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Prediction of the product quality of turned parts by real-time acoustic emission indicators

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Abstract

Nowadays, the product quality of turned parts is measured downstream of the actual manufacturing process. This leads to a time-consuming quality control and the risk of a high number of waste and reworking. Even incidents like the fracture of the lathe tool remain undetected until quality issues of the turned parts are measured. Furthermore, certain material defects can't be detected by post-production quality control, which leads to customer complaints because of damages during the use of the parts. This paper presents an in-process approach for evaluating the product quality and tool defects in real-time by using an acoustic emission sensor applied to the tool holder.

This paper outlines the identification of feasible quality indicators and explains how the data is recorded and which data sources have to be correlated. This includes for example the recording and correlation of high-frequent acoustic emission signal with further acquired data like machine and computer aided quality (CAQ) data. In dissociation to previous work, this correlation is used directly to develop characteristic factors to predict product quality and to detect tool defects. An overview of several characteristic factors is given. In addition, the test setup is shown and first results are presented, followed by an outlook on further research.

The test setup is implemented at a series production without disrupting the daily manufacturing processes. It is shown that solutions in context of Industry 4.0 can be implemented in small and medium-sized companies without a loss of production capacity. The venture is realized within a funded project regarding Industry 4.0 and intelligent quality control systems. Its target is to design smart technologies for manufacturing systems.

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Keywords: Acoustic emission, Quality control system, Condition monitoring, tool wear, turning process

1. Introduction

Nowadays machining is a fully automated process which is able to produce high quality products. With an increasing demand for a highly efficient manufacturing process, scrap has to be minimized, production speed maximized and the post-process quality control should be relocated to an online process control. However, at present time many producing companies, especially small and medium sized companies (SMCs) have to rely to their knowhow and to the data they can export by the machine interface. By online process control, companies can get a competitive advantage, especially if they obtain information about the used tools. Currently a tool breakage is only noticed after post-processing quality control, which leads to a high amount of waste and costs. A possible approach is the use of Acoustic Emission (AE) Analysis to monitor the turning process and detect tool fracture and regular wear. However, it has to be taken to account, that data measured by the AE-sensor requires a lot of memory capacity. Because of that, it is important to compute so called characteristic factors decentral and machine-oriented so that it can be processed in the company's software system. The aim is to use these factors in series production.

Therefore, the algorithms have to be implemented in a self-developed, standalone software tool. This tool runs on the machine-terminal and computes the factors immediately out of the big sensor data. The statistic process control (SPC) software imports this data directly and can trigger actions like a signal for an immediate tool exchange if one of the factors runs out of its tolerance. Furthermore, the factors can be used as an input

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for intelligent quality control software which is additionally interpreting the machine data exported by an Open Platform Communications (OPC) interface.

Therewith, tool changing intervals can be replaced by an exchange-as-required and even a prediction of a quantity of good parts till a necessary tool exchange has to be made.

Using that, application with appropriate characteristic factors enables the manufacturing SMC to monitor tool status and product quality online in their series production which greatly increases production efficiency.

To reach this aim, in a first step it is necessary to determine such appropriate factors. Several research works already show successful approaches [17], [18]. In practical applications, it is hard to forecast the suitability of specific factors for a specific system condition or product quality. Because of that, the development and the selection of factors has to be done based on received data from the monitored system. Only if the factors are chosen successfully, they can indicate the actual condition of the system and allow a correlation with product quality.

2. Fundamentals and State of the art

The most common approach to optimize cutting tip exchange cycles is a frequent quality control of the workpieces to identify tool related trends for output quality. Based on the trend and deviation of measures a suitable time for a cutting tip exchange can be anticipated. Such an approach leads to a high effort of downstream quality management and provides no advantage in terms of service cycles [1], [2].

A cost efficient approach for in-line production quality evaluation may be provided by Acoustic Emission sensor technology and evaluation. State of the art findings present the application of AE sensors as suitable for the analysis of the cutting tip's condition [3][4][5][11].

