Lappeenranta
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MODELLING CUTTING STATES IN ROUGH TURNING OF 34CrNiMo6 STEEL

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ABSTRACT

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Rough turning is an important form of manufacturing cylinder-symmetric parts. Thus far, increasing the level of automation in rough turning has included process monitoring methods or adaptive turning control methods that aim to keep the process conditions constant. However, in order to improve process safety, quality and efficiency, an adaptive turning control should be transformed into an intelligent machining system optimizing cutting values to match process conditions or to actively seek to improve process conditions.

In this study, primary and secondary chatter and chip formation are studied to understand how to measure the effect of these phenomena to the process conditions and how to avoid undesired cutting conditions. The concept of cutting state is used to address the combination of these phenomena and the current use of the power capacity of the lathe. The measures to the phenomena are not developed based on physical measures, but instead, the severity of the measures is modelled against expert opinion.

Based on the concept of cutting state, an expert system style fuzzy control system capable of optimizing the cutting process was created. Important aspects of the system include the capability to adapt to several cutting phenomena appearing at once, even if the said phenomena would potentially require conflicting control action.

Keywords: rough turning, adaptive turning control, fuzzy systems, expert systems

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First and foremost I would like to thank my advisors, Professor Juha Varis and Dr. Mika Lohtander both for the opportunity to engage in this work as well as their support for its completion. The so-called "Aura of Logical Distortion" (around your advisor, within which even the most impossible problems seem to make sense – a term coined by Dr. Jorge Cham) has been referred to before and has had a strong influence in my case as well. Also, I would like to thank the pre-examiners of this work, Professor Esko Niemi and Dr. Andri Riid of their valuable commentary and suggestions on improving the quality and understandability of this work.

In addition, I would like to offer heartfelt thanks to both my workmates at LUT as well as my trainees and coach colleagues at the swimming club who have been most helpful of keeping me sane during the process. Even if I may occasionally have suspected opposite intent.

If going to the very beginning, the initial spark for this work started back in 2007 as I, an oblivious IT student, was looking for a traineeship and noticed an opening for a programmer at the Department of Mechanical Engineering and thought "well, why not". How little I could have expected that this job would have eventually lead to both the completion of my Masters studies and the eventually tying up the loose ends by starting to compile this work. The data has now been analysed, the models have been fitted, and the reports are written.

Ja aivan lopuksi haluaisin kiittää vanhempiani kaikesta siitä tuesta, jota olen heiltä saanut opintojeni aikana. Kotiväkihän se oli, joka patisti poikaa koulutielle ja yrittämään aina paremmin. Nyt alkaa taitaa olla hetken aika hengähtää opinnoista.

Lappeenranta, May 2015

Juho Ratava

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1 LIST OF THE ORIGINAL ARTICLES AND THE AUTHOR'S CONTRIBUTION

This thesis consists of an introductory part and six scientific articles. The articles and the author's contributions to them are summarized below.

I. Ratava, J., Rikkonen, M., Ryynänen, V., Leppänen, J., Lindh, T., Varis, J. and Sihvo, I., 2011. An adaptive fuzzy control system to maximize rough turning productivity and avoid the onset of instability. *International Journal of Advanced Manufacturing Technology*, volume 53, pages 71-79.
II. Ratava, J., Lohtander, M. and Varis, J., 2015. Modelling cutting instability in rough turning 34CrNiMo6 steel. Accepted for Publication in *International Journal of Operational Research*.
III. Hynynen, K.M., Ratava, J., Lindh, T., Rikkonen, M., Ryynänen, V., Lohtander, M. and Varis, J., 2014. Chatter Detection in Turning Processes Using Coherence of Acceleration and Audio Signals. *Journal of Manufacturing Science and Engineering*, 2014, volume 136, issue 4, 044503.
IV. Ryynänen, V., Ratava, J., Lindh, T., Rikkonen, M., Sihvo, I., Leppänen, J. and Varis, J., 2009. Chip control system for monitoring the breaking of chips and elimination of continuous chips in rough turning. *Mechanika*, volume 4, issue 78, pages 57-62.
V. Ratava, J., Lindh, T., Lohtander, M. and Varis, J., 2014. Comparison of methods for chipping quality estimation in turning. *International Journal of Advanced Manufacturing Technology*. Published online.
VI. Ratava, J., Luukka, P., Lohtander, M. and Varis, J., 2014. A Sugeno-type fuzzy expert system for rough turning. *Key Engineering Materials*, volume 572, pages 597-600.

The author has participated in the experimental design and computed the statistical analysis in paper I and designed and implemented the software for the adaptive fuzzy control system the article discusses. The author has actively participated in the writing of the article, especially the sections titled "Developing the fuzzy adaptive control" and "Validating the fuzzy adaptive control system."

The author has participated in the experimental design and is responsible for the analyses performed in paper II. The author has been responsible for writing the article.

In paper III, the author has participated in recording and processing the data captured in the experiments. The author has participated in the design and implemented the software used in the adaptive control system described in section 5.2 "Chatter control experiment." The author has participated in the writing of the article.

In paper IV, the author has participated in the design of experiments and computed the statistical analyses as well as designed and implemented the software for the adaptive fuzzy control system used in the article. In paper V, the author is responsible for the additional detection methods and has been responsible for writing the article.

The development from previous papers to paper VI are mainly from the author. The author has designed and implemented the adaptive fuzzy control system and has been responsible for writing the article.

2 INTRODUCTION

This work introduces a new approach for an intelligent machining system for rough turning. Intelligent machining, also known as adaptive control of machining (Billatos & Tseng 1991), is a concept where some parameters affecting the cutting process are modified to improve some aspect of the process. It should be noted that unlike in control theory, in (computer) numerically controlled or (C)NC machining “control” refers to the device managing a CNC lathe (or, more widely, another type of a machine such as a milling machine or machining centre). “Adaptive control” thus corresponds to what in control theory is called “control system”, implementing a sensor-based feedback loop. The traditional approach, described by researchers such as Masory et al. (1980) is to measure a physical quantity, such as power use or cutting force magnitude, and apply feedback to a parameter (typically cutting feed) to keep this quantity within pre-set limits. The limits may also be established during a “teaching” phase. More advanced systems may also be taught variable limits, but then again the system simply follows the predetermined limits established during the teaching phase. This results in constant conditions for the cutting process and helps to keep the process predictable.

Another aspect of intelligent machining is process monitoring. Phenomena such as power consumption, tool wear, workpiece surface integrity or potential collisions in the machining cabinet can be monitored, and in case of a failure happening or about to happen, the process is halted. While some of these process monitoring systems may be implemented according to the same principles as the traditional adaptive control of machining, by monitoring specific physical quantities and considering anomalies indicative of failure, some process monitoring – such as tool wear and surface integrity monitoring – already includes the idea of understanding the process instead of merely measuring it. In terms of information science, this is taking the leap from using raw data to using information: data with a meaning.

Yet another aspect of intelligent machining is intelligent process planning. This answers the question “if these results are wanted, what the process parameters should be like?” This is, by terms of information science, a leap forward from information to knowledge: information being applied. Some of these systems might be merely automating the use of tabled information though some might be “expert systems”: Artificial intelligent systems emulating human decision-making. Unfortunately, in the frame of control theory, this is often a leap backwards, as these expert systems are used to estimate process parameters beforehand and then the “online” or process time control may be handed off to “dumber” systems.

In this work, it is attempted to bring expert system level “understanding” of the machining process to adaptive control of turning. It must be noted that even state-of-the-art artificial intelligences merely follow programming to emulate human decision-making and do not truly “understand” the subject. In some cases, the programming process may include “learning” phases where instead of relatively simple instructions, the decision-making process is based on collected data. In this work, the intelligence is split into two principal parts. The first one is process monitoring, or the ability to tell what is happening in the process. The second part is a simple inference system type artificial intelligence using the process monitoring information to optimize process parameters in real time. Together with a suitable lathe and control, these systems can be combined to an intelligent machining system.

In the process monitoring part, it is sought to understand the process instead of merely measuring it. Thus, measured signals are processed to comprehend what kind of phenomena (such as “chatter” or “long chips”) might appear in the cutting process. And, as an important distinction from the concept of “maintaining process conditions” style of adaptive control, the main spindle power of the lathe is monitored and used as an input together with other detected issues to decide whether the process could be made more productive. The power measurement uses a physical quantity; however, the rest of the process monitoring is matched against expert data provided by human experts. These relationships between measured features in signals and expert data are statistically modelled for rapid use.

In the artificial intelligence part, human experience has been collected in the form of rules. To deal with the concept of uncertainty in human decision-making (“maybe this parameter should be increased”), fuzzy logic is applied. Since the system monitors multiple separate cutting phenomena, the expert system managing the control must also be able to deal with multiple cutting phenomena appearing at once, even if each phenomenon would require distinct control actions.

This work is multidisciplinary in nature. Understanding the machining process itself and the effects of changing process parameters is production engineering, a subfield of mechanical engineering. However, To apply that knowledge, signal processing and an understanding of fuzzy expert systems and control systems is required.

2.1. Research problem

In rough turning, the conditions for metal cutting vary because of multiple reasons. Some of these may be relatively constant during the cutting process, such as the behaviour of the machining equipment used. Some may vary during the cutting process, including but not limited to variation in stock material quality and tool condition. The cutting parameters must be adapted to the current process conditions to maximize the efficiency of the process, while maintaining operational safety, as well as high enough quality.

In this study, the current process conditions are described by various phenomena. In this study, the combination of these phenomena is called “cutting state”. There are numerous variables that affect the cutting state in efficient rough turning, making its modelling quite challenging. The general groups of variables are shown in Figure 2.1. Within rough turning, the changing conditions may be caused by factors relating to the control (CNC or computer numerical control system) and the lathe. While the digital CNC system can be assumed to be predictable (within its intended operating limits), the lathes will most certainly be individuals. Thus, the lathes may vary from manufacturer specifications making physical models inaccurate, even if all the necessary information for a physical model would be available. Modern lathes and controls offer some sensors, allowing the measurement of power, tool position, current cutting parameters and other information about the cutting process. Some may include acceleration and acoustic emission sensors. To use a system described in this study, older models may need to be retrofit.

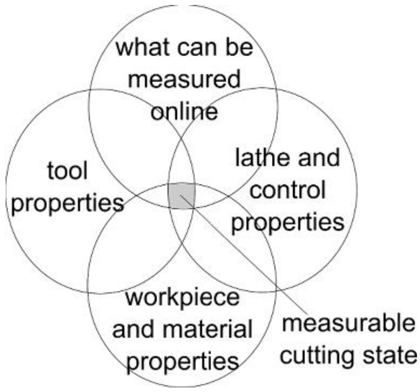

Figure 2.1: Some factors affecting the intelligent rough turning.

Additional variance is caused by different shapes and sizes of the workpiece as well as varying qualities of the stock material. The workpiece also affects how well it can be attached to the lathe. If the required surface quality is high, the amount of force allowed to clamp the workpiece is limited. With some workpieces, a tailstock can be used; others must be held in place by the headstock alone. The human operator or the programming of the FMS (flexible manufacturing system) cell does also affect the workpiece as described, as improperly attached workpieces severely limit applicable power. Thus, the workpiece interacts with the lathe via the clamping, with the control via its intended geometry (and predesigned tool path). Naturally, the workpiece interacts with the tool as the cutting process progresses. The workpiece behaviour is typically measured by secondary effects such as tool or stock vibration or spindle power use though it is possible to measure directly by no-contact sensors such as infrared temperature sensors and laser interferometry. The tool-workpiece interaction creates a sound that can be captured with a microphone.

The tools and tool holders available – especially the part most subject to wear, the tool insert – have a great effect on cutting performance and cutting state. The change in tool wear is not readily apparent in instantaneous measurements and may require tracking over time; in this work, methods for tool condition monitoring are subject to a literature study.

While sensor placement is not within the scope of this study, some thought must be given to what sensors are available and how to possibly mitigate interference in the signals recorded from the sensors. The mitigating can be done by applying signal processing methods to the recorded signals as well as comparing multiple sensors.

A combination of all these factors affects the cutting state as well as the possible accuracy of observations made of the cutting state. The prime concern of this work is to reach the best possible cutting state allowed by the factors affecting the cutting process.

The description of the research problem introduces some terms that need to be defined: “rough turning”, “cutting process efficiency”, “safety” and “high enough quality”. Rough turning is a process where material is removed from a stock piece to produce cylindrically symmetric parts.

In this work, longitudinal turning is mainly concerned; that is, the tool removing the material chiefly moves in a direction parallel to the turning axis of the part. The axial movement is called feed, and the movement speed is called feed rate, typically measured in millimetres per revolution of the workpiece (matching the width of cut). The thickness of the layer to be removed is called depth of cut, typically measured in millimetres. Finally, the speed of the tool on the newly-cut surface is called cutting speed, typically measured in meters per minute. These three parameters are also called “cutting values” (Figures 2.2 and 2.3).

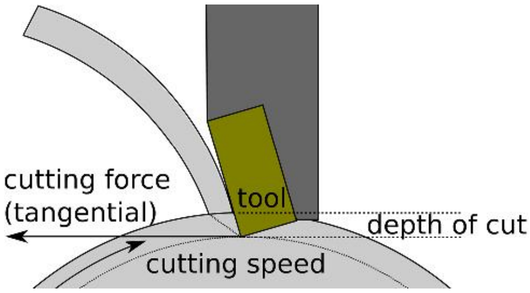

Figure 2.2: Conceptual drawing of the turning process (not to scale), showing the tool cutting the rotating workpiece. Cutting speed is the speed of the tool on the new surface, and the thickness is the depth of cut. The main cutting force is tangential to the surface. Not labelled: Cut chip (being cast to the upper left), shear plane (location where chip breaks near the cutting tool).

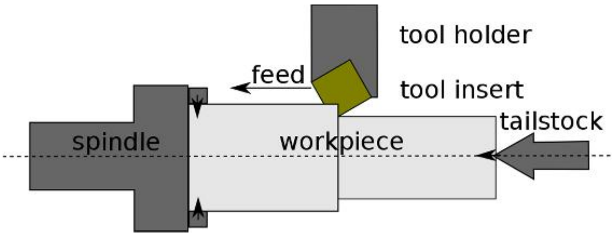

Figure 2.3: Simplified model of the workpiece and the lathe (not to scale) showing the workpiece from the tangential direction, showing the workpiece clamped to the spindle and supported by an (optional) tailstock and being cut by a tool insert (replaceable part, partially obscured by yet uncut workpiece) attached to a tool holder. In this drawing, the feed direction is to the left.

The momentary cutting process efficiency is defined by the chip flow or the volume of material removed over time, more volume removed faster being better. The volume flow can be computed by multiplying feed rate, depth of cut and cutting speed and is used as a measure of productivity. The resulting unit is cubic centimetres per minute. In addition, tool wear and tool life should be predictable and controlled. Of the cutting values, depth of cut depends on the path of the tool and typically cannot be adjusted online. However, cutting speed (or spindle speed, if rotational speed is used) and feed rate can be changed online and used for feedback.

When the radius of the newly-cut surface is known, it is trivial to compute cutting speed from spindle speed or vice versa.

Operational safety includes matters relating to the ability to continue the use of the equipment and cutting process, both for the good health of the machinery involved as well as that of its operators. High enough quality depends on the requirements set for the rough turning process. In a traditional case, this would mean sufficient geometrical dimensions (shape and size) and surface integrity (the smoothness and internal composition of the surface) for the part to execute a finishing phase fine-tuning these. In some cases, it may be desirable to achieve high quality without a separate finishing phase. In this work, both safety and quality are measured qualitatively, based on expert data. The ideal process conditions of “good rough turning” are such that safety and quality are maintained while productivity is maximized (figure 2.4).

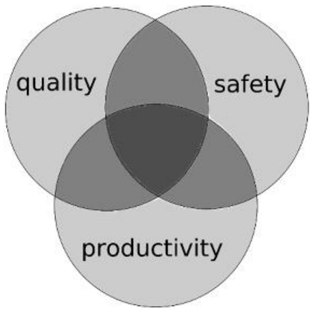

Figure 2.4: Objectives in intelligent rough turning.

The approach taken in this study imitates the actions of a human expert. A machinist supervising a CNC machine will use his (or her) senses to observe the cutting process, such as the sound emitted by the process and the behaviour of the chips. This departs from the approach of monitoring a cutting process to maintain a physical quantity (typically main spindle power or cutting force) within acceptable limits. Instead of maintaining the measured physical quantity within constant limits or within an experimentally discovered pattern, a set of phenomena observed by the machinist is identified. When the causes of the changes in these phenomena are identified, it may be possible to maintain safety and quality at parameter combinations previously thought unusable.

As the physical modelling of the cutting state or even individual cutting phenomena are considered very challenging, the proposed solution to the research problem is to emulate the reasoning and actions of a human operator supervising a CNC machining process. The human operator will monitor various phenomena that may occur during the machining process. Based on the appearance or lack of these phenomena the machinist will consider the state of the machining process as a whole and based on this information, the machinist may either abort the operation or decide to adjust cutting parameters. This work introduces statistical black box models that enable the intelligent machining system to measure phenomena observed by human operators and to perform reasoning based on these results.

2.2. Research questions

The first and foremost amongst the research questions is

> *What factors define and enable a good rough turning process?*

Using the model of cutting states, this question can be rephrased as

> *What the current cutting state needs to be in order to maintain a good rough turning process?*

A question immediately arising from this definition is

> *How can the current cutting state be defined?*

Moreover, finally,

> *In case the current cutting state is not the desired cutting state, how can the desired cutting state be reached from the current cutting state?*

The last question needs to be amended with the question

> *In case the current cutting state is the desired cutting state, how can this cutting state be maintained?*

Thus in the ideal scenario, the intelligent machining system enters the desired cutting state, maximally efficient (within constraints such as power use or tool wear rate), and maintains such a cutting state without switching to an undesired cutting state which might jeopardize the safety or quality of the cutting process. (See Figure 2.3.) As a reminder, the "cutting state" is in this study considered a combination of the phenomena observed by a human machinist supervising a cutting process.

There are also some auxiliary issues in the chosen approach on imitating a human machinist. Most important of these is finding out what phenomena the human expert monitors and how these phenomena correlate and can be modelled with sensor measurements. Once the phenomena are identified, a suitable method for inferring the cutting state must be selected. This requires the use of fuzzy logic (or some other way of approximate reasoning) to imitate the human mind.

In this thesis, three cutting phenomena – unstable turning, regenerative chatter and chip length – are studied by analysis of a library of sensor data recorded from cutting, showing that these phenomena can be identified in the turning process. In addition, the well-established field of tool condition monitoring is studied by means of literature review. It is shown that unstable turning, regenerative chatter and chip length can be detected in real time or even predicted. Tool wear is conceptually slightly different, as change over time must be taken into account. Then, it is shown that based on the data collected of the various cutting phenomena, a fuzzy expert system is able to deduce the cutting state by comparing the detected levels of the cutting phenomena and decide a proper response based on expert knowledge.

