the refurbishment. At this stage the physical cutting edge offset is measured.

4.2.1. Tool Usage Data

The variables which are stored as tool usage history are:

- Material used
- Feed rate per tooth f_z
- Cutting width a_e
- Cutting speed v_c
- Cutting path l_c
- Number of revolutions n

4.2.2. Cutting Edge Offset Measurement

The cutting edge offset can be measured via different methods. Common methods include optical measurement with an amplified shadow image or tactile using the profile method.

The data of the post process measurement contains the following:

- Tool-ID
- Cutting edge offset (SV)
- Time of measurement

4.2.3. Matching of Data Sets

The two data sets, the in-situ and the post process data set have to be combined for this approach.

The primary key for matching the two data sets is the tool-ID. The time of the cutting edge offset measurement reveals between which operation the measurement for that specific tool took place.

4.2.4. Learning Method

The machine learning category is supervised learning since the target value is known for training. The data captured in process consists of multiple variables per message and is received in the thousands per tool operation depending on the operation duration. All this data has just one output parameter, the tool wear measurement, after the operation is complete. This means the prediction during the process is not checked against a training value. After the operation has ended training can be performed based on physical measurements.

A function is created, which expresses the features x to fit the target value y by multiplying with β. Equation 4 states the generic form of this function.

$$\dot{y}(t) = x(t)^T \beta \tag{4}$$

The least squared error is the sum of the errors for one specific fit. The function which states this error for a certain factor setting is the *Loss Function*.

$$L(y,t) = \sum_{i=1}^{n} (\int_0^{f_i} y\dot{(t)} dt - y_i)^2 \tag{5}$$

Equation 5 states the Loss Function with i being the current feature value. The minimum of the function is determined by Equation 6.

$$\hat{\beta} = (X^T X)^{-1} X^T y \tag{6}$$

5. Implementation Concept

An implementation prototype was carried out using a woodworking machine by *Holz-Her GmbH* and push messages by the machine tool were sent to a web-service instance running on *Apache WildFly*. The Tool Management System used proprietary Tool Management Software Suite by *Leitz GmbH & Co. KG*. Within this tool management solution cutting tool by the same type were distinguishable due to unique IDs. Each unique tool recorded its own operation history.

The implementation showed that an upper limit of measuring point has to be considered before the data point have to be aggregated. A feasible on-online prediction can be done with a data set up to 4000 measuring points before calculation time exceeds the time between two messages.

6. Conclusion

In order to predict the remaining tool life accurately as-is-process parameters are necessary. An existing tool wear model was expanded. The expansion included the cutting speed and feed rate. Previously, the wear model only based on geometry and the time dimension was not necessary due to fixed parameter settings. This was achieved by breaking down of the cutting operation into small line segments instead of one continuous operation at constant parameter settings. The collected data created a unique tool history for each cutting tool. This data was used to match prediction with physical measurements.

The proposed model enables a prediction of the occurring tool wear during the operation. Test runs were conducted and showed the feasibility of the model.

The models works in the context of woodworking due to the fact that abrasive wear is the dominant wear type. This is not the case in metal cutting.

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