The Acoustic Emission Analysis utilizes the fact that during cutting processes, a part of the process energy is transducing into elastic waves in the solid body. The elastic waves are generated especially due to fundamental phenomena within the material, mainly initiated by tribological stress and strain. Typical sources for the then so called Acoustic Emissions are growing cracks, motion of dislocations, or elastic and plastic deformations. All these fundamental processes within the material emit a part of the released energy as high frequency elastic waves into the material (with frequencies up to 600 kHz) [6]–[8].

Consequently, the measured elastic waves in a solid body are a result of a sum of single events, which occur in the material during operation and leads to a continuously changing system and a continuous emission of elastic waves into the material [9]. Due to that, the Acoustic Emission signal contains information about a change of the system condition. Accordingly, a variation of signal characteristics can be used as an indicator for a change in the condition of the system [8].

Further potential of AE based cutting tool monitoring lies in the deduction of workpiece quality findings. Being able to identify the grade of a cutting tip's wear leads to the ability to interpret the very same AE signal concerning the workpiece quality. With this, time consuming and expensive post-manufacturing workpiece measuring could be reduced.

3. Identification of potential quality indicators

After the system of objectives for the quality control system has been defined [12], the resulting information was used for identifying potential quality indicators. For this purpose, quality management methods were used in a two-day expert workshop. Hereby, the machine process and the already identified quality failure, as part of the defined system of objectives, were used as preparation material for the expert workshops.

In a first step, the process models (based on *Icam DEFinition for Function Modeling* - IDEF0) were introduced, checked for correctness and then analyzed for quality failures. The resulting quality failure modes were assigned to machine functions and described in a failure mode and effects analysis (FMEA). For all failure modes the related failure effects were identified and the severity rated.

In the second step, a first prioritization of failure modes was conducted based on each severity rating. Therefore, an upper threshold value of the severity rating was defined together with the project partner. The remaining failure modes were structured and failure causes identified using a fault tree analysis (FTA). As recognizable in the detail of the FTA Fig. 1, the severity of each failure is linked to the quality factors, pointed out by the numbers next to the quality factors.

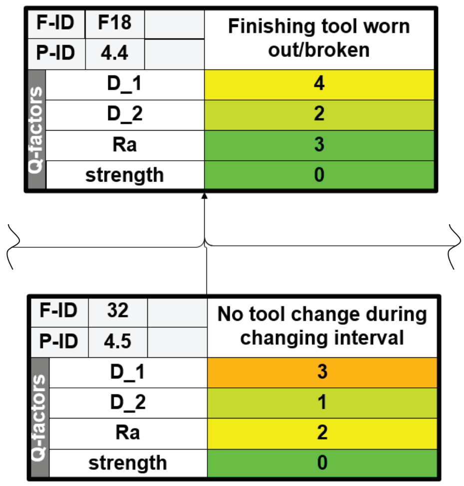

Fig. 1. Excerpt of the FTA – failures linked to the quality indicators

It has proven necessary to understand the failure mechanism of each failure [13] to identify suitable failure predictors or quality indicators. For this purpose, a failure mechanism analysis based on the Contact and Channel Approach (C&C²-A) [14] was used.

4. Approach

The aim of the experiments is to develop so called characteristic factors for the product quality represented by the diameter and surface roughness after the finishing cut. As a result of the FTA, these parameters are primarily affected by the condition of the cutting tip. As shown in Fig. 2, data from three different measurement and control systems have to be monitored and correlated. There is a 100% quality control of the turned parts for generating the characteristic factors in the test-phase. Furthermore, an interface at the machine terminal was installed by the software supplier so the machine operator can select the reason why the machine was stopped. These selections include, amongst others, machine stop because of work break, tool change because of the changing interval or tool change because of breakage.