2.3. Limitations and scope

The empirical part of this work has been conducted by mainly rough turning 34CrNiMo6 steel (0.3 – 0.38% carbon, < 0.4% silicon, 0.5 – 0.8% manganese, 1.3 – 1.7% nickel, < 0.025% phosphorus, < 0.035% sulphur, 1.3 – 1.7% chromium, 0.15 – 0.3% molybdenum) tempered to a hardness of 320 HB and machined with a SNMM 12 04 12-PR square insert manufactured by Sandvik. Some tests have been conducted using other tools and materials producing qualitative evidence on the applicability of the results on a softer material (P355NH, <0.18% carbon, < 0.5% silicon, 1.1 – 1.7% manganese, < 0.5% nickel, < 0.025% phosphorus, < 0.015% sulphur, < 0.3% chromium, < 0.08% manganese, < 0.1% vanadium, < 0.012% nitrogen, < 0.05% niobium, < 0.03% titanium, < 0.02% aluminium, < 0.3% copper, combined niobium, titanium and vanadium content not exceeding 0.12%) and a different tool (CNMM 120412 PR 4015). Some experiments were also recorded with calcium-treated 34CrNiMo6 (calcium content unknown). While it should be possible to generalize the results, evidence is presented only for machining 34CrNiMo6 steel, which was selected as an object of study for being a common steel beset with a number of problems examined in this study. The regenerative chatter tests were done mainly using 42CrMo4 (0.38 – 0.45% carbon, < 0.4% silicon, 0.6 – 0.9% manganese, < 0.025% phosphorus, < 0.035% sulphur, 0.9 – 1.2% chromium, 0.15 – 0.3% molybdenum) treated with calcium (content unknown), of the same hardness 320 HB.

In addition, this study concentrates on phenomena that can be affected online, during the machining process, by changing interaction of the tool and the workpiece. Therefore, important issues such as planning the NC program for the lathe, collision detection or workpiece handling are ignored. Some of the feedback given by the system may be useful in eliminating unwanted phenomena by other means, such as difficult vibrational problems suggesting that it may be necessarily to support the workpiece better during the cutting process.

2.4. Contribution of this work

In this work is shown that several cutting phenomena identified in a rough cutting process can be automatically measured during the cutting process. Some of the phenomena may be modelled and thus predicted. The measurement of different cutting phenomena imitates the observation by an experienced human machinist and allows the definition of the current cutting state.

The safety and the quality of the rough turning process can be ensured by applying such a cutting state model. Since the safety and quality measurements of the process are now decoupled from the traditional control approach of maintaining a predefined parameter at its predefined constant range, an intelligent machining system aware of the current cutting state may increase cutting efficiency.

The viability of such a system has been shown to work earlier by Leppänen et al. (2009) by constructing a basic proof-of-concept system. In this study, the related phenomena are studied in detail. As far as the author is aware, this constitutes the first such study matching primary chatter and chipping quality to expert data, as well as the first system (besides of the proof-of-concept) for optimizing machining parameters using the mentioned and other phenomena for input.

2.5. Societal and environmental impact

The chief purpose of this work is to improve the effectiveness of the metal cutting process. This may also have social and environmental effects. Four different categories are considered in this section: Possible effects on work organizations, employment and worker motivation, and the possible effect on the environment. Each of these is hard to predict and depend on the rate of adoption of such systems.

Considering work organization, effects are not clear or may be dependent on cultural matters. Not so long ago, based on interviews with industry and expert sources, it was assumed that the industry might be facing a shortage of trained labour. An intelligent system would answer this need, either by allowing less experienced employees to work at a higher efficiency or perhaps assisting the training of new employees. Come the recession, and instead of a labour shortage, a shortage of work to be done appeared instead. Thus, an intelligent system might be used to watch over the shop floor and spot inefficiencies. At a wider scale, if the effects of new information and automation systems are examined, it can be concluded that new technology most likely will make some old tasks obsolete and hopefully create others. This probably leads to organizational changes and moves tasks and responsibilities elsewhere in the organization. A production line relying heavily on manual labour depends on the skill of the workers for effectiveness. Heavily automated production line may depend more on planning and the management of the flow of materials.

In this picture, the system described in this work is but one cog in the machine, and to be truly effective it would need to affect other parts, as well. For example, with ill-supported workpieces possibly prone to chatter, it might be imperative to give feedback to part handling so that special care is taken to fix the workpiece to the lathe. When giving feedback at the shop floor level, special attention must be given to the clarity of the feedback and the usability of the system. Based on interviews with industrial contacts, monitoring systems for cutting processes reporting only e.g. power consumption or cutting force values can be seen as difficult to comprehend. The man-machine interface could be improved by giving user feedback with shop-floor concepts.

Considering employment opportunities, heavy use of automation may cause changes in the required skills (Gupta 1989, Ngin & Wong 1997) as well as the skilling and deskilling processes. There might be fewer skilled labourers required though more work for less skilled labour. Secondary effects would include new industries to maintain the automation systems, as well as different kind of skill set required from the management to benefit from the opportunities offered by the automated systems, such as unmanned production cycles. This change in the labour profile may mean that the suitability of a location for a production site changes, with some locations formerly used becoming unsuitable and other locations becoming suitable while they previously were not. (Gupta 1989) Typically automation is also expected to increase the level of safety at the workplace. (Ngin & Wong 1997)

The effect increased automation might have on worker motivation has been found to be culture and experience level dependent. Agnew et al. (1997) note that in developed countries workers generally think of the work as less motivating, and foremen and middle management consider the work more demanding. However, Ngin and Wong (1997) note that the local workers in recently industrialized countries consider working at an automated line more demanding. In general, workers having experience outside automated lines seemed to esteem less working at an automated line. The pacing of the work does also affect worker motivation. While more varied tasks require a higher level of skill, ability to see a subassembly completed was more rewarding than more monotonous tasks. (Peltokorpi et al. 2013)

The environmental impact may be difficult to estimate. Most notably, should the site of the production plant change, there might be changes in the transportation and energy infrastructure in both the old and the new sites. The energy consumption of the production plant may also change: Ideally, the process is more energy efficient after being optimized by an intelligent machining system. Automation may also affect the production environment: For example, computer vision might require specific lighting conditions. If the parts are not visually examined and the production site is not manned, it might not be necessary to keep lights on. This also means that the automated work can be done in the plant (and thus the plant may consume energy) during night-time. In the case of production sites with hot or cold climate, the production environment might not need to be kept at temperatures suitable for long duration human occupation. If the effect of the human component on the final price decreases, the ideal site for a production plant depends on raw material availability and cost, transportation costs and energy costs.

2.6. Outline of the thesis

The main content of the thesis begins with answering the first research question of defining and enabling an efficient cutting process and the related cutting phenomena. Then the measurements of other cutting phenomena are discussed, and a suitable method for inferring the cutting state is selected. The reasoning on what action (if any) to take based on the cutting state is organically tied to this inference method. Finally, with the research questions answered, it is discussed how the approach proposes to solve (or improve the current situation related to) the research problem.

In chapter 3, a review of the previous study is performed, and the niche for this work is identified. The effect of tool wear, possibly not apparent at a momentary observation, is discussed in more detail in section 3.1. In addition, review of most important previous studies on fuzzy systems is reviewed in chapter 8, which discusses the intelligent machining system.

In chapter 4 the setup used in the experiments done to collect the signal library is detailed.

In chapter 5 the phenomenon called primary chatter or unstable machining and the required action to mitigate or eliminate it is discussed. This chapter is based on results of papers I and II.

In chapter 6, the phenomenon called regenerative (or secondary) chatter is discussed. This includes a method for the measurement of regenerative chatter and required actions to mitigate it. This chapter is based on results of paper III.

In chapter 7, chip control is discussed. This includes the measurement of chip length, detection of the continuous chip, and the required actions to control chipping or cut the continuous chip. This chapter is based on results of papers IV and V.

In chapter 8, the key principles of fuzzy control are first described. Then the structure of an intelligent machining system is discussed, including the requirements posed by the phenomena and actions discussed in previous chapters. This chapter is based on results of Papers I, III, IV and VI.

In chapter 9, the conclusions based on this work are discussed along with the possible effects of the use of an intelligent machining system described in this work.

3 REVIEW OF PREVIOUS STUDY

In this chapter, the published literature of the field is examined. Special care is paid to tool condition monitoring (section 3.1), and important topic left mostly untouched in the experiments done to collect the signal library. Thus, little experimental data is available for analysis. The study of previous literature is important to be able to locate the niche this thesis occupies in the field, and in the case of tool condition monitoring it is to display that the information necessary for an intelligent machining system described later in this thesis can be acquired by applying results from earlier studies. The studies discussed in this chapter (except tool condition monitoring studies) are listed in Table 3.1 on page 21.

The currently established theory of adaptive control has been established in the 70s and 80s by researchers such as Yoram Koren and Oren Masory (Masory et al. 1980). The current state of the art is to measure some physical quantity or physical quantities of the process, typically cutting force (as by Koren and Masory) or power consumption, (Stryczek & Orawczak 2013) and base the feedback on the change in these physical quantities. There are also efforts to circumvent the use of cutting force, such as in the study by Huh and Pak (2003), using accelerometers instead. The term “cutting state” does, however, appear in literature, in the study of Moriwaki and Mori (1993). In addition, a similar concept has been used in process monitoring applications, though most often using classical logic, i.e. two states of “ the process can continue” and “ the process cannot continue”.

Primary chatter is a vibrational phenomenon caused by friction between the tool flank and the workpiece (Marui et al. 1983, Khraisheh et al. 1995) causing chaotic behaviour at high feed rate (Hamdan & Bayoumi 1989). Therefore, the simplest way to control the onset of instability caused by the primary chatter in turning is to decrease cutting feed, at the cost of decreased productivity. More recent results, such as studies by Wang et al. (2010) and Abuthakeer et al. (2011) aim to avoid the issue by modelling or predicting surface roughness.

While the different types of chatter have been long identified (Taylor 1907, Tobias & Fishwick 1958), the more studied form of chatter in the recent years is the regenerative or secondary chatter caused by the interaction of the tool vibration with the surface profile of the workpiece (Merritt 1965) and less attention has been paid to primary chatter. Secondary chatter appears most commonly on ill-supported or long and narrow workpieces. Interestingly for this study, Moriwaki and Mori (1993) have used the concept of cutting states when describing chatter – though as a slight difference in terminology, for the purposes of this work, regenerative or secondary chatter is one of the phenomena observed, and the combined states of all the phenomena define the cutting state of the machining process. Other notable authors include Y. S. Tarng (et al. 1996a; et al. 2000; Tarng & Lee 1997).

Regenerative chatter may be recognized by observing cutting force (Bao et al. 1994, Liao & Young 1996, Tangjitsitcharoen 2009, Rao & Shin 2008), tool vibration (Choi & Shin 2003, Eynian & Altintas 2009, Li et al. 1997, Rao & Shin 2008) or the (audible) sound of cutting (Eynian & Altintas 2009, Schmitz 2003, Schmitz et al. 2001, Yu & Shah 2008), and ultrasonics (Chiou & Liang 2000, Abu-Zahra & Lange 2002). There are passive methods for controlling chatter, such as tuned vibration absorbers (Tarng et al. 2000, Yang et al. 2010) and various forms of spindle speed modulation (Namachchivaya & Beddini 2003, Otto & Radons 2013). In addition, the damping and stiffness parameters of the system may be manipulated (Chen & Knospe 2007, Ganguli 2005) or the spindle speed can be modified (Tarng 1996a, Tarng & Lee 1997, Bediaga et al. 2009).

Chip control is perhaps one of the most important security issues in unmanned high-speed turning. Several meters of swarf (also known as chip) are produced each second, and the chip must be effectively removed from the immediate vicinity of the cutting process. Ideally, the chip breaks or is cut at short, even intervals, producing easily transported granular matter. Notable researchers studying the breaking of chips include David Dornfeld (Dornfeld & Pan 1985) and Ibrahim Jawahir (1988, Fei & Jawahir 1993). The chip breakage can be detected in the axial (feed direction) force (Andreasen & De Chiffre 1998) or in acoustic emission signal (Dolinsek et al. 1999, Inasaki 1998, Govekar et al. 2000). The traditional method for ensuring chip control is choosing suitable tool geometry (Nedelß et al. 1989) though it can be managed with active control once information about the chip breaking is available.

One of the perhaps most studied matters of metal cutting monitoring is tool condition monitoring. This topic has not received an experiment-based examination in this work due to focus on phenomena which may be measured based on momentary data. Instead, a more detailed literature review is performed in section 3.1.

When harmful phenomena are absent of the cutting, in the modern competitive environment it should be attempted to increase productivity, which practically means removing a higher volume of metal in a shorter amount of time. While there are few industrial applications, online cutting parameter optimization (done during the cutting process) has been studied, with notable studies including Koren (1989) and Tarng et al. (1996b).

In order to apply the measures matching features extracted from the recorded signals into expert knowledge, it must be possible to emulate human thought processes. This is achieved by using approximate reasoning. While it might be possible to use multiple-valued logic, this work has so many grades of a cutting state that it makes sense to use fuzzy (infinite-valued) logic to represent the grade of appearance of a cutting phenomenon by a real value on the unit interval. The key parts of the background for fuzzy logic and fuzzy control are reviewed in chapter 8.

Local studies and immediate predecessors of this work do include very heavily product research and development oriented projects Feedchip 1 and 2, which concern rough turning and finishing, respectively. (Leppänen et al. 2009; Leppänen et al. 2010) These projects are heavily grounded on a study by Juha Varis, Juho Pirnes and Jari Selesvuo (Varis et al. 2005). During the research it was shown that it is possible to detect and measure several cutting phenomena and use them as decision parameters in an expert system type artificial intelligence, including the collection of the library of data used in this work.

In this work, the principles used previously to create proof-of-concept system are put under a more rigorous analysis to discover and to expand the limits of the approach. Better models are developed to model primary chatter and chipping quality, and the control system for mitigating regenerative chatter is integrated with the system for controlling primary chatter, chipping quality and tool life. The collection of these factors as “cutting state” information expands the earlier concept of a cutting state.

Publication	Detect Primary Chatter	Predict Primary Chatter	Detect Secondary Chatter	Predict Secondary Chatter	Control Secondary Chatter	Detect Chipping Quality	Predict Chipping Quality	Control Chip Length	Detect Surface Quality	Predict Surface Quality	Adaptive Turning Control	Optimize Parameters	Article Concerns Milling
Abuthakeer et al. 2011									X				
Abu-Zahra & Lange 2002			X										
Andreasen & De Chiffre 1998						X							
Bao et al. 1994				X									
Bediaga et al. 2009					X								
Bushan 2013												X	
Chen & Knospe 2007					X								
Chiou & Liang 2000			X										
Choi & Shin 2003			X										
Dolinsek et al. 1999									X				
Dornfeld & Pan 1985						X							
Eynian & Altintas 2009			X										
Fei & Jawahir 1993							X				X		
Ganguli 2005				X	X								
Govekar et al. 2000			X			X							
Hamdan & Boyoumi 1989		X											
Huh & Pak 2003											X		
Inasaki 1998	X					X							
Jawahir 1988								X					
Koren 1989											X	X	X
Khraisheh et al. 1995	X												
Li et al. 1997			X										
Liao & Young 1996					X								
Marui et al. 1983			X										
Masory et al. 1980											X		
Merritt 1965				X									
Moriwaki & Mori 1993			X										
Namachchivaya & Beddini 2003					X								
Nedelß et al. 1989							X						
Otto & Radons 2013					X								
Pavel et al. 2005										X			
Rao & Shin 2008			X										X
Schmitz 2003				X									
Schmitz et al. 2001					X							X	
Stryczek & Orawczak 2013											X		
Tangjitsitcharoen 2009				X		X							
Tarng et al. 1996a					X								
Tarng et al. 1996b												X	
Tarng & Lee 1997					X								
Tarng et al. 2000				X									
Wang et al. 2010										X			
Yang et al. 2010				X									
Yu & Shah 2008			X										
Article category totals	2	1	10	7	9	5	2	1	2	2	5	4	2

Table 3.1: A list of publications concerning the detection, prediction and control of cutting phenomena.

3.1. Tool wear and tool condition monitoring

Tool wear is a significant factor in cutting. In this study, we consider tool wear to be any flow of material away from the cutting tool or the deformation of the tool geometry, may it be a result of adhesion, abrasion, plastic deformation or electrochemical phenomena. The speed of change caused by these phenomena in the condition of the tool is tool wear rate. At the end of tool life, the tool is no longer suitable for machining. In manufacturing bulk products, tool life is often measured in a number of minutes in order to increase productivity (Astakhov 2006). According to the vendor of the tools used in this study, the tool life using recommended values should be 15 minutes. However, in interviews with industrial contacts, it is suggested that for some subcontractors, the cutting time of an entire production batch may be only ten minutes and, therefore, longer tool life is not necessary. In applications such as large parts requiring great surface quality longer tool life up to days is necessary to avoid changing the tool during the machining process.

The tool wear and tool wear rate must be controlled or at least predicted to enable fully automated machining processes. Since the collection of data used in experiments contains snapshots of sensor signals and mostly has no records of tool condition, in this work a literature study is used to examine the most important aspects of tool control monitoring. First the different relationships between various factors affecting and affected by tool wear are examined. Then, methods of tool condition monitoring are briefly reviewed.

Laakso et al. (2013) have graphed various factors relating to each other in machining. The cutting speed is traditionally considered the primary factor affecting tool wear and the connection is one of the most studied phenomena in the field of machining. It is considered that tool wear rate increases at higher cutting speeds, though the exact relationship between these two factors is heavily case dependent, requiring experimental verification. (Cui et al. 2012)

Tool wear is also affected by cutting temperature (Ghani et al. 2008). However, the exact effect of cutting temperature on tool wear appears to be also highly case-sensitive and thus requires separate models for separate cases. Cutting temperature is also affected by cutting speed, tying these factors together (Saglan et al. 2007).

The effect of feed rate on tool wear is considered to be dependent on other variables (Astakhov 2007) though it is not as major as that of the depth of cut and cutting speed. However, when optimizing cutting parameters and staying within an optimal set of cutting parameters, change in depth of cut comes with a change in other cutting parameters, nullifying the effect depth of cut has on tool wear (Bushan 2013). Furthermore, for the purposes of online real-time intelligent machining, adaptive control of depth of cut is much more complex to implement, as the final geometry needs to be taken into account and varying the depth of cut may affect the amount of passes needed to make on the workpiece.

Feed rate does, however, have an effect on tool deflection at high feeds, which can cause primary chatter to appear. Vibrational phenomena have a significant effect on tool wear rate, and thus, suitable feed rate selection or feed rate control is an important factor in controlling tool life (Hynynen et al. 2014). On the other hand, tool wear can also cause chatter (Astakhov

2006), causing a possible feedback loop. This makes chatter control an important aspect of maintaining predictable tool wear rate.

Tool wear has an effect on the surface quality; the flank wear profile, in particular, is seen on the surface of the workpiece (Pavel et al. 2005). Tool wear and the cutting temperature have a strong omnidirectional effect on each other, and the cause-effect relationship should be investigated more thoroughly by experiments (Ghani et al. 2008). Tolerances are critical concerning tool wear rate because if the wear is fast, the tool compensation changes quickly and is inaccurate, therefore leading to poor tolerances.

Astakhov (2006) notes that fretting wear is caused by repeated loading and unloading causing cyclic stresses. While this may happen if the tool vibrates during continuous cutting, the tool is especially prone to wear and break in interrupted cutting. In the paper by Ryynänen et al. (2010), the phenomenon studied was interrupted cutting in finish turning. It was concluded that the small cutting edge breakage and fretting wear could be detected before catastrophic tool break by monitoring tangential force; accelerometers were used to estimate the force. Notably, Ryynänen et al. (2010) suggest that in extreme cases, the type of wear resembles more punching than rough turning.