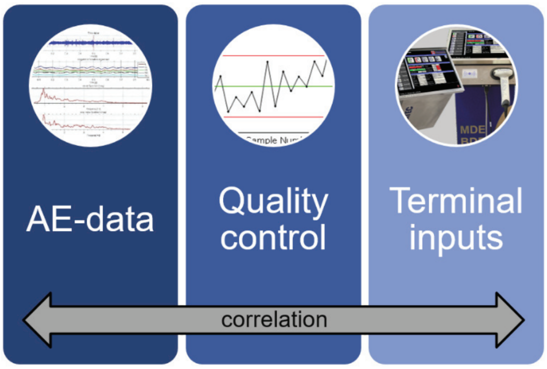

Fig. 2. Overview about the correlated data

The sensor data in the experimental phase is recorded by a Matlab script at a computer next to the turning machine. The data is directly stored at a FTP server, where it is zipped automatically every night. The proximate evaluation of the data is performed at the institute by using algorithms for calculating the characteristic factors. The factors for product quality and the inputs of the machine operator are correlated with the calculated factors and therewith a selection of a few characteristic factors can be made. Fig 4. shows a schematic sketch of the IT setup during the first experiments.

Figure 3 shows the used Acoustics Emission measurement chain schematically.

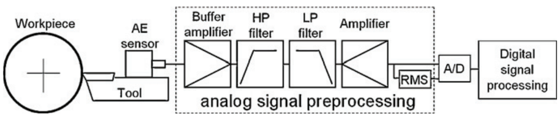

Fig. 3: Measuring chain used for gathering sensor data [3]

It consists of a sensor, an amplifier, an analog/digital converter (ADC) and a computer system. To be able to perform an Acoustic Emission Analysis the components have to fulfill certain requirements:

- Sensor: Suitable sensors are typically made of piezo ceramics. The transfer functions of these sensors allow an acquisition of Acoustic Emission waves in a range of 50 kHz

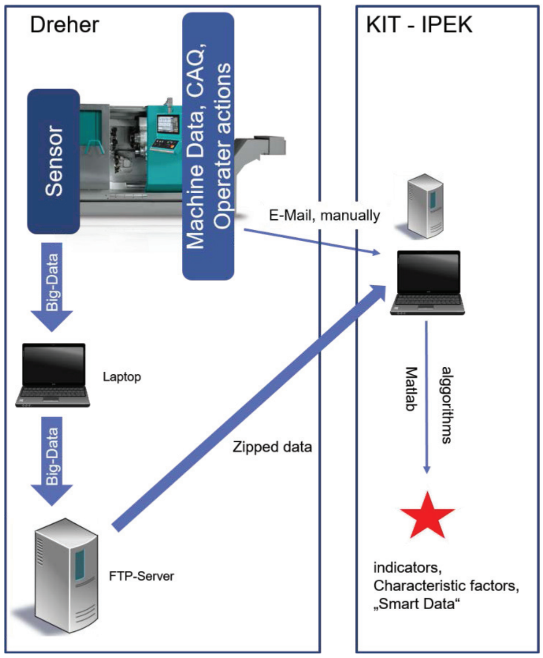

Fig. 4. IT-structure during test-phase to collect data

and 600 kHz. Frequencies lower than 50 kHz are usually neglected because of interfering signals from the environment and because a separation between disturbing signal and useful signal is not possible anymore.

- ADC: According to the Nyquist-Shannon Theorem, it is necessary to sample the signal with a sampling rate of two times the highest frequency. Therewith, a suitable ADC needs a sampling rate that is higher than 1.2 mega samples per second. [12]
- Computer system: The high sampling rate leads to a big amount of data, which has to be processed and stored. During acquisition with a sampling rate of 1.2 mega samples per second, around 20 MB of data per second is generated. Hard- and software has to be able to handle the amount of data.

5. Characteristic factors for tool wear and product quality

It is not possible to derive the important characteristics directly out of the raw signal, due to the amount of data. The signal is processed to a small number of factors which contain the needed information. Common methods to get the characteristics of any signal are calculating the mean value, the root mean square, the maximum, the number of peaks or the number of values exceeding a certain amplitude. The signal can also be described by a time series model and examined with an energy analysis of different frequency bands. The AE signal is a transient vibration. To describe a transient vibration an Analysis in frequency and time domain, like the short time Fourier transform (STFT) or wavelet transform is needed. Both approaches provide information in both domains and generate new signals. To deal with the amount of data those signals are also processed and characterized with methods like a root mean square or maximum mentioned above. The whole process of feature extraction is shown in Fig 5.