The research group of David Dornfeld has studied different methods for detecting tool wear (Byrne et al. 1995, Lan & Dornfeld 1984). Another leading researcher in the field is Krzysztof Jemielniak (Jemielniak & Otman 1998, Jemielniak & Szafarczyk 1992). An early study of the use of acoustic emission in detecting tool fracture was conducted by Toshimichi Moriwaki (1980). Moriwaki and Mori (1993) were also able to classify tool wear and chatter into distinct cutting states. If cutting forces can be measured or reliably estimated, cutting force has been shown to have a relationship with tool wear rate and the change in the ratio of cutting force vectors has been shown to be an indicator of tool wear state (Choudhury & Kishore 2000). The coherence function of twinned accelerations has also been shown as an effective method of detecting tool wear, another connection between tool wear and chatter. (Li et al. 1997)

Naturally, to use tool wear state or tool wear rate as a parameter for adaptive control, it must be possible to predict or measure tool wear during the machining process. This has been an active research field. Of notable interest with regards to this study are the fuzzy models developed, such as those by Ren et al. (2011). Jemielniak et al. (2012) have also presented other tool condition monitoring systems, including a study allowing the estimation of the used-up portion of tool life. Once the relationship between the cutting values and tool wear with the tool-workpiece couple used are known, these can be used as a parameter for feedback.

Tool condition monitoring methods briefly reviewed are thus a useable parameter for an intelligent machining system. In the desired cutting state, the tool wear is predictable and controlled. There are two parameters that are easily changed during the machining, cutting feed and speed. As noted above, of these the cutting speed has a major effect on tool wear rate while the effect of cutting feed depends on other parameters.

Considering an intelligent machining system attempting to maximise the productivity by increasing feed rate, this would leave adaptive cutting speed control to try and maintain tool wear rate. Naturally, this assumes that there are no issues apparent in the cutting process that require cutting speed control; for example regenerative chatter may be mitigated by adaptive cutting speed control and may be considered more important to mitigate than increased tool wear – especially when chatter causes increased tool wear.

4 EXPERIMENTAL SETUP

In this work, most of the results are based on a series of cutting tests done on a Daewoo Puma 2500Y CNC lathe, mainly using a Sandvik Coromant SNMM 12 04 12-PR square insert attached to a DSBNL 2,525 M 12 holder with a 75 degree lead cutting angle. The material used was 34CrNiMo6 steel with a hardness of approximately 320 HB. Cutting values were selected to compare both machining at near-optimal conditions as well as intentionally causing unwanted phenomena for the purposes of collecting data on how to measure the relevant phenomena. Some of the 231 experiments done in this manner were allowed to run using constant parameters. On some of the experiments, the machinist applied manual override of either cutting feed, cutting speed or both in effort to demonstrate corrective measures to the unwanted phenomenon apparent in the cutting process. On some of the experiments, a prototype version of an adaptive machining control system was allowed to attempt the same, or to attempt to optimize cutting feed and speed.

All in all, rough turning signal samples were collected from 231 cutting experiments showcasing various cutting phenomena at the sampling rate of 40,000 samples per channel per second. Of these, in 229 samples the machinist could qualitatively (based on experience) estimate the level of cutting instability (primary chatter), chipping quality and the sound of the cutting process, labeled as “whistling noise” or “heavy noise.” The cutting process was recorded using a number of sensors. Two PCB Piezotronics model 353B03 ICP accelerometers (tangential and axial) with a nominal sensitivity of 10 mV/g (peak +-500 g) and a nominal range of 0.7 – 11,000 Hz and a retrofitted Nordmann SEA acoustic emission transducer were mounted on the tool holder. In addition, the sound of the cutting was recorded with a Shure Prologue 14L broadband (40 – 13,000 Hz) microphone in the machining cabinet, directed by the application of a cardboard cone. The cabinet also housed a camera used to photograph some of the cutting tool inserts; this data, not concerning online measurements, is not used in this study. To protect the sensors in the machining cabinet, cutting fluid was not used in any of the experiments. Information about the power consumption of the spindles of the lathe was recorded with retrofitted Nordmann WLM current sensors. The root mean square output voltage of thpindlin spindlsensorent sensor (P_V) has been modelled to have an exponential relationship to the power consumption of the main spindle (P_{kW}, equation 4.1).

$$P_{kW} = 0.126e^{0.5648P_V} \tag{4.1}$$

The cutting feed and speed could be polled from the Fanuc 18i-TB control of the Puma 2500Y using Fanuc’s proprietary FOCAS (GE Fanuc OpenFactory CNC API Specifications) application programming interface. The depth of cut is controlled by the predetermined CNC program used in each cutting experiment and is thus trivial to compute.

Partial dataset for primary chatter is described in Paper I (experiments designed to cause cutting instability). The full dataset for primary chatter is described in Paper II. Partial dataset for chipping quality was used for Paper IV (experiments captured until the writing of the paper). Full dataset for chipping quality is described in Paper V. It must be noted that on some papers, the expert’s scale is noted to be from 1 – 10 and in some papers, 0.1 – 1.0. The expert did record his estimates on the scale from 1 to 10, but for use with fuzzy logic, this information was scaled to the interval from 0.1 to 1.0. As a notable artefact of the original scaling, the value of 0 (which would correspond to “this phenomenon does not appear at all in this sample”) was not actually used to keep the values easily human-readable.

In addition to the experiments done on the Puma, 11 regenerative chatter tests of longitudinal turning were ran using a ZMM CU500M manual lathe, using Sandvik Coromant DNMG 150608 WM inserts attached to a Coromant Capto holder, with a lead cutting angle of 75 degrees. The stock material in these experiments was 42CrMo4 treated with Ca, having the same hardness of 320 HB as the stock material used in other experiments. The workpiece was 800 mm long and 60 mm in diameter; each experiment had the depth of cut 1.0 mm, thus reducing the diameter of the workpiece. SKF CMSS786A acceleration sensors having a sensitivity of 100 mV/g and a measurement range of +-80 g and a frequency response of 1 – 9000 Hz were used in various locations on the lathe. In addition, the same Shure Prologue 14L microphone was used to record the sound of the cutting, and the spindle speed of the lathe was measured by a proximity sensor generating three pulses per revolution. The sampling rate used was 10,000 samples per channel per second.

An adaptive control experiment was done on the ZMM CU500M fitted with an ABB ACS800 frequency converter to adjust the cutting speed via controlling the spindle speed and the sensor suite described above. In addition, some data was recorded of facing a hollow drum in an industrial machine shop using a Puma 700LM CNC lathe and tools provided by an industrial partner. The 700LM was instrumented using the same SKF CMSS786A sensor (radially on the tool holder) and the Shure Prologue 14L microphone. The data from these experiments was analysed for the writing of Paper III.

5 PRIMARY CHATTER

Vibrational phenomena grouped under the title “chatter” are amongst the most studied phenomena in machining. This chapter concerns so-called primary chatter that typically happens at high feed rates. The vibration causes poor surface quality, and, therefore, primary chatter can be seen as a limit on productivity by limiting the maximum value of feed rate.

In order to better understand the phenomenon, it is necessary to understand that chatter can be roughly organized into two major categories: Forced chatter and self-excited chatter. Of self-excited chatter, it is possible to differentiate between waveforms and causes. Primary chatter is caused by friction between the tool and the workpiece; secondary chatter is caused by the interaction between the tool vibrations and the surface patterns of the workpiece, and so on. Of these forms of chatter, the more studied is the secondary or regenerative chatter, which may appear on ill-supported or narrow workpieces, whereas the primary chatter typically appears when the cutting feed is too high for the combination of cutting tool and stock material. The primary chatter in turning processes is also identified by the shop-floor term of “unstable turning.”

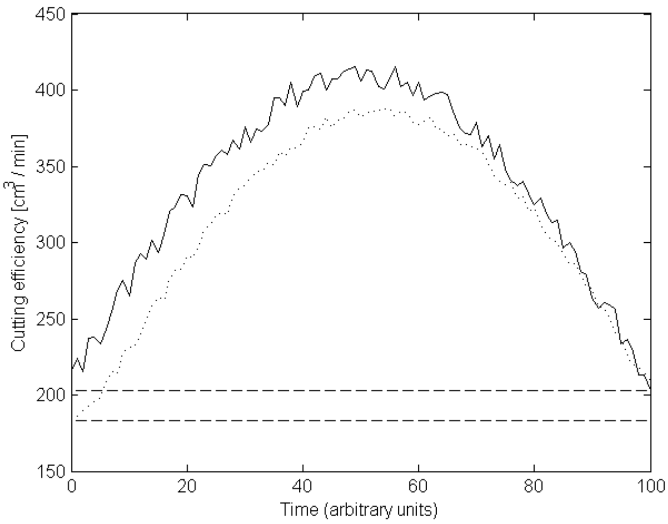

Figure 5.1: Comparison of cutting efficiency between constant cutting parameters (dashed lines, with or without a safety margin), an adaptive control seeking to optimize cutting parameters (dotted line) and a theoretical maximal efficiency (solid line). The demonstrated variation is based on the extremes of material quality variation within the same batch of stock bar. It is also of note that even an intelligent, adaptive control system requires some safety margin to avoid instability in the case of rapid changes.

As noted in chapter 3, primary chatter mainly appears at high feed rates. Thus, in order to avoid unstable turning, if an adaptive control is not used, profitability is lost due to need of having a “safety margin” (difference of dotted and solid lines) on feed rate (Figure 5.1). For the “traditional” adaptive feed rate controls focused on constant cutting conditions, primary chatter might not be considered a major problem. As noted in papers I and II, the chief predictor for primary chatter is high power consumption, and thus a system that attempts to maintain constant power use will naturally avoid primary chatter, unless the original target for power consumption is selected in such a way that primary chatter is unavoidable. It can be concluded based on this observation that such an adaptive control either will by its nature avoid primary chatter (if robust parameters are set) or will be unable to do much to primary chatter. In the case of robust parameters (low reference value for power consumption or cutting force), productivity is impaired.

For a type of adaptive control attempting to actively increase feed rate in order to maximise productivity, such as the one described in this work (especially paper I), detecting primary chatter is vital to maintaining a balance between productivity and quality. The maximal productivity achievable by such a system is essentially limited by either the maximum continuous power consumption limit of the lathe or the appearance of primary chatter at high feed rates, whichever is encountered first. In the case of stable cutting conditions and soft material, an intelligent machining system can maximize feed solely based on the appearance of primary chatter, surpassing feed rates achievable by main spindle power based adaptive control systems. An intelligent control system detecting primary chatter is also able to react to the appearance of the phenomenon, even if the power consumption levels are normal.

Ideally, it would be possible to construct a physical model capable of predicting the appearance of primary chatter. Due to multiple factors which cannot be reliably measured, including possible variations within the stock material not discovered until the cutting process is underway and individual variations between lathes, constructing a physical model robust enough can be seen as challenging. Instead, in this work several measures were statistically compared to collected expert data.

Based on 21 initial experiments, simple characteristics were identified to enable feature extraction and measurement of primary chatter based on recorded signals. Based on this data, a simple rule-based fuzzy expert system was implemented. The thus created system was validated by conducting a second round of 54 experiments and both comparing the results to the first round of experiments as well as assessing the performance of the expert system used for adaptive feed rate control. Some of these second round experiments were performed using another tool geometry to see if tool geometry would affect the behaviour of the extracted features.

Initially, the several characteristics of primary chatter were identified in 21 recorded signals. The cutting sound changed, with the signal power increasing in general and near 6 kHz in specific. Vibrations increased, especially in the axial direction. A slight increase in the signal power of the acoustic emission sensor was also observed. In addition, the main spindle power seemed to correlate very well with cutting instability, though initially this observation was discarded as prone to false positives due to the objective of the system being developed being to maximize removed volume over time, naturally consuming more power. On a further examination of the spectra of captured signals, it was discovered that at the equipment used, a resonant frequency appeared within 2 – 8 kHz. The power measured at this frequency correlated with increased cutting instability seen in the available data. A sensor fusion based system was implemented based on this data. A simple fuzzy control system was used to verify that the estimate could be used as a parameter for feedback.

In the second round of experiments, 54 more samples were collected. A human expert estimated the initial situation and whether or not the adaptive fuzzy managed to react properly to the cutting state. The expert noted that in 44 cases out of 54 (81%) the system seemed to make the correct response, though noted that it was difficult to judge the cutting state between successive control actions quickly. After tuning the expert system with the data gathered in the validation experiments, it was estimated that the system could correctly classify 86% of all the cases (75 recorded signals included in the test set). Tool geometry change was not found to be significant. However, it was still noted that the implemented expert system was acting rather slowly considering the demands of high-speed machining.

Finally (as shown in Paper II), it was attempted to construct a statistical model of the behaviour of primary chatter based on a greatly expanded set of available experimental data compiled from 229 cutting experiments gathered over an extended period of time (including the initial and the validation set). This set contains 164 samples of stable cutting, 28 clearly unstable and 37 samples where the expert was uncertain whether or not the primary chatter phenomenon was apparent in the cutting state.

As more data was available, a more detailed analysis of the characteristics of primary chatter was done, developing three models: One based on cutting parameters (cutting feed, speed and depth of cut) only, one based on measured signal features only and the final one combining cutting parameters and measured signal features.

In agreement with the theory of primary chatter appearing at high feed rates, a double reciprocal model of feed rate was found to be able to explain 51.5% of the variability within the expert data, when the best models based on cutting parameters only could explain slightly over 60% of the variability in the data. Despite the low coefficient of determination r^2, the cutting parameter based model involving exponential depth of cut and linear cutting feed and speed, when having the entire model squared, could be used to classify the data to great effect, correctly classifying 90.6% of the cases where the expert was certain of his assessment. However, of the unstable machining samples, only 53.6% could be predicted.

Using signals recorded from the sensors, it was noticed that the correlation between the expert's assessment of the cutting instability and a second-degree model using only main spindle power was 61.5%. 87.2% of the variability in the power consumption of the lathe could be explained by the depth of cut and cutting feed and speed changes. This would suggest that almost 54% of the variability in the expert data could be explained by first estimating the main spindle power based on cutting parameters only, and then using the estimated main spindle power to predict the grade of primary chatter.

The overall best estimate of the grade of primary chatter based on sensors only could explain 72.5% of the variation, a significant improvement over using only cutting parameter data. Classification is not improved as much, being correct in 91.1% of the cases where the human expert was certain of his assessment. However, 60.7% of the unstable samples were correctly classified.

When using the combined model using cutting feed rate, main spindle power and the sensor fusion based system created in the first set of experiments, explaining 70.8% of the data and achieving the same classification accuracy (91.1%) as the sensor data only method. However, the errors in classification tend to be on the samples closer to uncertain classification, and 64.3% of the unstable samples were correctly classified. Notably, dropping the sensor fusion based estimate and using only feed rate and (second degree model of) power consumption allows still to explain 69.2% of the variability in the expert data at relatively minimal computational cost.

The primary chatter phenomenon does not appear in a good rough turning process. Based on the experiments it can be concluded that it is possible to measure and model the grade of primary chatter apparent in the cutting process, partially answering the question on how the current cutting state can be defined. The change in this grade as cutting parameters change is fairly predictable, allowing the grade and its change to be used as a parameter on how a good, stable cutting can be maintained while attempting to maximize productivity by adaptive feed rate control. Should the cutting process turn unstable, the model can be used to estimate what kind of an adaptive feed rate control is necessary to return the process to a stable cutting state, partially answering the research question on achieving and maintaining the desired cutting state.

6 REGENERATIVE CHATTER

The secondary or regenerative chatter typically appears at narrow or ill-supported workpieces. It is a dynamic instability resulting from a resonating interaction between the surface of the workpiece and the vibration of the machine tool, causing poor surface roughness (Fig 6.1) and integrity, spoiling the workpiece. Unlike primary chatter, which is caused by the friction between the tool and the workpiece (thus appearing when feed rate and depth of cut are high), secondary chatter may appear at nearly any cutting values, perhaps save situations when the cutting values (especially depth of cut) are very low. Thus, in effort to maintain the efficiency of the cutting process, regenerative chatter must be detected and controlled.

Figure 6.1: Visible chatter marks. Surface roughness values measured in micrometers (R_a or arithmetic average).

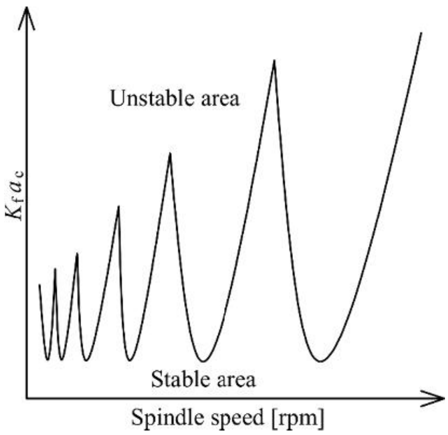

Figure 6.2: Typical form of stable and unstable areas of cutting values with regards to secondary chatter. Vertical axis is experimentally determined cutting coefficient K_f times depth of cut a_c.

As the vibrational phenomenon depends on a resonating interaction, it is possible to model the strength of the vibration as a function of the cutting coefficient times depth of cut and spindle speed (workpiece rotational speed, Fig. 6.2). Selecting a spindle speed at a stable lobe should suppress the vibration, though the stable lobes move as the geometry and the support of the workpiece change during the cutting process, requiring repeated feedback as cutting conditions change. It is additionally noticed that higher spindle speeds are inherently more stable than low spindle speeds.

In order to the gather sensor data of the cutting process, a number of experiments were performed with the experimental setup detailed in chapter 4. At first, 11 experiments were performed to record accelerometer and audio data about the regenerative chatter phenomenon in laboratory conditions. An additional experiment was performed in an industrial machine shop to test if the model developed based on the initial 11 experiments would still be valid under different conditions. Based on a literature survey and data recorded in these experiments, a model for detecting regenerative chatter was formulated.

The model for detecting regenerative chatter was used together with a simple adaptive cutting speed control system to test chatter mitigation by adaptive machining control. The theory of regenerative chatter indicates that the phenomenon is at its worst when the vibrations of the cutting tool and the workpiece are phase shifted in such a way that they are resonating. Thus, the effect of regenerative chatter can be minimized by selecting such a cutting speed where the resonance is broken, ideally with a phase shift of 0 degrees. The phase shift between two successive rotations can be calculated from equation 6.1:

$$\omega_c T = 2\pi p - \varepsilon \tag{6.1}$$

ω_c is the detected frequency of chatter (in rad/s); T is the time of a full rotation of the workpiece and p is the number of the whole undulations during one rotation. ε is the phase shift. When the rotational speed is set in such a way that the phase shift is zero, the magnitude of regenerative chatter should be minimized.

Based on the literature survey on methods to detect chatter, it was concluded that a coherence function of either two acceleration signals or an acceleration signal and an audio signal could be used as a measure for regenerative chatter. Experimental data suggests that the best results can be achieved with a coherence function of a radial acceleration signal and an audio signal.

Using the coherence function of the radial direction acceleration and audio signals recorded, it was possible to detect the onset of regenerative chatter typically 0.8 – 1.0 seconds before the onset of chatter begins to affect the amplitude of tool vibration significantly (as shown by the acceleration signal) in the experiments done in laboratory conditions. The regenerative chatter was also detected in the tests conducted in the facilities of the industrial partner. The machinist agreed that the chatter was present in the cutting process but did not consider the level of chatter harmful. Therefore, it must be concluded that the exact threshold for the measure may vary between different workpieces, but the measure is certainly suitable for faster-than-realtime detection (i.e. prediction) of chatter. The coherence function can be considered a somewhat robust way of detecting chatter, as the phenomenon must appear in signals recorded by both sensors to trigger a detection. There is some concern on whether a microphone could capture audio from other sources though the chance of a directional microphone placed close to the cutting process doing so was considered low.

The applicability of the chatter detection method for active machining control was experimentally tested and discovered to be effective together with the suggested chatter mitigation method, though not before the onset of chatter had managed to cause some changes in the quality of the machined surface. However, the surface roughness was much better than if the spindle speed had not been adjusted.

Secondary or regenerative chatter does not appear in good rough turning. It has been shown that the appearance of regenerative chatter can be efficiently measured, and furthermore, should the phenomenon be apparent in the current cutting state, a more desirable cutting state can be reached by selecting a suitable spindle speed. It may be necessary to maintain feedback to keep regenerative chatter suppressed.

7 CHIP CONTROL

Controlled chip formation is an important aspect of any cutting process. The desired behaviour of the cutting process is such that the length of chip is regular, and chip length is short. Long chips are difficult to remove from the vicinity of the cutting process (Fig. 7.1). Thus, unless the control of chip length is reliable, it will not be possible to leave the cutting process unsupervised, spoiling any opportunity of partially manned or unmanned production.

Fig. 7.1: Handling long chips is difficult, as the swarf may clog conveyor systems (such as the one seen on top of this figure).

It is established that chip length can be detected by spectral analysis of several signals recorded from a cutting process. The method used in paper IV uses an acoustic emission signal to accomplish this. While the term acoustic emission is often used for any audio signal, in this context acoustic emission is high frequency (100 – 1000 kHz) vibrations measured from the tool holder. Due to the high frequency of the vibration this is inaudible to humans. A traditional microphone is unable to capture this signal; a specific acoustic emission sensor is used. An enveloping filter is used to avoid aliasing when sampling the signal at a lower frequency. The burst events in acoustic emission originate from fracture events, either tool fracture, fracture within the workpiece or most likely, chip break events.

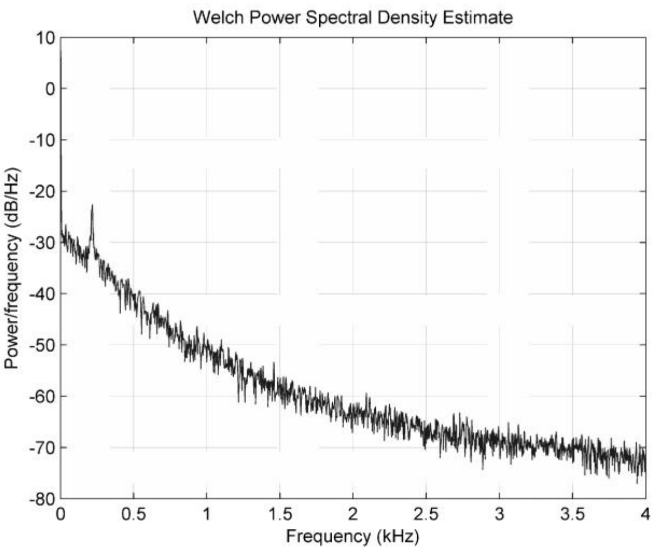

Fig. 7.2: Power spectral density estimate of an acoustic emission signal, chip break frequency clearly visible at 217 Hz. The vertical axis is logarithmic.

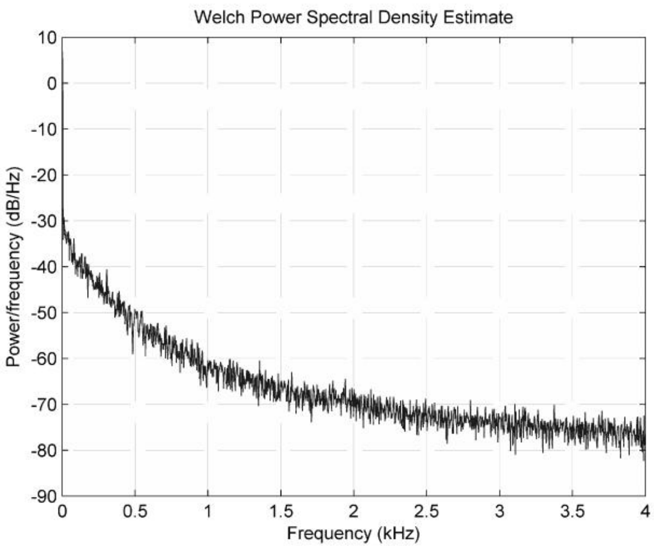

Fig 7.3: Power spectral density estimate of an acoustic emission signal, continuous chip. The vertical axis is logarithmic.

The chip break frequency is visible in the spectrum as a “peak” on the spectrogram of an acoustic emission signal. However, since low-frequency components are typically of vastly higher magnitude than high-frequency components (as shown in Figures 7.2 and 7.3), direct comparison of component magnitudes is not applicable. In order the extract the peak feature, it must be possible to detrend the signal someway. The desired de-trending behavior is estimating the low bound of the signal.

In the first prototype of this method of measuring chip length, de-trending was accomplished by a “ray casting” method. Ray casting is a term originating in computer graphics and computational geometry. A “ray” is extended (“cast”) to a specific direction until it hits a surface. In the two-dimensional case of the spectrogram, the surface is the polygonal chain formed by connecting the different frequency components of the spectrogram. Thus, the path where the rays just-by-just hit the surface of the spectral power density estimate data forms a polygonal chain estimating the lower bound of the spectral component magnitude. The difference between the lower bound and the signal data gives an estimate of which frequencies contain energy besides of the base machining noise. (Fig. 7.3) Additionally, this method is capable of following any possible changes in the trend in the case of high-energy bands. Different peaks in the de-trended data will be compared, and the one containing most energy will be selected as a candidate for chip break frequency. Once the chip break frequency θ_c (hertz) is found and the cutting speed v_c (meters per minute) is known, calculating the chip length l_c (meters) can be done simply by (Eq. 7.1)

$$l_c = \frac{v_c}{60\theta_c} \tag{7.1}$$

This algorithm was combined with an adaptive turning control capable of adjusting feed rate based on chipping quality. Bad chipping quality is considered to show as low-frequency chip break frequency, either because of long chip or because of high-frequency “peak” being too spread out to be visible due to uneven chipping frequency (heterogeneous chip length) making the peak appear low-energy. The control behavior on bad chipping quality was to increase cutting feed. Additionally, a case where a peak was not detected at all was assumed to correspond with continuous chip. Continuous chip should be cut by setting the feed momentarily to zero and then continuing at a higher feed – in case the feed used was not in the upper half of the recommended feed rates suggested by the manufacturer, then it would be increased to the halfway of the given feed rate range or the value it would be increased due to bad chip break quality, whichever greater. The control gain was decided based on observing a human machinist, varying between 0 and 15 %, using a Mamdani-type fuzzy system to control the feed rate override.

The measures were calibrated using several long signals of continuous and good cutting. Then the prototype system was subjected to a series of 80 cutting tests. It was discovered that during the tests, in 76 out of 80 cases the system could correctly classify the cutting state, and improve the situation by applying feedback if necessary. Some individual experimentation was also done with a different material (P355NH) and tool (CNMM120412-PR). Tool change seemed to have no effect on classification accuracy, but with the softer steel, numerous cases of false positives were observed. Also, the system did take a good amount of time to react and optimize – between five to ten seconds, which is unacceptably long. It is notable that the inference engine itself works fast, but much of the time is taken by sample recording, signal processing, overhead and actuation delay.

However, experimentation this far has shown that the research questions can be partially answered. In an efficient rough turning process, the removed chips form a granular flow that can be easily removed from the immediate vicinity of the tool and workpiece. Thus, the phenomena “long chip” and “continuous chip” must be absent in the cutting state. The current cutting state can be defined by detecting the chip break frequency. With the researched materials this far, long chips can be eliminated by increasing feed rate and continuous chip can be cut by setting the feed to zero before increasing feed rate. Additionally, if the chips are long, but not yet alarmingly so, the feed rate should not be decreased.

7.1. Alternative detection methods

In order to discover a more generalizable and preferably faster method, several different methods for detecting long or continuous chip were compared. The dataset used for the comparison is the 229-signal library described in chapter 4.

Four different methods for detecting long or continuous chip were compared. Conditions where various types and lengths of chip appeared are included in the recorded data. The cutting frequency has been identified to appear as a high-energy component in the spectrum of several sensors, including acoustic emission and cutting force. In this study, the acoustic emission signal is used. Initially, a method was developed to extract such high-energy components from a periodogram. This requires trend removal, ideally resulting only “anomalous” frequency components to remain nonzero.

Another frequency plane method notes that it appears that the trend in the periodograms appears to be an exponential curve, and, therefore, fitting an exponential curve to the lower bound of the data should be sufficient to remove most of the trend. Least square error and similar fits cannot be used, because the high-energy components may be several orders of magnitude higher than the baseline, and, therefore, the “average level” of the signal magnitude is higher than the trend. The lower bound of the data is estimated by dividing the signal into several frequency bands and then extracting the frequency and component magnitude of each band. To compensate for the lower energy at higher frequencies, the ratio between the signal and the fit model is examined to discover peaks.

Third method notes that the acoustic emission burst event corresponding to chip break should be visible on the time-domain data (Fig. 7.4), though it must be noted that some of the peaks can be caused by metal fracture other than chips breaking (Fig. 7.5). However, by comparing the amount of bursts in cases where the chip breaks and does not break, it appears clear that the vast majority of burst events seen in the experiments are caused by metal fracture connected to chips breaking. A simple windowing peak detection algorithm is used to process the data, and the statistics of the identified chip break event candidates are compared. The window length is set equivalent to the minimum chip length to be detected; in addition peaks are required to be at least 40 % higher in magnitude than the detected baseline (minimum) of the signal. In case the signal contains very high peaks, the height of peaks is normalized on the unit interval, and the peaks higher than 0.4 on the normalized interval are considered to be chip break events.

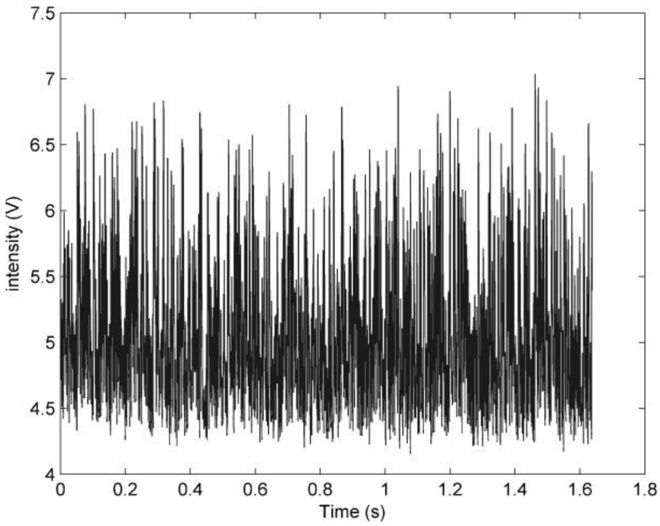

Fig. 7.4: An acoustic emission signal is showing characteristic bursts caused by metal fracture.

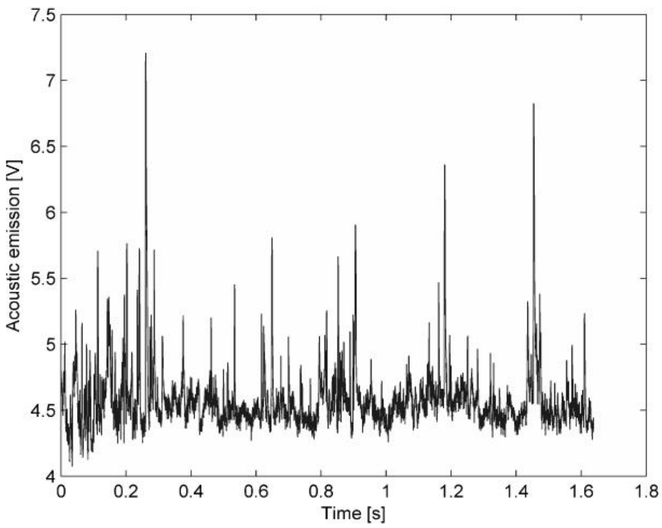

Fig. 7.5: An acoustic emission signal with no chips breaking

A fourth method notes that by visual inspection of the graphed signals, the general level and composition of the acoustic emission data varies between different cutting states. Therefore, merely computing the histograms of the data, counting the samples below a specific threshold and above a specific threshold could be sufficient to detect chipping quality. The method is unable to estimate chip length. However, the desirable property of the method is its extreme computational simplicity.

During the examination of the second of these four methods, it was found out that when trying to fit a curve to the low bound of the frequency plane signal, occasionally artefacts (computational errors) would crop up as the low bound was approaching zero, or in some cases went negative in the last frequency band sampled. This resulted in minor variation in the last frequency band to appear as major “peaks” after detrending. This was removed by adding a scaling factor to both the peridogram data and the fitted lower-bound model. A comparison of different averages suggests that the median magnitude of frequency components in the examined area is the most suitable scaling factor; in addition, it was found out that the value of this scaling factor is a very strong classifier for continuous chip. (Continuous chip and thus the absence of chip breakage resulting in much lower magnitude signal.)

After comparing the different methods, it was found out that the best classifier of the methods examined is the frequency plane peak detection with trend removal by model fitting, with the assistance of examining the scaling factor to detect continuous chip. 97.7% of the cases where chipping was of good quality were classified correctly. However, only 65.3% of the long chips were classified correctly though this included all the continuous chips. Considering the results the other way, it is important to note that there were no false positive detections of the long chip. The overall classification accuracy was 88.8% (158 out of 178 samples where the expert data was not unsure). Reduced amount of computations improved the average (arithmetic mean) amount of computation time consumed from 265 milliseconds to 11 milliseconds, a significant improvement of a quarter of a second. It has to be noted that the classification accuracy is slightly lower than reported in Paper IV. This is because of a different and less clear data set.

When the computing time is considered, the most simple of the methods compared cannot be ignored, however. The overall accuracy of the method was merely 71.8% of the samples which the expert had not graded “unsure”, but the method required less than a millisecond of computing time – the exact computing time cannot be accurately measured by the personal computer clock (except by taking averages of a large amount of computations) due to it being so short. If accuracy could be further increased, this method could be very promising.

In the good rough turning process, the chip length is short and regular. Should the chip length increase, this cutting state can be maintained by increasing feed rate. In extreme cases, where the chip does not break at all, the chip can be forced to be cut by setting the feed rate momentarily to zero before increasing it beyond the initial value, or if necessary cutting the chip by pulsing feed rate. This allows the chip rate to be kept relatively short even in challenging cutting conditions, answering the research questions on the part of chip control.

8 EXPERT SYSTEM FOR MACHINING

In this chapter, the basics of fuzzy control are briefly introduced. Then the Mamdani-style expert system developed for an earlier study (Leppänen et al. 2009) is described. The chronologically earlier Papers I and IV present systems that were intended to be used with this control system. Finally, a Takagi-Sugeno style expert system described in Paper VI incorporating some minor improvements and combining the regenerative chatter mitigation method from Paper III is introduced.

The founder of the theory of fuzzy logic and fuzzy sets is considered to be Lotfi A. Zadeh (1965) though others have earlier introduced similar ideas. While classical logic concerns values that are either true or false, in fuzzy logic there are an infinite amount of possible values of "partial truth". If "true" is considered to be 1 (one) and "false" is 0 (zero), then the fuzzy logic values can be mapped to the unit interval. In fuzzy set theory, the fuzzy value represents partial membership in a set. Zadeh also introduced (1975) the concept of "linguistic variables", which allow the description of fuzzy sets in formalised but almost natural language, easing the collection of expert data.

The Mamdani-type fuzzy control system used in parts of this work was introduced by Ebrahim Mamdani (1974, Mamdani & Assilian 1975). The Mamdani system makes it simple to use linguistic variables. For example, in the sentence "if 'primary chatter' is 'very bad', 'feed rate' should be 'significantly decreased'," "very bad" and "significantly decreased" are linguistic variables which can be mapped into a corresponding fuzzy set – and vice versa, the stored rule may be presented with natural language. However, with large systems the Mamdani-style fuzzy control system is not necessarily very efficient, or the rules may become very complex, degrading the readability of the rule set.

Michio Sugeno (1974) and Tomohiro Takagi (Takagi & Sugeno 1983, Takagi & Sugeno 1985) introduced the Takagi-Sugeno fuzzy control system, which splits the rules into a firing strength and a function. Using the function allows for more complex rules to be represented by mathematical formulae, resulting potentially in a more effective and flexible control system at the loss of human-readability.

Both of the main types of fuzzy control systems use a similar principle, shown in figure 8.1. "Crisp input values," such as physical quantities, are "fuzzified". Essentially, some feature is extracted and represented as a fuzzy logic value or a fuzzy set membership value (which are analogous) in the unit interval. These values are used as the parameters for a "fuzzy inference engine," which in this work is either Mamdani-style or Takagi-Sugeno style. The fuzzy inference engine interprets the rules contained in the fuzzy rule base, processing its input values according to the rules. This results in a fuzzy output value (or several fuzzy output values) which are then "defuzzified" or a crisp value (such as a physical quantity) is calculated based on the fuzzy set or the fuzzy logic value.

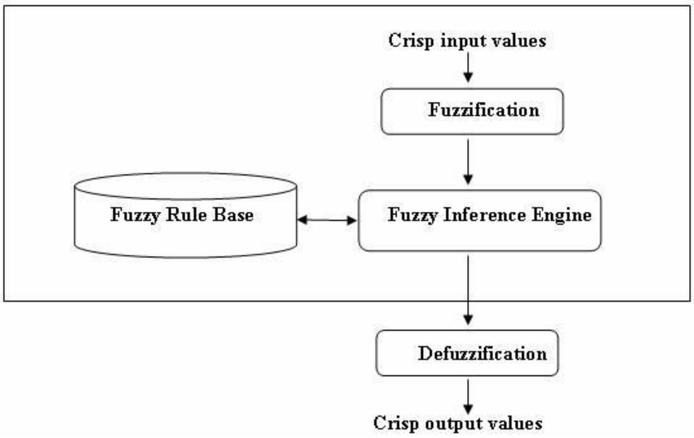

Figure 8.1: A fuzzy control system. Sensor data and other parameters ("crisp input values") are mapped to the unit interval according to some models ("fuzzification"). This information is then processed by the inference engine according to the rules contained in the rule base. Output values for feedback ("crisp output values") are achieved by processing the fuzzy decision ("defuzzification").

8.1. Mamdani-style fuzzy adaptive control system for rough turning

Based on literature review and expert interviews, rules were collected for an intelligent machining system. These rules were used to create an expert system used in a proof-of-concept type adaptive fuzzy turning control. The combined expert system was described in detail in a thesis (Ratava 2008). The measurement and fuzzification systems for two use cases for this system, maximizing feed rate and chip control are presented in more detail in Papers I and IV.

The primary objective is to improve productivity (removed volume over time) in rough turning while maintaining quality and ensuring safety. Quality is ensured by monitoring the phenomena as described in chapters 5 (primary chatter) and 7 (chip control). The results of the classifiers thus developed are used as parameters of this machining system; in addition, if a tool condition estimate is available, the system is capable of attempting to maintain predictable tool wear rate. Adaptive turning control is achieved by varying feed rate and cutting speed; the NC program dictates the tool path and thus depth of cut.