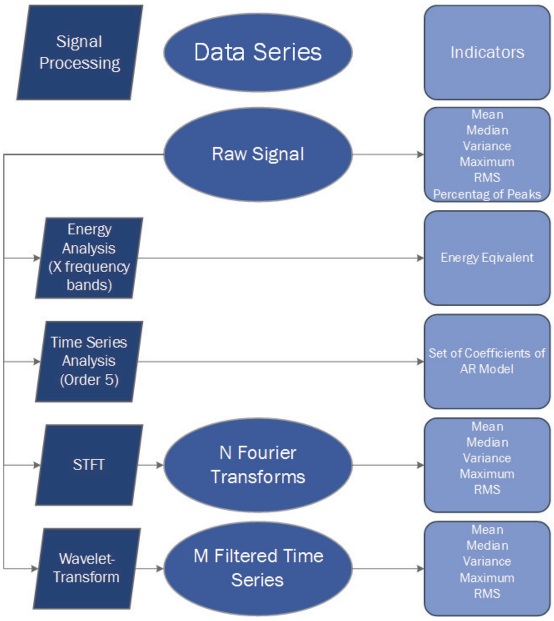

Fig. 5. Feature extraction out of the raw data

The features and evaluation methods that are presented in the results chapter are shortly described in the following:

- Energy analysis

The energy analysis uses a bandpass filter which extracts a frequency band out of the signal. The filtered signal is rectified and low pass filtered. The result is a very smooth signal. The Integral of the squared amplitude of the signal is proportional to the energy in the frequency band of the signal. [15]

- STFT

The Fourier Transform decomposes a signal in a limited number of sinus functions. Those sinus functions can be observed in frequency domain. The Short Time Fourier Transform analysis the signal through a window function which deletes everything outside the window. The remaining signal is analyzed with the Fourier transform. It is possible to observe changes of the frequency spectrum in a signal over time, when the window function is moved through the signal. [15]

- Analysis of Variances (ANOVA)

In every problem of classification it is necessary to examine the relation of a feature to a result. ANOVA uses statistics to find relationships. A gaussian distribution is assumed and for a chosen feature the mean value and variance for all classes is calculated. This is repeated for every class in particular. This method divides the variance in variance between classes and within classes. [16] In this case the mean value and variance of all energy equivalents is calculated and compared to the mean value and variance of all energy equivalents which relate to a broken part.

6. Test setup

The lathe used in the experiments is an INDEX C200 production turning machine at an SMC. The sensor “Kistler 8152B1” is attached at the tool holder close to the cutting tip by screw and is connected by cable to the Kistler 5125B1 Piezotron Coupler which amplifies the electric charge of the piezo sensor. This enables the analog/digital conversion by the National Instruments NI USB-6251. Finally, the data is recorded at a Laptop using Matlab and can be downloaded from a FTP server via remote access.

In difference to laboratory tests, the application in series production has further requirements to the installation of the sensor. Since the monitored product is produced in many manufacturing steps with different kind of tools at various revolvers, there is a lot of rotational and translational movement that endangers the sensor and the cable to rip off.