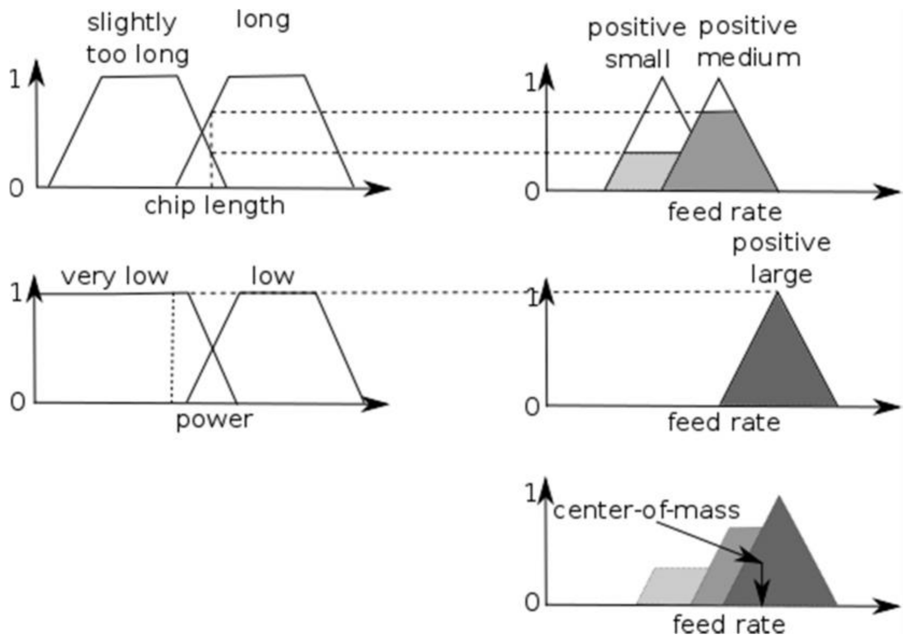

Fig. 8.2: Example of Mamdani-type fuzzy control with trapezoid input sets and triangular output sets demonstrating the rules “if ‘chip length’ is ‘slightly too long’, ‘feed rate’ is ‘slightly increased’”, “if ‘chip length’ is ‘long’, ‘feed rate’ is ‘increased’” and “if ‘power use’ is ‘very low’, ‘feed rate’ is ‘increased much’”. The final result is achieved by calculating centre-of-mass of the union of resulting fuzzy sets and projecting it on the feed rate axis.

The initial system developed was based on a Mamdani-type fuzzy control system (Fig. 8.2), including parts detailed in paper I and paper IV and a phenomenon called “high-pitched noise” detected using a naïve classifier comparing signal power at bands where vibrations had been observed to occur. In the absence of any detected harmful phenomena, the power consumption of the lathe was monitored to discover if feed rate could be increased. The expert rules for the system concerning feed rate are:

> *“If the cutting is stable, cutting feed should be increased.”*
>
> *“If the cutting is unstable, cutting feed should be decreased.”*
>
> *“If the chip is long, cutting feed should be increased.”*
>
> *“If the chip is continuous, the chip must be cut and then cutting feed increased.”*

It was noticed that the first rule could at high depths of cut cause the lathe to exceed its rated continuous power limit, and thus the first two rules were amended to:

> *“If the cutting is stable and the current power consumption of the lathe is less than the maximum continuous power consumption limit, cutting feed should be increased.”*

"If the cutting is unstable, cutting feed should be decreased."

"If the power consumption of the lathe is greater than the continuous power consumption limit, cutting feed should be decreased."

The cutting speed control was used to control tool life with the following rules:

"If the observed tool life is longer than intended, slightly increase cutting speed."

"If the observed tool life is shorter than intended, decrease cutting speed."

In addition, the "high-pitched noise" phenomenon was mitigated by increasing feed rate:

"If there is high-pitched noise, increase cutting speed."

The rule base was finalized by one last rule:

"If the cutting is good, maintain current cutting values."

It is notable that the rule base contains conflicting rules. Experts were consulted, and the following priority order was established for feed rate control: First, safety must be ensured by eliminating long chip. Second, quality must be ensured by removing cutting instability (primary chatter.) Finally, if there is power capacity left, the feed rate can be increased. Similarly for cutting speed, the high-pitched noise is to be eliminated first, and then if possible the tool life should be held as predictable as possible. As a safeguard against tool breakage, a computer vision system monitoring tool wear (though not online) could be attached to the expert system, triggering a tool life warning.

The Mamdani-type fuzzy control system fuzzified the input parameters into three sets: "small", "medium" and "big", with corresponding control action, e.g.

"If 'cutting instability' is 'small', then 'feed rate' is 'negative small'".

The priority between rules was enforced by an "if-not" type rule, e.g.

"If 'cutting instability' is 'small' and 'chip length' is not a straight sum of 'small', 'medium' and 'big', then 'feed rate' is 'negative small'"

The use of straight sum (Eq. 8.1) was necessary to avoid artefacts in the "and another phenomenon is not apparent" case, in which case the straight sum of the "small", "medium" and "big" sets of the phenomenon was used for comparison.

$$a \oplus b = \min(a + b, 1) \tag{8.1}$$

Additionally, it pays to remember that the fuzzy logic is an extension of classical logic such that (Equations 8.2, 8.3 and 8.4):

$$\mathrm{or}(a, b) = \max(a, b) \tag{8.2}$$

$$\mathrm{and}(a, b) = \min(a, b) \tag{8.3}$$

$$\mathrm{not}(a) = 1 - a \tag{8.4}$$

Defuzzification was done by taking the union of the output of the rules, forming seven sets for both feed rate and cutting speed: “negative big”, “negative medium”, “negative small”, “zero”, “positive small”, “positive medium” and “positive big”. The crisp output value (feed rate or cutting speed to be set) was then achieved by the center-of-area method (Fig. 8.2). The output sets are formed in such a way that the “small” change is approximately 5% of the reference value (e.g. programmed or learned reasonable initial value), “medium” is 10% and “big” is 15%. In addition, the cutting of a continuous chip was output as a separate parameter handled by the control implementation.

Some cutting tests were done with the adaptive turning control active. While the control system functionally worked as intended, non-functional issues (such as slow operation, 5 – 10 seconds for each decision) limit the usefulness of the system. In addition, the primary benefit of the use of linguistic variables is to make the rule base human-readable. However, due to the numerous “if-not” cases, the rule base turned out to be more difficult to comprehend than intended.

8.2. Takagi-Sugeno style fuzzy adaptive control system for rough turning

In a Takagi-Sugeno type system, the fuzzification is done the same way as in the Mamdani system. In the inference phase, the firing strengths of each rule are computed with fuzzy logic operators. This is where the “if this and not these” type priority rules will be placed, cleanly separated from the rule concerning control action itself. Importantly, the control rule can be any mathematical function, and its output is crisp – the “fuzziness” is contained in the firing strength part of the rule. Defuzzification is achieved by taking the average of the functional part of the rule base weighted by the firing strength part.

The chief reasons for abandoning the Mamdani-style fuzzy control system for the Takagi-Sugeno style fuzzy control system are the structure of the rule base and the inclusion of the appearance of secondary or regenerative chatter phenomenon as an input. In the Takagi-Sugeno style system, the priority of the rules can be cleanly separated into the firing strength part and the control action required by the rule into the functional part. The control action required to mitigate regenerative chatter requires exact cutting speed changes, and therefore it does not easily fit into the “small, medium and big control action” style fuzzy sets used with the previous system, whereas it is a perfect fit for the Takagi-Sugeno style functional rules. The Mamdani and Takagi-Sugeno systems are two the most studied and common fuzzy control systems, and both types of systems are universal approximators (Castro 1995).

The fuzzification part of the expert system for phenomena described in chapters 5, 6 and 7 is achieved by the models described in Papers II, III and V, where models in Paper II can be seen as an evolution of the models in Paper I and models Paper V can be seen as an evolution of models in Paper IV. Additionally, an estimate of tool wear or tool wear rate is needed. While the decision of feedback to the system is computed in the fuzzy control part, supplying cutting state information by accurate estimates of the level of individual cutting phenomena is a crucial part of the complete system.

The rule base is analogous to the one presented for the previous system, with the exception that the high-pitched noise rule is replaced by regenerative chatter detection with spindle speed selection as the output. This rule is essentially crisp and takes precedence over tool wear rate control: If the phenomenon appears at all, the system must be able to select the exact rotational speed to mitigate it. For the other rules, different levels of the phenomenon previously designated by the three fuzzy sets are mapped into the unit interval, such that 1 corresponds to approximately 15% control action and 0 corresponds to no control action.

In general, the functions describing the rules in a Takagi-Sugeno system may be of any form, in this study each rule is required to be a first-order polynomial. This allows storing the coefficients into a sparse matrix. Computing the output takes the form shown in Equation 8.5, where u is the output, row vector w is the weights (firing strength) containing rule priority information, C is a matrix containing the main part of the rule base and column vector x^* is the input consisting of modelled fuzzy membership values for the phenomena and required crisp values (current cutting values and required cutting speed to mitigate chatter). Two MISO (multiple input, single output) systems are needed, one for feed rate and one for cutting speed.

$$u = w\,(\mathrm{C}x^*)/\sum w \tag{8.5}$$

The matrix C is unchanging (unless the rule base is changed), but the firing strength vector w which decides rule priority needs to be recomputed as the cutting state changed to be adapted to the new cutting state. Each row of the multiplication Cx^* produces a crisp control result based on that rule. If only one rule is active for each output parameter (feed rate and cutting speed), computing the result is trivial. If multiple rules are active, the potentially different outputs need to be combined. This is done by weighting each rule according to the priority information and then taking a weighted average. The firing strength for each rule is the union of the fuzzy membership value of the corresponding phenomenon triggering the rule and the negations of the fuzzy membership values of the phenomena of higher priority.

The operation of this variant of the system has been simulated. The decision surfaces are shown in Figures 8.3 and 8.4. The overhead related to the inference system is reduced. The inference system is taking less than a millisecond to compute a suitable output. It has to be remembered that the lathe takes some time to actuate the control, and the capturing and processing of the signals does take some time. This adds up to three seconds if using the same measurement time as with the system described in (Ratava 2008), including 1.6 seconds to measure a sample and 0.5 – 1.0 seconds to actuate the lathe. With parallel computing, such as having a separate process to control the cutting parameters and a separate process to keep a recorded sample ready for processing, the reaction time of the system should be much improved. The signal length and actuation time of the lathe are expected to be the limiting factors. With more accurate and computationally efficient models, signal length and computation time both can be reduced.

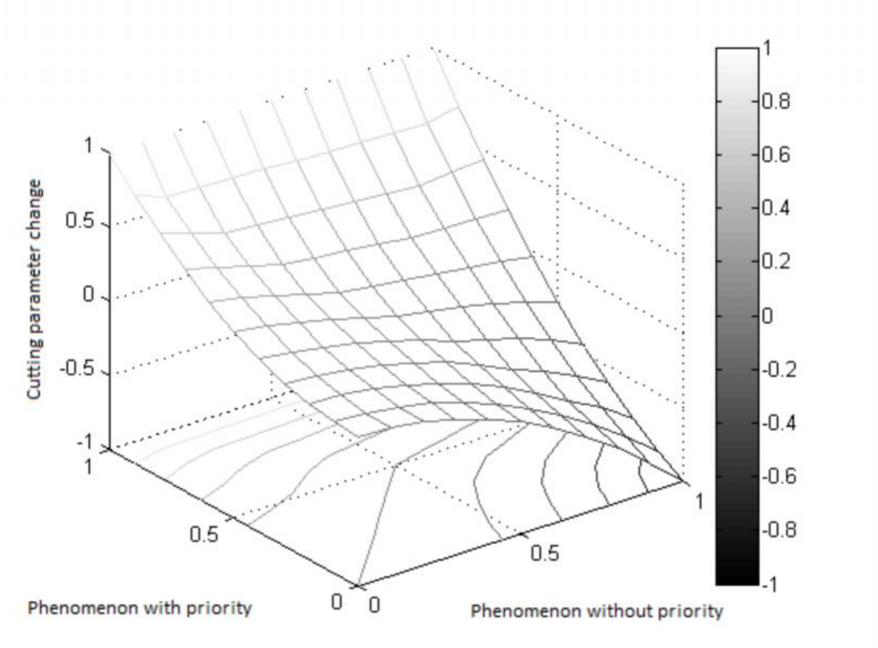

Figure 8.3: Two conflicting rules are requiring opposite control action. The more important rule requires positive parameter change in this example.

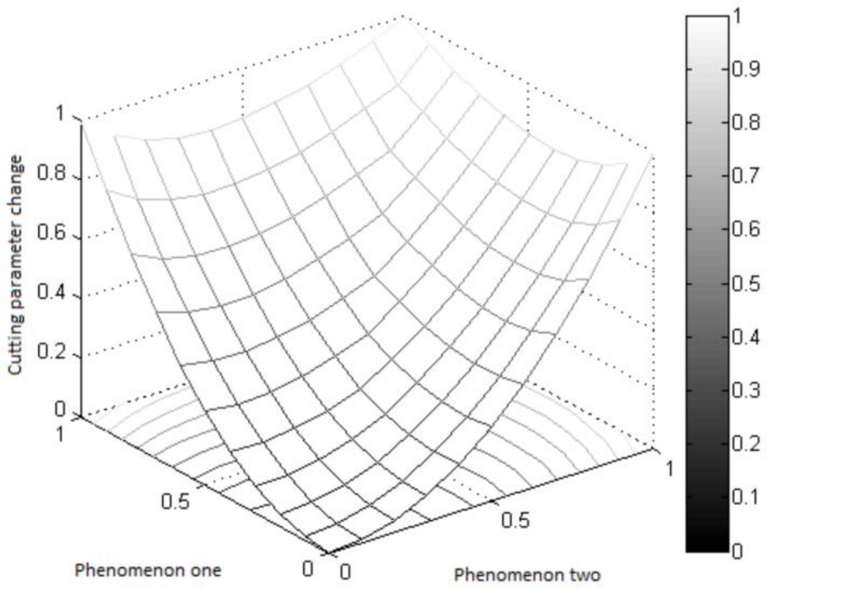

Figure 8.4: Two rules are requiring same direction control action.

8.3. Summary of Studied Expert Systems

The expert systems do collect the individual phenomena into a comprehensive estimate called in this work the "cutting state." In order for a good rough turning process to be maintained, the cutting state must be such that there is no long or continuous chip and no primary chatter, and feed rate is maximal or limited by the appearance of primary chatter. There must be no regenerative or secondary chatter, and the tool wear rate should be maintained to be predictable. However, if regenerative chatter appears during the process, the chatter must be mitigated even if it happens at the expense of tool life.

When using the described expert systems, the current cutting state is defined as a combination of the membership levels of the fuzzy sets "primary chatter", "regenerative chatter", "chip length", "tool life is too short", "tool life is too long" and the current power consumption physical quantity. In a user interface component, it is possible to display the cutting state in a human-understandable form, such as "there is some primary chatter", based on the work done on the first fuzzy control system.

In case the current cutting state is not the desired one, by acting according to the expert knowledge formulated in the rule base, it is possible to optimize feed rate and cutting speed in order to reach the desired cutting state of good rough turning. In case of tool life, with challenging vibrating workpieces, it might not be possible to reach the good rough turning state – then the best possible state is reached instead by mitigating chatter at the possible cost of tool life. Human-understandable feedback on the reasons behind the decisions can make the system more comprehensible to end users, potentially increasing user acceptance and trust.

The good rough turning state can be maintained by predicting the appearance of undesired phenomena, such as primary and secondary chatter before they yet reach a harmful level. Then preventive control action may be taken to avoid the undesired phenomena.

9 CONCLUSIONS AND DISCUSSION

In this study, measurements and features extracted from measurements of the cutting process are compared to expert knowledge relating to cutting phenomena apparent in the cutting process. The first notable result is that it is possible to determine automatically the level of these phenomena based on knowledge of cutting parameters and the measured signals.

Second, expert knowledge and theoretical data were collected of the control action necessary to possibly avoid, mitigate or eliminate harmful phenomena. Combined with an automatic estimation of the level of the phenomena, adaptive control systems were designed and experimentally verified to automate the process of avoiding, mitigating or eliminating detected harmful phenomena.

Third, an expert system was designed and experimentally verified to combine all of the individual control systems designed above. The system was found to be valid but computationally heavy, prompting for the improvement of the detection algorithms and a design of an improved adaptive fuzzy control system. The search for improved algorithms has been concluded, increasing classification accuracy and reducing computational load. Moreover, improved adaptive fuzzy system increasing flexibility and decreasing computational load has been designed, and the design has been verified by simulation.

The research questions formulated in chapter 2.2 can be answered thus:

> *What factors define and enable a good rough turning process?*
>
> *What the current cutting state needs to be in order to maintain a good rough turning process?*

The good rough turning process is considered to be safe, of high quality and efficient. These aspects can be collected to the “cutting state”. In practice, the cutting state is thus a collection of measures that indicate safety, quality and efficiency of the cutting process. In this study, good cutting is considered to be such that the feed rate should be maximized within the limitations that primary or secondary chatter should not appear, chipping quality should be controlled and tool life predictable.

> *How can the current cutting state be defined?*

This study presents several new models that allow the individual phenomena measured online during the cutting process. These measures are calibrated with expert data collected from human machinists. Tool wear monitoring in rough turning is not researched experimentally during this study; this is a very much studied field, and there do exist numerous methods using which tool wear can be estimated.

> *In case the current cutting state is not the desired cutting state, how can the desired cutting state be reached from the current cutting state?*

This study presents expert knowledge regarding how to mend each undesired phenomenon. In addition, the behaviour of the primary chatter phenomenon, critical knowledge for maximal feed rate while maintaining quality, has been modelled and thus, suitable cutting values may be selected according to this model. In case there are more than one undesired phenomena apparent in the cutting process, the expert system presented in this study allows the resolution of potentially conflicting objectives. In very challenging conditions, it may not be possible to reach a truly error-free cutting state. In such a case, the phenomena apparent in the cutting may be prioritized based on expert knowledge and the highest-priority issues dealt first.

> *In case the current cutting state is the desired cutting state, how can this cutting state be maintained?*

In many cases, the cutting state can be maintained by keeping the current cutting values. However, in case of changing cutting conditions, it is possible to detect the onset of a new cutting phenomenon and react to the newly apparent phenomenon, thus again reaching the desired cutting state. Ideally, this happens before the effects of the new phenomenon are truly apparent in the cutting process, preventing its occurrence. This is possible by modelling the behaviour of the phenomena (as in the case of primary chatter) or by being able to detect the cutting phenomenon before it may overtly affect the cutting process (such as in the case of secondary chatter and possibly in the case of increasing chip length).

Compared to earlier approaches to optimizing a machining process, this study presents an alternative point of view based on expert qualitative estimation of the cutting process instead of monitoring physical quantities, estimating phenomena such as primary chatter where the traditional approach might be to monitor cutting force. This allows abandoning the cutting values designed to work in the worst cutting conditions that can be encountered and optimizing cutting parameters for efficiency during the cutting process. The development of the system is continued from an earlier proof-of-concept system and presents experimental models improving the detection and classification of the phenomena. A new expert system designed to control both cutting speed and feed rate is introduced. The system can maximize removed volume over time while avoiding harmful phenomena, including both primary and secondary chatter while maintaining desired tool life.

The systems of the kind of the intelligent machining expert system described in this study are an enabling technology for further automation, including partially manned or unmanned production when manufacturing products suitable for such processes. Suitable products for unmanned production include those capable of being handled by robots or products where the cutting process takes a considerable amount of time. Additionally, some products that require manual handling of the workpiece (such as fixing and removing the workpiece from the lathe) may be suitable for partially manned production. This kind of development may increase the importance of transportation and production site energy costs while reducing the importance of the price of manual labour, thus potentially changing which sites are suitable for the manufacture of turned parts.