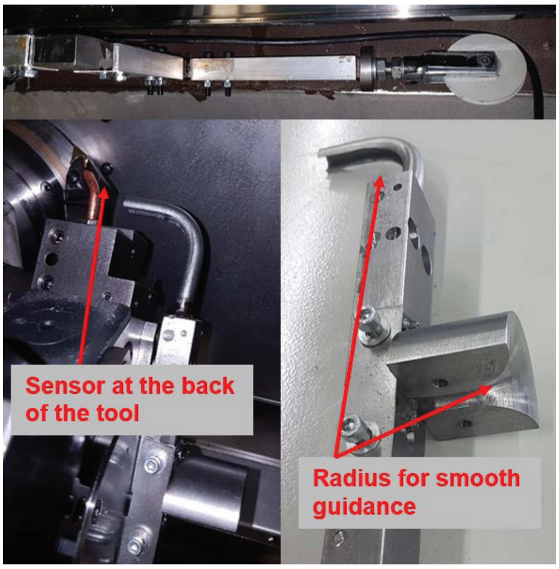

Fig. 6. Guidance rail for a safe sensor application. (top) top rail with deflection roller; (bottom) rail at the revolver

Hence, the machine program had to be reconfigured so the revolver spins forth and back in order not to twist the cable. Additionally, a guidance rail (Fig. 6) had to be implemented to both the machine and the revolver so the cable is protected and has enough clearance when connected to the measurement chain.

The observed cut produces three different features at the turning part. For a clear distinguishing of the features the boundary time values for the features are chosen broadly. The first feature is represented by a diameter of 10,9 $_{-0,2}$ mm which is produced in a period between 0,1 to 4,4 seconds after the machine trigger to start the recording of sensor data. The second feature is a diameter of 11 $_{-0,1}$ mm and is produced in a period between 4,4 to 8,8 seconds after the trigger. The third feature is a phase at the end of the part that is not further observed.

During the tests about 700 parts were produced and there are AE-signals of the observed cut to all of these parts. About 210 of these AE-signals could be assigned to parts created within whole tool life spans with a breakage at the end, so the characteristic factor in Fig. 10 shows about 210 data tuples. The circa 500 other parts are either waste or produced with a tool that was exchanged regularly after a certain time which wasn't considered in the algorithms for the calculation of the shown characteristic factor.

7. Test results

The raw output time signal of the sensor is shown in Fig. 7.

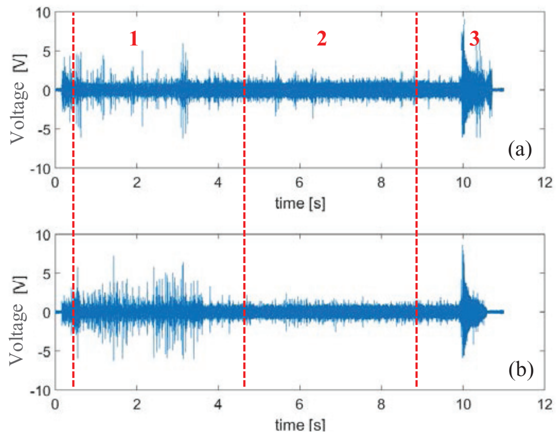

Fig. 7. Time series of the raw sensor data with the segments 1 to three. (a) during the production of a part within tolerance (b) broken tool

The top signal displays the observed cut of a part within tolerance, the bottom signal shows the signal for a broken tool and a part out of tolerance. The three different features described above are pointed out in the segments one to three.

The signal of the broken tool exhibits a greater noise in the first section and looks similar in the second section. To detect the tool breakage explicit, a clear scalar factor has to be extracted out of the time series.

For that, the time series of each signal is transformed to the frequency series by calculating a fast fourier transformation (FFT). As apparent in Fig. 8, the transformed signal is in the range of 0 to ~ $6*10^5$ Hz with significantly high peaks at about 20 and 90 kHz.

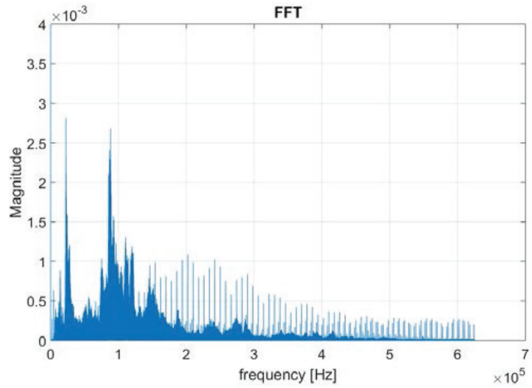

Fig. 8. FFT of the observed section for a part within tolerance

Out of the many possible indicators (see Fig. 5), an energy analysis has proven to be a significant characteristic factor to detect tool damage immediately. Therefore, the time series has to be filtered to a certain frequency. To find out the most characteristic frequency, several energy analyses for a $n*10^5$ Hz filtered signal were executed. A ANOVA analysis showed the most significant frequency at 400 kHz for a correlation to the corresponding quality factors. Hence, more frequencies at an interval of $0,25*n*10^5$ Hz were examined around the approached frequency.