Interesting topics for future study include experimenting with the methods presented in this study using other tools and materials, examining what further information (if any) is required for generalizing this work for a wider variety of production environments. In addition, since the models presented in this study were fitted to qualitative data, a larger amount of experts should be consulted to study the variance in expert opinion.

10 BIBLIOGRAPHY

(Abuthakeer et al. 2011) Abuthakeer, S.S., Mohanram, P.V. & Mohankumar, G. (2011). The effect of spindle vibration on surface roughness of workpiece in dry turning using ANN. *International Journal of Lean Thinking*, 2(2), 42-58.

(Abu-Zahra & Lange 2002) Abu-Zahra, N.H. & Lange, J.J. (2002). Tool Chatter Monitoring in Turning Operations Using Wavelet Analysis of Ultrasound Waves. *International Journal of Advanced Manufacturing Technology*, 20, 248-254.

(Agnew et al. 1997) Agnew, A., Forrester, P., Hassard, J. & Procter, S. (1997). Deskilling and reskilling within the labour process: The case of computer integrated manufacturing. *International Journal of Production Economics*, 52, 317-324.

(Andreasen & De Chiffre 1998) Andreasen, J.L. & De Chiffre, L. (1998). Automatic Chip-Breaking Detection in Turning by Frequency Analysis of Cutting Force. *CIRP Annals - Manufacturing Technology*, 47(1), 35-40.

(Astakhov 2006) Astakhov, V.P. (2006). Cutting Tool Wear, Tool Life and Cutting Tool Physical Resource. In Astakhov, V.P.: Tribology of Metal Cutting. *Tribology and Interface Engineering*, 52, Elsevier.

(Astakhov 2007) Astakhov, V.P. (2007). Effects of the cutting feed, depth of cut, and workpiece (bore) diameter on the tool wear rate. *International Journal of Advanced Manufacturing Technology*, 34(7-8), 631-640

(Bao et al. 1994) Bao, S. F., Zhang, W. G., Yu, J. Y., Qiao, S. M., & Yang, F. L. (1994). A new approach to the early prediction of turning chatter. *Journal of Vibration and Acoustics*, 116(4), 485-488.

(Billatos & Tseng 1991) Billatos, S. B., & Tseng, P. C. (1991). Knowledge-based optimization for intelligent machining. *Journal of Manufacturing Systems*, *10*(6), 464-475.

(Bushan 2013) Bushan, R. K. (2013). Optimization of cutting parameters for minimizing power consumption and maximizing tool life during machining of Al alloy SiC particle composites. *Journal of Cleaner Production*, 39, 242-254

(Byrne et al. 1995) Byrne, G., Dornfeld, D., Inasaki, I., Ketteler, G., Konig, W. & Teti, R. (1995). Tool condition monitoring (TCM) – the status of research and industrial application. *CIRP Annals – Manufacturing Technology*, 44(2).

(Castro 1995) Castro, J. L. (1995). Fuzzy logic controllers are universal approximators. *Systems, Man and Cybernetics, IEEE Transactions on*, *25*(4), 629-635.

(Chen & Knospe 2007) Chen, M. & Knospe, C. (2007). Control approaches to the suppression of machining chatter using active magnetic bearings. *IEEE Transactions on Control System Technology*, 15(2), 220-232.

(Chiou & Liang 2000) Chiou, R.Y. & Liang, S.Y. (2000). Analysis of Acoustic emission in chatter vibration with tool wear effect in turning. *International Journal of Machine Tools and Manufacturing*, 40, 927-941.

(Choi & Shin 2003) Choi, T. & Shin, Y.C. (2003). On-line chatter detection using wavelet-based parameter estimation. *ASME Journal of Manufacturing Science and Engineering*, 125:21-28.

(Choudhury & Kishore 2000) Choudhury S. K. & Kishore, K. K. (2000). Tool wear measurement in turning using force ratio. *International Journal of Machine Tools and Manufacturing*, 40(6), 899-909.

(Cui et al. 2012) Cui X., Zhao J. & Dong, Y. (2012). The effect of cutting parameters on tool life and wear mechanisms of CBN tool in high-speed face milling of hardened steel. *International Journal of Advanced Manufacturing Technology*, 66(5-8), 955-964.

(Dolinsek et al. 1999) Dolinsek, S., Kopac, J., Viharos, Zs. J. & Monostori, L. (1999). An intelligent AE sensor for the monitoring of finish machining process. *The Second International Conference on Intelligent Processing and Manufacturing of Materials*, July 10-15, 1999.

(Dornfeld & Pan 1985) Dornfeld, D. A. & Pan, C. S. (1985) A Study of Continuous/Discontinuous Chip Formation Using Acoustic Emission. *Journal of Applied Metalworking*, 4(1), 8-29.

(Eynian & Altintas 2009) Eynian, M. & Altintas, Y. (2009). Chatter stability of general turning operations with process damping. *ASME Journal of Manufacturing Science and Engineering*, 131, 041005.

(Fei & Jawahir 1993) Fei, J. & Jawahir, I.S. (1993). A Fuzzy Classification Technique for Predictive Assessment of Chip Breakability for Use in Intelligent Machining Systems. *IEEE International Conference on Fuzzy Systems*, San Francisco, CA, 1993.

(Ganguli 2005) Ganguli, A. (2005). *Chatter reduction through active vibration damping*. Brussels, Belgium: Université Libre de Bruxelles.

(Ghani et al. 2008) Ghani, M.U., Abukhshim, N.A. & Sheikh, M.A. (2008). An investigation of heat partition and tool wear in hard turning of H13 tool steel with CBN cutting tools. *International Journal of Advanced Manufacturing Technology*, 39(9-10), 874-888.

(Goverkar et al. 2000) Govekar, E., Gradishek, J., & Grabec, I. (2000). Analysis of acoustic emission signals and monitoring of machining process. *Ultrasonics*, 38, 598-603.

(Gupta 1989) Gupta, G. (1989). A System Dynamics Model for Automation, In: *System Dynamics Society, the 7th International Conference of the System Dynamics Society*. Stuttgart, Germany 11-13 July 1989.

(Hamdan & Bayoumi 1989) Hamdan, M. N., & A. E. Bayoumi. (1989) An approach to study the effects of tool geometry on the primary chatter vibration in orthogonal cutting. *Journal of Sound and Vibration*, 128(3), 451-469.

(Huh & Pak 2003) Huh, K. & Pak, C. (2003). Unmanned turning force control based on the spindle drive characteristics. *JSME International Journal Series C*, 46(1), 314-321.

(Inasaki 1998) Inasaki, I. (1998). Application of acoustic emission sensor for monitoring machining processes. *Ultrasonics*, 36, 273-281.

(Jawahir 1988) Jawahir, I. S. (1988). A Survey and Future Predictions for the Use of Chip Breaking in Unmanned Systems. *International Journal of Advanced Manufacturing Technology*, 3(4), 87-104.

(Jemielniak & Otman 1998) Jemielniak, K. & Otman, O. (1998). Tool failure detection based on analysis of acoustic emission signals. *Journal of Materials Processing Technology*, 76(1-3), 192-197.

(Jemielniak & Szafarczyk 1992) Jemielniak, K. & Szafarczyk, M. (1992). Detection of Cutting Edge Breakage in Turning. *Annals of the CIRP*, 41(1), 97-100.

(Jemielniak et al. 2012) Jemielniak K., Urbánski T., Kossakowska J. & Bombínski S. (2012). Tool condition monitoring based on numerous signal features. *International Journal of Advanced Manufacturing Technology*, 59, 73-81

(Koren 1989) Koren, Y. (1989). The optimal locus approach with machining applications. *Journal of Dynamic Systems, Measurement, and Control*, 111, 260-267.

(Khraisheh et al. 1995) Khraisheh, M. K., Pezeshki, C. & Bayoumi, A. E. (1995). Time series based analysis for primary chatter in metal cutting. *Journal of Sound and Vibration*, 180(1), 67-87.

(Laakso et al. 2013) Laakso, S., Peltokorpi, J., Ratava, J., Lohtander, M. & Varis, J. (2013). Graph-Based Analysis of Metal Cutting Parameters. In Américo Azevedo (Ed.) *Advances in Sustainable and Competitive Manufacturing Systems* (627-636). Springer International Publishing.

(Lan & Dornfeld 1984) Lan, M.S. & Dornfeld, D.A. (1984). In-process tool fracture detection. *ASME Journal of Engineering Materials and Technology*, 106, 111-118.

(Leppänen et al. 2009) Leppänen, J., Ryynänen, V., Ratava, J., Lindh, T., Rikkonen, M., Kyrki, V., Varis, J. & Kälviäinen, H. (2009). *Oppiva reaaliaikainen analysointi- ja säätöjärjestelmä sorvaukseen (FeedChip)*. Sihvo, I. (Ed.) Lappeenranta, Finland: Lappeenranta University of Technology.

(Leppänen et al. 2010) Leppänen, J., Ryynänen, V., Ratava, J., Hynynen, K., Vian, A., Jastrzebski, R., Lindh, T., Rikkonen, M., Varis, J. & Sihvo, I. (2010) *Viimeistelysorvauksen analysointi- ja säätöjärjestelmä (FeedChip2)*. Lappeenranta, Finland: Lappeenranta University of Technology.

(Li et al. 1997) Li, X.Q., Wong, Y.S. & Nee, A.Y.C. (1997). Tool wear and chatter detection using the coherence function of two crossed accelerations. *International Journal of Machine Tools and Manufacturing*, 37(4), 425-435.

(Liao & Young 1996) Liao, Y.S. & Young, Y.C. (1996). A new on-line spindle speed regulation strategy for hatter control. *International Journal of Machine Tools and Manufacturing*, 36, 651-660.

(Mamdani 1974) Mamdani, E.H. (1974). Application of fuzzy algorithms for control of simple dynamic plant. *Proceedings of the Institution of Electrical Engineers*, 121(12), 1585-1588.

(Mamdani & Assilian 1975) Mamdani, E.H. & Assilian, S. (1975). An experiment in linguistic synthesis with a fuzzy logic controller. *International Journal of Man-Machine Studies*, 7(1), 1-13.

(Marui et al. 1983) Marui, E., S. Ema, & S. Kato. (1983) Chatter vibration of lathe tools. Part 1: General characteristics of chatter vibration. *Journal of Manufacturing Science and Engineering*, 105(2), 100-106.

(Masory et al. 1980) Masory, O., Koren Y. & Weill R. (1980). Adaptive Control System for Turning. *CIRP Annals - Manufacturing Technology*, 29, 281-284.

(Merritt 1965) Merritt, H. E. (1965). Theory of Self-Excited Machine-Tool Chatter, Contribution to Machine-Tool Chatter, Research-1. *Journal of Manufacturing Science and Engineering*, 87(4), 447-454.

(Moriwaki 1980) Moriwaki, T. (1980). Detection for cutting tool fracture by acoustic emission measurement. *CIRP Annals – Manufacturing Technology*, 29(1), 35-40.

(Moriwaki & Mori 1993) Moriwaki, T. & Mori, Y. (1993). Recognition of cutting state based on neural network sensor fusion. *Journal of the Japan Society of Precision Engineering*, 59(5), 779-784.

(Namachchivaya & Beddini 2003) Namachchivaya, N.S. & Beddini, R. (2003). Spindle Speed Variation for the Suppression of Regenerative Chatter. *Journal of Nonlinear Science*, 13, 265-288.

(Nedelß et al. 1989) Nedelß, C., Hintze, W. & Van Luttervelt, C.A. (1989). Characteristic parameters of chip control in turning operations with indexable inserts and three-dimensionally shaped chip formers. *CIRP Annals – Manufacturing Technology*, 38, 75-79.

(Ngin & Wong 1997) Ngin, P.M. & Wong, P.-K. (1997). Workers' perceptions of automated production work in Singapore's electronics industry. *Asia Pacific Journal of Management*, 14, 67-87.

(Otto & Radons 2013) Otto, A. & Radons, G. (2013). Application of spindle speed variation for chatter suppression in turning. *CIRP Journal of Manufacturing Science and Technology*, 6, 102-109.

(Pavel et al. 2005) Pavel R., Marinescu I., Deis, M. & Pillar, J. (2005). Effect of tool wear on surface finish for a case of continuous and interrupted hard turning. *Journal of Materials Processing Technology*, 170(1-2), 341-349.

(Peltokorpi et al. 2013) Peltokorpi, J., Laakso, S., Ratava, J., Lohtander, M. & Varis, J. (2013). Relationships of Factors in a Manual Assembly Line Environment. In *Advances in Sustainable and Competitive Manufacturing Systems* (985-996). Springer International Publishing.

(Rao & Shin 2008) Rao, B.C., & Shin, Y.C. (2008) Multisensor approaches for chatter detection in milling. *Journal of Sound and Vibration*, 312, 672-693.

(Ratava 2008) Ratava, J. (2008) *Lastuamisen sumea säätö rouhintasorvauksessa*. Lappeenranta, Finland: Lappeenranta University of Technology.

(Ren et al. 2011) Ren, Q., Balazinski, M., Baron, L. & Jemielniak, K. (2011). TSK fuzzy modeling for tool wear condition in turning processes: An experimental study. *Engineering Applications of Artificial Intelligence*, 24(2), 260-265.

(Ryynänen et al. 2010) Ryynänen, V., Vian, A., Ratava, J., Lindh, T., Rikkonen, M., Sihvo, I., Leppänen, J. & Varis, J. (2010) Recognizing Small Tool Breakage during Interrupted Cutting for Turning Operations. In *Proceedings of the 15th International Conference. Mechanika*. 8-9 May 2010, Kaunas, Lithuania.

(Saglan et al. 2007) Saglan, H., Yaldiz, S. & Unsacar, F. (2007) The effect of tool geometry and cutting speed on main cutting force and tool tip temperature. *Materials & Design*, 28(1), 101-111.

(Schmitz 2003) Schmitz, T. (2003) Chatter recognition by a statistical evaluation of the synchronously sampled audio signal. *Journal of Sound and Vibration*, 262, 721-730.

(Schmitz et al. 2001) Schmitz, T., Davies, M., Medicus, K., & Snyder, J. (2001) Improving high-speed machining material removal rates by rapid dynamic analysis. *Annals of the CIRP*, 50, 263-268.

(Stryczek & Orawczak 2013) Stryczek, R, & Orawczak, K. (2013). A fuzzy control strategy in the turning process. *Advances in Manufacturing Science and Technology*, 37(1), 79-88.

(Sugeno 1974) Sugeno, M. (1974). Theory of fuzzy integrals and its applications. Tokyo, Japan: Tokyo Institute of Technology.

(Takagi & Sugeno 1983) Takagi, T. & Sugeno, M. (1983). Multi-dimensional fuzzy reasoning. *Fuzzy Sets and Systems*, 9(2), 313-325.

(Takagi & Sugeno 1985) Takagi, T. & Sugeno, M. (1985). Fuzzy identification of systems and its applications to modeling and control. *IEEE Transactions on Systems, Man and Cybernetics* SMC-15(1), 116-132.

(Tangjitsitcharoen 2009) Tangjitsitcharoen, S. (2009). In-process monitoring and detection of chip formation and chatter for CNC turning. *Journal of Materials Processing Technology*, 209, 4682-4688.

(Tarng et al. 1996a) Tarng, Y.S., Hseih, Y. W. & Li, T. C. (1996). Automatic selection of spindle speed for suppression of regenerative chatter in turning. *International Journal of Advanced Manufacturing Technology*, 11, 12-17.

(Tarng et al. 1996b) Tarng, Y. S., Lin, C. Y., & Nian, C. Y. (1996). An optimization approach for the fuzzy control of turning operations. *Fuzzy Sets and Systems*, 83(3).

(Tarng & Lee 1997) Tarng, Y.S. & Lee, E. C. (1997). A critical investigation of the phase shift between the inner and outer modulation for the control of machine tool chatter. *International Journal of Machine Tools and Manufacture*, 37(12), 1661-1672.

(Tarng et al. 2000) Tarng, Y.S.; Kao, J. Y., & Lee, E. C. (2000). Chatter suppression in turning operations with a tuned vibration absorber. *Journal of Materials Processing Technology*, 105:55-60.

(Taylor 1907) Taylor, F.W. (1907). On the art of cutting metals. *Transactions of the American Society of Mechanical Engineers*, 28, 31-350.

(Tobias & Fishwick 1958) Tobias, S.A. & Fishwick, W. (1958). Theory of regenerative machine tool chatter. *Engineering*, 205.

(Varis et al. 2005)	Varis, J., Pirnes, J. & Selesvuo, J. (2005). Työstönvalvonnan ja -säädön state-of-the-art. Lappeenranta: Lappeenranta University of Technology.
(Wang et al. 2010)	Wang, H., To, S., Chan, C.Y., Cheung, C.F. & Lee, W.B. (2010). A theoretical and experimental investigation of the tool-tip vibration and its influence upon surface generation in single-point diamond turning. *International Journal of Machine Tools and Manufacture*, 50(3), 241-252.
(Yang et al. 2010)	Yang, Y., Muñoa, J. & Altintas, Y. (2010). Optimization of Multiple Tuned Mass Dampers to Suppress Machine Tool Chatter, *International Journal of Machine Tools and Manufacture*, 50(9), 834-842.
(Yu & Shah 2008)	Yu, S.D. & Shah, V. (2008) Theoretical and experimental studies of chatter in turning for uniform and stepped workpieces. *Journal of vibration and acoustics*, 130, 061005.
(Zadeh 1965)	Zadeh, L. A. (1965) Fuzzy sets. *Information and Control,* 8(3), 338-353.
(Zadeh 1975)	Zadeh, L. A. (1975) The Concept of a Linguistic Variable and its Application to Approximate Reasoning – I, *Information Sciences*, 8(3), 199-249.

Publ. I

An adaptive fuzzy control system to maximize rough turning productivity and avoid the onset of instability

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Publ. II

Modelling cutting instability in rough turning 34CrNiMo6 steel

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Publ. III

Chatter detection in turning processes using coherence of acceleration and audio signals

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Chatter Detection in Turning Processes Using Coherence of Acceleration and Audio Signals

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Chatter is an unfavorable phenomenon in turning operation causing poor surface quality. Active chatter elimination methods require the chatter to be detected before the control reacts. In this paper, a chatter detection method based on a coherence function of the acceleration of the tool in the x *direction and an audio signal is proposed. The method was experimentally tested on longitudinal turning of a stock bar and facing of a hollow bar. The results show that the proposed method detects the chatter in an early stage and allows correcting control actions before the chatter influences the surface quality of the workpiece. The method is applicable both to facing and longitudinal turning.*
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1 Introduction

Chatter is a dynamic instability that results from the interaction between the structural dynamics of the system and the metal cutting process. Chatter is characterized by violent vibrations that cause poor surface quality, damage of the cutting tool, and loud noise. Poor surface quality in rough turning may be tolerated as long as surface integrity is maintained on the last machining passes. However, the occurrence of chatter in finishing will spoil the workpiece.

In modern production, an objective is to increase the productivity of the manufacturing processes. Therefore, a control that significantly reduces the material removal rate to eliminate chatter is not desirable. The passive chatter detection methods include, for example, tuned vibration absorbers that tend to increase the damping and stiffness of the system [1,2], and a spindle speed modulation approach where the spindle speed is varied continuously in order to avoid the chatter [3,4]. The active chatter elimination methods are based on a feedback with the sensors examining the state of the system and eliminating chatter by applying control once the phenomenon appears. Magnetic dampers have been used to actively change the damping and stiffness parameters of the system [5,6]. The spindle speed [7–9] may also be varied until the chatter free state is achieved.