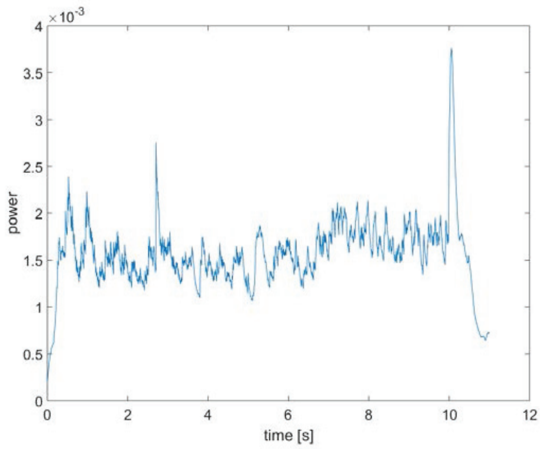

Fig. 9. Power-time signal for a broken tool

The resulting energy time series for the most significant frequency 425 kHz is presented in Fig. 9 for a broken tool.

To get a power-equivalent indicator for the tool condition, the integral over the above signal is built and squared. In Fig. 10. you can see the trend of this process over a whole life span of a tool from new to tool its breakage.

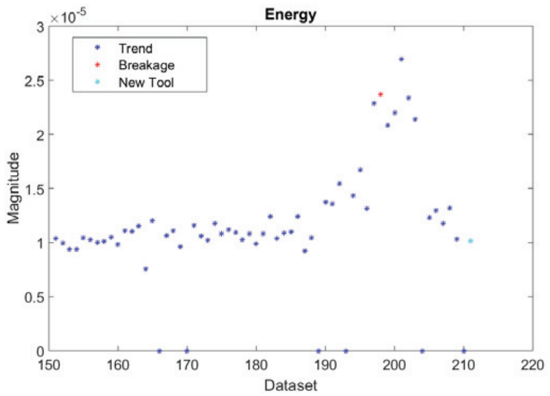

Fig. 10. Indicator for tool condition over a whole tool-lifespan

Even the trend for a greater diameter in both sections can be seen, but is not proven significant yet for a larger amount of quality data so further investigations have to be made.

8. Conclusion

To improve efficiency in the manufacturing process for turned parts an analysis of failures pointed out that acoustic emission signals are a great indicator for the lathe tools condition.

The correlation of sensor signal, quality data and tool information showed that by monitoring the raw signals, no significant conclusions can be made. The raw signal of the sensor provides a big amount of data with a huge noise so the data has to be compacted to characteristic factors.

Out of many possible methods, an energy equivalent factor turned out to be a significant characteristic factor for the tool state. This factor rises up to three times the value a tool in good condition has. By implementing the algorithm for detecting tool brakeage in real time, in our examined case about one hour of producing waste could have been avoided. This is a significant improvement of production efficiency because one tool breakage could have been monitored at a day in average. Furthermore, with the described energy equivalent in the specific frequency a correlation to the work pieces' diameter can be made. The statistically calculated significance is about 40% with the used factor but was increased through detailed analyses of certain frequencies. Further investigations with more experimental data and calculating more characteristic factors like including the time, amplitudes of certain frequencies or other wavelets are promising to get good correlations for predicting the quality data of the turned parts and thereby reducing offline quality control. In a second step after the experimental phase – which still was executed in series production – the algorithms will be implemented decentral at the machine terminal for a real time process control.

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