The active chatter elimination methods require that the chatter is detected before a corrective action is taken. Incipient chatter rapidly proceeds to harmful chatter, spoiling the machined surface. Hence, a fast detection of an early chatter is an absolute demand. Several sensors can be used to recognize chatter: dynamometers to measure cutting forces [10–13], accelerometers to detect tool vibrations [13–15], a microphone to record an audio signal [15–18], acoustic emission [19], and ultrasound [20]. In addition, there are machine vision applications to detect chatter [21]. Kuljanic et al. [22] propose a multisensor approach in order to detect the chatter accurately and robustly. The most common analysis methods to detect the chatter include frequency domain methods such as a Fourier transform [11,13,19], a power spectral density (PSD) estimate [12], a probability density function [10], and a coherence function between two sensor signals [23]. Time domain methods include a variance [17,18], coarse-grained entropy rate [24,25], and a wavelet transform [14] analysis.

In this paper, a coherence function is used to predict the onset of chatter. A similar method has been applied to detect chatter in machining of superalloys from the coherence function of two crossed accelerations measured from the tool [23]. However, the accelerations, being dependent from each other, may contain similar frequency content, thus making the chatter detection difficult. Either the chatter may not be detected or other oscillations may be erroneously detected as chatter. In order to avoid that, the coherence function is determined from two independent measurements measuring different consequences of chatter, that is, from the acceleration in the x direction and the audio signal. The chatter causes vibration to the structure that is measured by accelerometer. On the other hand, the microphone measures the sound caused by the tool contact force. The chosen combination of signals can detect chatter both for a stock bar and for a hollow workpiece such as a drum. The method is applicable both to facing and longitudinal turning.

2 Regenerative Chatter

Regenerative chatter is commonly modeled as a closed-loop interaction between the structural dynamics of the system and the cutting process [26]. Structural vibrations of the workpiece, the tool and the lathe structure induce waviness in the surface of the workpiece during the turning operation causing the radial chip thickness to fluctuate. After one full turn of the workpiece, the tool meets the undulations of the previous turn. If the phase shift of the undulations is unfavorable, the structural vibrations may transform into harmful regenerative chatter [6,26,27].

The phase shift ε between two successive rotations is determined as

$$\omega_c T = 2\pi p - \varepsilon \tag{1}$$

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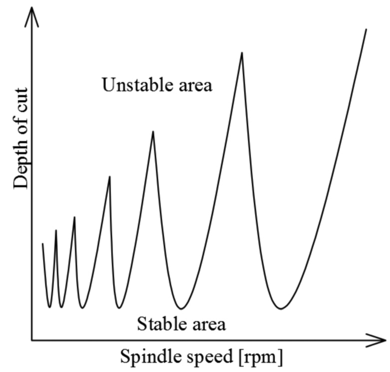

Fig. 1 Stability diagram represents the stable cutting areas as a function of spindle speed and depth of cut

where ω_c is a chatter frequency in rad/s, T is the time of a full rotation of the workpiece, and $p = 0, 1, \ldots$ is the number of the whole undulations during one rotation [7]. At the most stable spindle speeds, shown as peaks in a stability diagram such as Fig. 1, the phase shift of the successive cuts is 0 deg [6].

3 Chatter Detection

The proposed chatter detection method is based on the coherence function of the acceleration of the tool in the x direction and the audio signal. The applied sensor combination has been chosen while the chatter generates as a result of the vibrations in the direction normal to the tool, that is, in the x direction, and the audio signal has been found to detect chatter very well [28]. The operation of the microphone in chatter detection is based on the acoustic pressure during the machining that is proportional to the displacement of the tool [29].

A coherence function between the acceleration in the x direction $x(t)$ and the audio signal $a(t)$ is calculated as

$$\gamma^2(f) = \frac{|G_{xa}(f)|^2}{G_x(f)G_a(f)}, \qquad 0 \le \gamma^2(f) \le 1 \tag{2}$$

where $G_x(f)$ and $G_a(f)$ are the auto spectra of the signals $x(t)$ and $a(t)$, and $G_{xa}(f)$ is their cross spectrum. If the measured signals $x(t)$ and $a(t)$ are correlated at certain frequencies f, the coherence function at those frequencies $\gamma^2(f) = 1$. At those frequencies where the signals are not correlated, the coherence function $\gamma^2(f) = 0$. In practice, the coherence function gets values $0 \le \gamma^2(f) \le 1$ if the system contains additional noise or if the relation of the signals in consideration is not linear. The threshold value of the chatter is chosen close to 1.

The coherence function can be used to detect chatter while at the onset of chatter, the behavior of the vibration changes from random to harmonic, causing the autospectra of the measured signals to contain a single peak at the chatter frequency [23].

4 Experimental Setup

The experimental test were carried out using two types of lathes. A ZMM CU500M manual lathe in laboratory conditions was used in longitudinal turning (axial direction tool movement) and a Doosan Puma 700LM computer numerical control (CNC) lathe in industrial environment for facing (radial direction tool movement).

In longitudinal turning, the workpiece was quenched and tempered steel 42CrMo4 treated with Ca (hardness 320 HB), 800 mm × ∅ 60 mm (initially). The cutter insert was Sandvik Coromant DNMG 150608 WM with a capto holder. The lead cutting angle was 75 deg. After removing the surface layer, the initial cutting diameter was 53 mm. Eleven samples were collected at depth of cut a_c 1.0 mm and feed rate f_c 0.3 mm/rev, with spindle speeds varying between 1001 and 1425 rpm. The manual lathe was also used in control tests, equipped with an ABB ACS800 frequency converter in order to control the spindle speed. In the control test, the depth of cut was 1.0 mm and the feed rate 0.3 mm/rev, with an initial spindle speed of 1253 rpm.

The workpiece in facing was a 640 mm outer diameter hollow cylinder made of structural steel. Tools were supplied by an industrial partner. A total of 12 samples were collected, nine of which had the depth of cut a_c 1.0 mm with initial feed rates f_c 0.1–0.3 mm/rev and initial spindle speed 50 rpm. The cutting speed v_c was 100–150 m/min. Additionally, three samples were collected at a_c of 2.0 mm and initial f_c 0.3 mm.

The acceleration along the x axis was measured with a SKF CMSS786A acceleration sensor having a sensitivity of 100 mV/g and a measurement range of ±80 g and a frequency response of 1–9000 Hz (±10%). The sensor was secured to the tool holder directly opposite the tool with a screw to prevent movement. For the audio channel, a Shure Prologue 14 L microphone was used, mounted on a flexible mount on the tool carriage. The frequency response of the microphone is 40–13,000 Hz (±6 dB). The microphone was equipped with a cone to create a directional microphone. The spindle speed of the lathe was measured with a proximity sensor generating three pulses per revolution. The sensors were recorded at a sampling frequency of 10,000 Hz and recorded input was filtered with a three-element median filter. For the surface roughness measurements, a Taylor Hobson Surtronic 10 instrument was used.

5 Results

The proposed coherence function method for chatter detection was verified with two types of turning machines on two different types of workpieces. Initial tests were made in laboratory conditions with a manual lathe. In addition, some data were collected from an industrial machine shop, where a CNC turning machine was used. Finally, automatic chatter mitigation was tested in the laboratory with a manual lathe equipped with a frequency converter to control the motor speed and therefore, the spindle speed.

5.1 Chatter Detection Experiments. The first chatter detection experiment was carried out with a manual type lathe. In this experiment, longitudinal turning was used. The upper graph of Fig. 2 shows the acceleration of the tool holder in the x direction as a function of time, and the coherence function of the acceleration and the audio signal. The cutting starts at time 0.59 s and it can be divided into three sections. The first section lasts until the

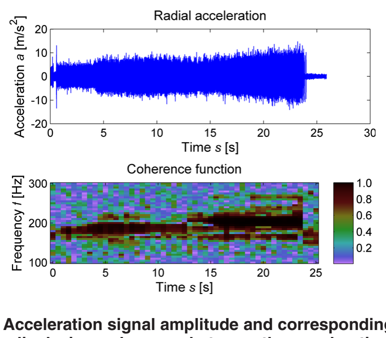

Fig. 2 Acceleration signal amplitude and corresponding spectrogram displaying coherence between the acceleration in the radial direction and the audio signal measured from the manual lathe

time 4 s. The amplitude of the acceleration is about 5 m/s^2, by visual examination there is no chatter, and the surface roughness is measured to be $R_a = 1.2$. Near the tail stock, where the workpiece is well supported, the result is expected. The second section lasts from 4 s to 14 s. The amplitude of the acceleration increases to about 7 m/s^2. The chatter is detected both from the surface quality, and the noise during the cutting and the surface roughness varies between $R_a = 2.0$–2.5. In the third section from 14 s to the end of the cut 23.5 s, the chatter degrades itself, the amplitude of the acceleration increases linearly, and the measured surface roughness is $R_a = 3.1$.

The lower graph of Fig. 2 shows the coherence function of the acceleration of the tool in the x direction and the audio signal as a function of time and frequency. The values of the coherence function are displayed with colors with the scale presented to the right of the graph. The lighter tones indicate low values of the coherence function, and thus, no chatter while the darker tones indicate higher values, and thus, chatter. In this paper, the value of 0.9 is set as a threshold for harmful chatter. The coherence function of Fig. 2 indicates chatter at time 3.2 s at frequency 181 Hz. That is 0.8 s before the amplitude of the acceleration starts to increase. While the chatter is not eliminated, several frequencies around 181 Hz increase above the threshold value 0.9. At time 13 s, the coherence function indicates that the chatter frequency has changed to 205 Hz when the amplitude of the acceleration starts to increase only at 14 s.

The second experiment was carried out in the machine shop industry with a CNC turning machine. Face cutting was performed for a hollow cylinder with the diameter of 640 mm. An experienced NC operator was able to detect the chatter from the fluting sound during the cutting process, and after the process, a low profile caused by minor chatter could be seen from the dull surface. However, the level of chatter was not yet considered harmful. Figure 3 shows the coherence function of the acceleration of the tool in the x direction and the audio signal for the experiment in consideration. The coherence function indicates values above 0.7 and occasionally up to 0.8 in the vicinity of the frequency 180 Hz. The threshold value 0.9 is not exceeded, agreeing with the human expert that the detected vibration is not considered harmful.

5.2 Chatter Elimination Experiment. The behavior of the proposed chatter detection method was evaluated together with a control similar to Tarng et al. [7,8]. Based on the theory of regenerative chatter, the cutting process is always stable with small enough depth of cut a, see Fig. 1. However, using a very low depth of cut turning rapidly increases the cutting time. With a higher depth of cut, the system remains stable only at certain spindle speeds. The highest stability limit is obtained at the spindle speeds that keep the phase shift of the undulations caused by vibrations at 0 deg. The stable spindle speeds, n, can be calculated based on Eq. (1). When the phase shift ϵ is set zero, the spindle speed is

$$n = \frac{f_c}{p}, \qquad p = 1, 2, 3, 4, \ldots \tag{3}$$

where f_c is the frequency of the detected chatter and p is the number of the undulations during one rotation. Upon detecting chatter, a stable spindle speed is calculated and selected. If the system stabilizes itself, the cutting continues at that spindle speed. If the chatter continues or starts again, the process is repeated. Since the stable regions are wider at higher spindle speeds, as shown in Fig. 1, the control attempts to use a higher spindle speed, if possible. Should this surpass a given maximum spindle speed limit, the control attempts to reach the next lower stable speed instead.

Figure 4 shows the coherence of the acceleration and audio signals as a function of time and frequency, and the spindle speed as a function of time. Machining started with a spindle speed of 1253 rpm, with a nearly instant onset of minor chatter at approximately 205 Hz as well as at higher frequencies. At 12.5 s to the experiment, the coherence of the chatter signal was high enough to trigger chatter detection. After reaffirming this assessment with three consecutive samples, the control automation took action at 14.1 s, increasing the spindle speed to 1259 rpm. The chatter decays but soon resumes, prompting a second control action to be taken at 16.3 s to 1399 rpm, this time eliminating all but the most major occurrence of chatter at 205 Hz, which decays but again reappears. The final control action was taken at 23.8 s to 1537 rpm, successfully eliminating all chatter. This result was verified by visual inspection of the workpiece as well as by measuring the average surface roughness R_a. The initial surface roughness was 1.5. During the onset of chatter, the surface roughness increased to 1.9, but was reduced to 1.6 by applying control.

6 Discussion

The performed chatter detection measurements show that the coherence function method can detect the chatter about 0.8–1 s before the amplitude of the acceleration starts to increase and degrade the surface quality of the workpiece. In the second experiment, detected vibrations were not yet considered harmful. Depending on the application, it may be necessary to change the threshold level when vibrations are considered harmful. Determining this level may require experiments. However, the method can clearly measure vibrations weaker than the threshold for materials used in these experiments and is therefore considered to be sensitive enough.

In the experiment to mitigate chatter by spindle speed control, the detection method was suitably fast in order the control to react and mitigate the vibrations. However, the challenge of spindle speed selection to mitigate chatter is that the stable lobes at low spindle speeds are very narrow, requiring precise control. At

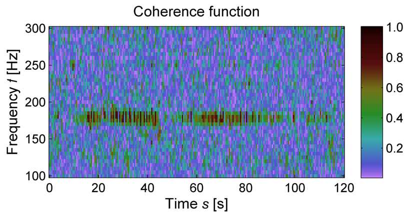

Fig. 3 Chatter detection measurement in facing with a CNC turning machine and a hollow cylinder. The coherence function between the acceleration of the tool in the *x* direction and the audio signal.

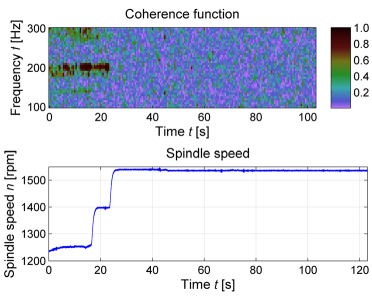

Fig. 4 Chatter elimination measurement. The coherence function between the acceleration of the tool in the *x* direction and the audio signal, and the spindle speed *n*.

higher spindle speeds, the stable lobes are wider but using these may decrease tool life. Therefore, other methods to mitigate chatter should be considered.

The audio signal has been considered inference-prone because of the high possibility of external interference in noisy surroundings such as industrial machine shops. Both sensors capture several frequency components caused by different sources. The coherence function only indicates the frequencies which are visible in both sensors and are assumed to be emitted by the same source, in this case chatter. External noise is omitted as it is not captured by both sensors.

7 Conclusions

A novel chatter detection method for turning operation was evaluated and concluded to detect chatter in an early phase. A coherence function of the acceleration of the tool in the radial direction and the audio signal were used. The feasibility of the method was evaluated by longitudinal turning of a stock bar with a manual and a facing a hollow cylinder with a CNC lathe. In addition, the method was evaluated as an input for spindle speed selection to mitigate chatter and found to be effective and easily implementable. Due to sensitivity of selecting the correct spindle speed, different control methods should be considered.

Acknowledgment

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References

[1] Tarng, Y. S., Kao, J. Y., and Lee, E. C., 2000, "Chatter Suppression in Turning Operations With a Tuned Vibration Absorber," J. Mater. Process. Tehnol., **105**, pp. 55–60.

[2] Yang, Y., Muñoa, J., and Altintas, Y., 2010, "Optimization of Multiple Tuned Mass Dampers to Suppress Machine Tool Chatter," Int. J. Mach. Tools Manuf., **50**(9), pp. 834–842.

[3] Namachchivaya, N. S., and Beddini, R., 2003, "Spindle Speed Variation for Suppression of Regenerative Chatter," J. Nonlinear Sci., **13**, pp. 265–288.

[4] Otto, A., and Radons, G., 2013, "Application of Spindle Speed Variation for Chatter Suppression in Turning," CIRP J. Manuf. Sci. Technol., **6**(2), pp. 102–109.

[5] Chen, M., and Knospe, C., 2007, "Control Approaches to the Suppression of Machining Chatter Using Active Magnetic Bearings," IEEE Trans. Control Syst. Technol., **15**(2), pp. 220–232.

[6] Ganguli, A., 2005, "Chatter Reduction Through Active Vibration Damping," Ph.D. thesis, Université Libre, de Bruxelles, Brussels, Belgium.

[7] Tarng, Y. S., Hseih, Y. W., and Li, T. C., 1996, "Automatic Selection of Spindle Speed for Suppression of Regenerative Chatter in Turning," Int. J. Adv. Manuf. Technol., **11**, pp. 12–17.

[8] Tarng, Y. S., and Lee, E. C., 1997, "A Critical Investigation of the Phase Shift Between the Inner and Outer Modulation for the Control of Machine Tool Chatter," Int. J. Mach. Tools Manuf., **37**(12), pp. 1661–1672.

[9] Bediaga, I., Muoa, J., Hernndez, J., and de Lacalle, L. N. L., 2009, "An Automatic Spindle Speed Selection Strategy to Obtain Stability in High-Speed Milling," Int. J. Mach. Tools Manuf., **49**, pp. 384–394.

[10] Bao, S.-F., Zhang, W.-G., Yu, J.-Y., Qiao, S.-M., and Yang, F.-L., 1994, "A New Approach to the Early Prediction of Turning Chatter," J. Vib. Acoust., **116**, pp. 485–488.

[11] Liao, Y. S., and Young, Y. C., 1996, "A New On-Line Spindle Speed Regulation Strategy for Chatter Control," Int. J. Mach. Tools Manuf., **36**, pp. 651–660.

[12] Tangjitsitcharoen, S., 2009, "In-Process Monitoring and Detection of Chip Formation and Chatter for CNC Turning," J. Mater. Process. Technol., **209**, pp. 4682–4688.

[13] Rao, B. C., and Shin, Y. C., 2008, "Multisensor Approaches for Chatter Detection in Milling," J. Sound Vib., **312**, pp. 672–693.

[14] Choi, T., and Shin, Y. C., 2003, "On-Line Chatter Detection Using Wavelet-Based Parameter Estimation," ASME J. Manuf. Sci. Eng., **125**, pp. 21–28.

[15] Eynian, M., and Altintas, Y., 2009, "Chatter Stability of General Turning Operations With Process Damping," ASME J. Manuf. Sci. Eng., **131**, p. 041005.

[16] Yu, S. D., and Shah, V., 2008, "Theoretical and Experimental Studies of Chatter in Turning for Uniform and Stepped Workpieces," J. Vib. Acoust., **130**, p. 061005.

[17] Schmitz, T., Davies, M., Medicus, K., and Snyder, J., 2001, "Improving High-Speed Machining Material Removal Rates by Rapid Dynamic Analysis," Ann. CIRP, **50**, pp. 263–268.

[18] Schmitz, T., 2003, "Chatter Recognition by a Statistical Evaluation of the Synchronously Sampled Audio Signal," J. Sound Vib., **262**, pp. 721–730.

[19] Chiou, R. Y., and Liang, S. Y., 2000, "Analysis of Acoustic Emission in Chatter Vibration With Tool Wear Effect in Turning," Int. J. Mach. Tools Manuf., **40**, pp. 927–941.

[20] Abu-Zahra, N. H., and Lange, J. H., 2002, "Tool Chatter Monitoring in Turning Operations Using Wavelet Analysis of Ultrasound Waves," Int. J. Adv. Manuf. Technol., **20**, pp. 248–254.

[21] Khalifa, O. O., Densibali, A., and Faris, W., 2006, "Image Processing for Chatter Identification in Machining Processess," Int. J. Adv. Manuf. Technol., **31**, pp. 443–449.

[22] Kuljanic, E., Sortino, M., and Totis, G., 1999, "A Comprehensive Dynamic Cutting Force Model for Chatter Prediction in Turning," Int. J. Mach. Tools Manuf., **39**, pp. 1631–1654.

[23] Li, X. Q., Wong, Y. S., and Nee, A. Y. C., 1997, "Tool Wear and Chatter Detection Using the Coherence Function of Two Crossed Accelerations," Int. J. Mach. Tools Manuf., **37**(4), pp. 425–435.

[24] Gradiek, J., Govekar, E., and Grabec, I., 1998, "Time Series Analysis in Metal Cutting: Chatter Versus Chatter-Free Cutting," Mech. Syst. Signal Process., **12**(6), pp. 839–854.

[25] Gradiek, J., Govekar, E., and Grabec, I., 1998, "Using Coarse-Grained Entropy Rate to Detect Chatter in Cutting," J. Sound Vib., **214**(5), pp. 941–952.

[26] Merritt, H. E., 1965, "Theory of Self-Excited Machine-Tool Chatter, Contribution to Machine-Tool Chatter, Research-1," ASME J. Eng. Ind., **87**(4), pp. 447–454.

[27] Tobias, S. A., and Fishwick, W., 1958, "Theory of Regenerative Machine Tool Chatter," Engineer, pp. 199–203.

[28] Delio, T., Tlusty, J., and Smith, S., 1992, "Use of Audio Signals for Chatter Detection and Control," ASME J. Eng. Ind., **114**(2), pp. 146–157.

[29] Nair, U., Krishna, B. M., Namboothiri, V. N. N., and Nampoori, V. P. N., 2010, "Permutation Entropy Based Real-Time Chatter Detection Using Audio Signal in Turning Processess," Int. J. Manuf. Technol., **46**, pp. 61–68.

Publ. IV

Chip control system for monitoring the breaking of chips and elimination of continuous chips in rough turning

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Chip control system for monitoring the breaking of chips and elimination of continuous chips in rough turning

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1. Introduction

All industrial activity must be productive. The search for ways to improve productivity is an ongoing pursuit. Measures that were sufficient for improving productivity a year ago are no longer adequate. The productivity of part manufacture in the metal cutting industries has been improved mainly by increasing automation in handling the work piece outside the machine tool. The processes themselves and their control also need to be developed – especially by making the cutting processes more efficient in terms of systems technology.

The formation of chips plays a key role in making the cutting process run smoothly. A continuous chip is formed when the chip does not break off. In normal cutting conditions, the chip breaks off on its own, against the tool or work piece. Discontinuous chips are a prerequisite for safe and productive machining. A continuous chip is a long metal string that becomes tangled or wraps around the cutting tool or around the turning work piece. A continuous chip may damage the machine tool if it forms a large enough tangle around the cutting tool.

A number of models have been generated to forecast the breaking of the chip [1]. They are not, however, directly applicable to the adaptive control of machining. Consequently, research on the form of the chip during machining [2, 3] is important. In some researches the shape, length and colour of the chips has been inspected visually during cutting tests [4]. Efforts have been made to forecast chip formation and control it during machining especially in unmanned production [5], in which continuous chips mean interruptions in production. Appropriate chip formation is necessary in order for the cutting to proceed without obstacles.

Monitoring the length of chips during machining may focus on measuring the length of the chip (e.g. with machine vision) or detecting the breaking of the chip with signals such as acoustic emission. Earlier studies [6] indicate that a force sensor attached to the tool holder can be used to define the breaking frequency of chips. However, attaching such sensors to the tool holder is problematic since tools are changed continuously. Several studies have shown that a continuous chip can also be detected with acoustic emission signals [7-9]. The studies have demonstrated that sources for AE signals in metal cutting include, e.g. the breaking of the tool or the chip [7, 9].

Microphone signals detect continuous chips only randomly, and therefore, their use as the only detection method is not justified [10].

1.1. Research objective

This study developed a chip control system for rough turning that monitors the breaking of chips, estimates the length of the chips and eliminates continuous chips if those are formed. Chip breaking was identified with acoustic emission signals during machining. The objective was to create a system that could break chips off (eliminate them) even when increasing the feed will no longer induce the breaking of the chip.

2. Created control system

The system was built around the NC turning machine Doosan Daewoo Puma 2500Y at Lappeenranta University of Technology. The turning machine included Fanuc 18i-TB control. The prototype system included a PC equipped with the Windows XP operating system and the National Instruments data acquisition board PCI-6251, and another PC with the GNU/Linux Debian 3 operating system and a Fire wire port.

2.1. Description of the system

The measurement system built in connection with this study for detecting continuous chips uses an acoustic emission sensor. Previous experiments include, e.g. two acceleration sensors (vertical and horizontal), a microphone and the measurement of electric power consumed by the spindle and feed motor. These practical tests indicated, however, that acoustic emission was the most reliable method for detecting continuous chips.

Acoustic emission was measured with an acoustic emission sensor (SEA) and amplifier (SEP) manufactured and used by Nordmann GmbH as a part of their machining control equipment. The AE sensor was attached to the tool holder with screws (Fig. 1), and was positioned as close to the tool as possible, taking into account usability and protection-related restrictions. The cables of the sensors are protected with steel tubes, and in addition, the sensors in the tool holder are protected with a metallic shell during cutting.

The measurement area of the acoustic emission sensor extends to approximately 1 MHz according to the manufacturer. The high-frequency signal (typically > 100 kHz) is modified in the amplifier (SEP), which allows the high-frequency vibration – the acoustic emission – to be detected at lower frequency bands.

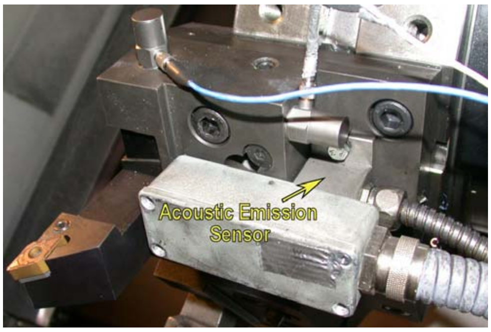

Fig. 1 Positioning of the sensor on the tool holder of the turning machine turret

The analogy signals received from the sensors are transmitted to one of the computers with the data acquisition board. The data acquisition board was a multichannel PCI-6251 model manufactured by National Instruments and attached to the PCI. The A/D conversion resolution of the data acquisition board is 16 bits, and the multichannel composite maximum sampling rate is 1 MS/s

The data from the data acquisition board is captured using National Instruments LabVIEW software suite. The program allows creating a measurement interface with which the captured measurements can be monitored in real time, and the sampling frequency can be changed. As a rule, a frequency of 20 kS/s (20 kHz) was used in the experiments. Thus for instance the information received through the AE sensor is read and saved on the hard drive at the rate of 20,000 samples per second. In addition the MathWorks Data Acquisition Toolbox (DAT) plug-in for MATLAB was installed on the computer. Consequently, the data from the data acquisition board could also be handled directly to MATLAB and Simulink software without using a separate data acquisition suite.

2.2. Signal processing

The purpose of the chip length estimator is to enable continuous real time chip length control so that the chip length can be set to any acceptable value. In such case, the recognition of continuous chips does not suffice, but the estimator should output a continuous value. Inasaki [7] has used an acoustic emission (AE) sensor to monitor a cutting process. The AE signal was analyzed in the time and frequency domains, and different indicators such as kurtosis and standard deviations were calculated. The calculated values were fed to a neural network, which classified the samples into continuous or discontinuous ones. Andreassen [6] has applied a feed force measurement to automatic detection of chip breakage; he uses power spectrum peak features to detect chip length.

The chip break initiates a stress wave that propagates in the tool and the turret. The AE sensor measures these stress waves that have a very high, material-dependent frequency (hundreads of kilohertz). By taking an envelope of the gathered signal and measuring the repetition frequency of the bursts, the time interval between the chip breaks can be estimated. The standard deviation of chip length can be relatively large, often half of the mean length. For example, using the cutting speed of 150 m/min, a 10 mm chip mean length with a 5 mm deviation produce a 270 Hz center frequency with a bandwidth of about 270 Hz. Correspondingly, a 10 cm mean chip length with a 5 cm deviation would produce a 27 Hz center frequency with a 27 Hz bandwidth. Therefore, the chip length is not estimated solely from the frequency peak amplitudes, but the developed algorithm searches for frequency ranges that have a high energy content compared to their neighbourhoods.

The chip length estimate is used as feedback in the feed control. The continuous chip should be recognized in a few seconds for the control. Therefore, a long average time is not possible. The proposed method calculates chip length from the power spectrum of the envelope of the AE signal. The power spectrum is formed using the Welch estimate from a 1.6 second sample with four overlapping sections to attenuate interference and noise. However, the power spectrum obtained still contains many narrowband frequency peaks that are filtered out by a median filter. The baseline of the spectrum plot is a monotonically decreasing curve. In order to find areas where the energy content is higher than in its neighbourhood (knobs), the baseline is removed from the spectrum (the baseline value is subtracted from the spectrum value of a corresponding frequency). In this, the baseline is removed by using ray casting. The spectrum obtained is divided into narrow frequency bands, and the highest peaks in all bands are selected. The energy of the knob containing any selected peak is calculated. Four knobs of the highest energy are selected as candidates for the repetition frequency of chip breakage. The ratio of the energy of the knob to the total energy of the spectrum is calculated. These four candidates and their energies and energy ratios are returned to the decision-making machine. In Fig. 2 the chip length detection procedure is illustrated. The three peaks near 300 Hz show the same knob with high energy, and the chip length is calculated from the knob including these frequencies.

The chip length estimator algorithm, according to tests with hundreds of samples, recognizes the chip length very accurately. However, the detection fails occasionally when the chip is long or continuous, as can be seen in Fig. 3 that illustrates detection of chip length with 30 consecutive data samples is illustrated. The observer has approximated the chip length visually without any measurement devices. The continuous chip is plotted as 75 mm. In the case of a continuous chip, the estimator finds the high energy frequency range at low frequencies corresponding to a long chip (> 50 mm). The estimator fails in the recognizing a continuous chip with samples 28 and 29, but recognizes the situation in the next sample 30.

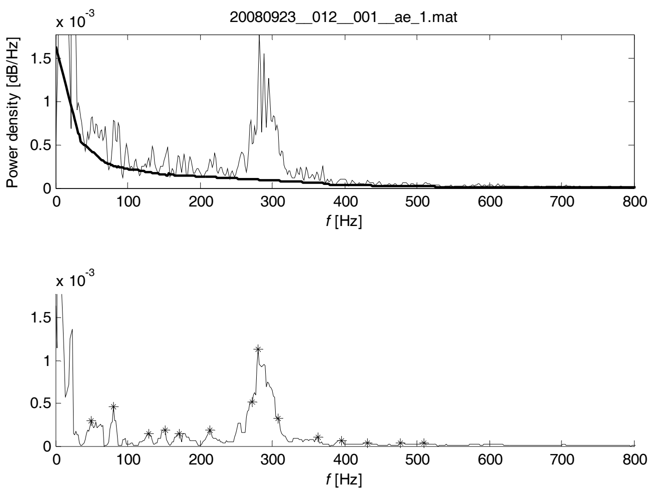

Fig. 2 Detection of chip breakage. In the upper figure, the power spectrum of the enveloped AE signal is presented with the calculated baseline of the spectrum. In the lower figure, the filtered baseline-removed spectrum is illustrated. The markers show the selected frequency peaks

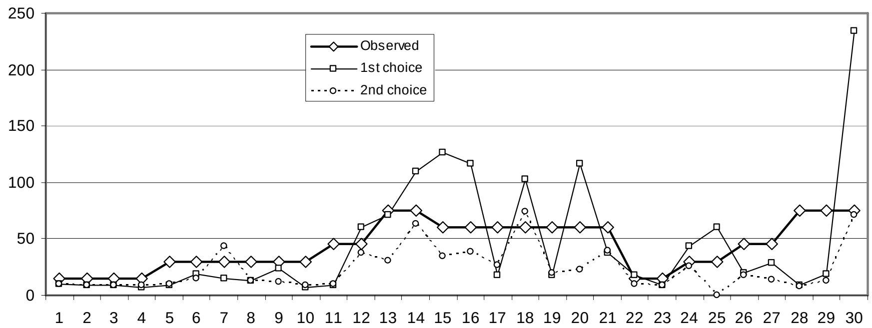

Fig. 3 Detection of chip length with 30 consecutive data samples. The thick curve illustrates the human observer's rough approximation for the chip length in millimetres with the exception that value 75 refers to a continuous chip. The other two curves are the chip length estimates given by the estimator algorithm ranked by energy ratio

2.3. Functionality of the software

The system detects continuous chips based on acoustic emission bursts generated when the chip breaks. Even though the detection of individual bursts may be difficult, examining measurement data collected over a longer time span in the frequency plane allows drawing accurate conclusions on chip length and, to some extent, also the quality of the break. When chips break at even frequencies, the burst generated by the breakage can be detected as a rise in the energy levels of acoustic emission frequency components of the matching frequencies, as described in section 2.2.

The information on the breakage of the chip is entered into the inference system, which also takes into account other possible machining-related observations from the sensors and aims to match the data collected from the turning machine with data on different cutting quality indicators entered into the system. Based on the data collected, on values calculated on the quality of the machining, and on the power consumption of the lathe turning machine, the system modifies the cutting values as needed. The inference system is based on fuzzy logic [11, 12] and can handle a number of demanding problems related to cutting speed and feed simultaneously. The inference system recommends adjustments to the cutting values as seven fuzzy sets: *negative big* (NB), *negative medium* (NM), *negative small* (NS), *zero* (ZE), *positive small* (PS), *positive medium* (PM), and *positive big* (PB). Since fuzzy logic deals with uncertainties, it is possible that more than one of these values are applicable at the same time. The final adjustment is calculated by projecting the geometric centroid of the area covered by the fuzzy sets or the "center of mass" of the adjustment recommendations onto the axis of the value being adjusted (centroid of area method).

The system also interprets long, yet breaking chips as an error in cutting and attempts to increase the feed any time such chips occur. In this case, how much the feed is increased depends on the length of the chip. A very long chip is interpreted as a continuous chip because the identification method applied cannot distinguish between the two cases.

If continuous chips occur, the feed is stopped for a moment, after which a greater feed defined by the inference system is adopted. The feed is stopped because previous tests have indicated that simply increasing the feed during machining does not induce chip breakage. Instead, the feed must be stopped and restarted at a higher rate. This is done also when the system is not quite sure that the chip is continuous, but it is long enough for the change in feed to be PB, i.e. "higher than PM", due to problems in differentiating between a continuous chip and simply a long one.

The software controlling the system is modular, and detection modules can be added to or removed from it. However, all possible scenarios were not explored when testing the prototype. The idea is to be able to add other machining control functions to the system in addition to detecting chip breakage and cutting off chips.

The control mechanism is based on communication between the software and the turning machine control (FOCAS application programming interface in Fanuc control). The software constantly monitors the cutting values of the turning machine with the help of a data transmission link. When they differ from the desired cutting values programmed into the system, the software calculates the difference between the actual cutting values and the desired values. This difference is entered into the memory of the CNC control, and the machine tool carries out the desired changes. When the system is active, the desired control setting takes over the function of the override switches. Correspondingly, the continuous chip is broken with a brief moment of zero feed input, which brings the feed to a halt. Shortly, a higher feed is adopted. In the prototype system, the fuzzy groups *small*, *medium* and *big* correspond to an approximate change of 5, 10, or 15 percent in the control value, respectively. The change can be either negative or positive, depending on the subgroup, and the subgroup *zero* maintains the prevailing feed.

The shortest cutting time needed to cut a continuous chip could not be determined because due to the control mechanism used in the prototype, as the adjustments took at least 0.5 seconds. In such cases, the stopping and restarting of the feed takes one second.

3. System testing

The main test material was quenched and tempered steel 34CrNiMo6 not treated with Ca (hardness 320 HB). In most tests, the tool was manufactured by Sandvik (SNMM 120412-PR GC4015) and was equipped with a tool holder from the same manufacturer (DSBNL 2525M12, positioning angle 75˚).

In addition, the tests used a rhomboidal tool by Sandvik (CNMM 120412-PR GC4015). The rhomboidal tool was held with a PCLNL 2525M12 holder (positioning angle 95˚). Tests were carried out with pressure vessel steel P355NH as the cut material.

3.1. Turning tests for continuous chips

The aim of the turning tests was to research and develop the capacity of the system to detect problems based on signal data saved from sensors. Continuous chips occur with the material 34CrNiMo6 when the feed is low, typically 0.5 mm/r or lower, and when the cutting speed is 150-160 m/min. Continuous chips were not detected at high feeds. However, the test material was hard. With softer and more ductile materials, continuous chips are produced also at higher feeds. The depth of the cut varied in the tests between 1 and 4.5 mm.

3.1.1. Compiling a signal bank

First the features that allowed detecting a continuous chip had to be identified from the sensor signals. An experienced machinist made observations throughout the tests and recorded the observations in a test report. The criticality of the problem (continuous chip) was evaluated on a scale of 1-10. If there was no problem, the test report entry was 1. If a problem occurred at its worst, the report entry was 10. The machinist also entered into the report situations which would have required adjusting the cutting values. On the scale of 1-10, the lower values 1-5 indicated that the problem was not serious enough to require adjustments, whereas the higher values 6-10 indicated a need for adjustment. The observations of the machinist were then compared to the signals emitted by the system. Thus it was possible to isolate the features from the signals that allowed detecting continuous chips.

3.1.2. Detection tests of continuous chips

The detection tests of continuous chips aimed to create a cutting situation that generates a continuous chip. The arrangements were similar to the collection of the signal bank and enabled determining the detection rate. The detection rate was the percentage of situations defined by the machinist that the system could detect correctly, i.e. situations which the system and the machinist interpreted in the same way. The most difficult part of detecting continuous chips was establishing the detection threshold. The detection easily became either too sensitive or too rigid. In the latter case, the chip grew excessively long before it was identified. On the other hand, when the detection was too sensitive, the system categorized chips as too long even if they were tolerable for the process. When the appropriate detection threshold was established, the system correctly identified 76 out of 80. Therefore, the detection rate with the material 34CrNiMo6 and the tool Sandvik SNMM 120412-PR GC4015 was 95%, which is extremely high. The most common error in the detection was a false positive analysis, which meant that the system signalled a continuous chip even if there was none.

Detection tests were also carried out on pressure vessel steel P355NH, which was considerably softer and less ductile than the tested basic material (34CrNiMo6), due to which a higher cutting speed was used (300-500 m/min). In the tests, the identification with the material P355NH was less reliable than with the basic material. The typical problem that occurred was that the system claimed to detect a continuous chip when in fact there was none. False detections occurred especially at high cutting speeds (500 m/min). An analysis of the test results revealed a reason for the false identifications. The different characteristics of the material P355NH require a high cutting speed, due to which the detection of continuous chips should be carried out at a different frequency than for the material 34CrNiMo6. Changing the detection frequency area in the system does not require great efforts. Therefore, the detection of continuous chips could rather easily be adapted also to the material P355NH. Due to the small test sample, no detection rate was calculated for the material P355NH.

For the rhomboidal tool CNMM 120412-PR GC4015 and the tool holder PCLNL 2525M12, the tool angle is 95˚, whereas for the tool SNMM 120412-PR GC4015 and the holder DSBNL 2525M12 the angle is 75˚. In tests with the rhomboidal tool, the detection of continuous chips was flawless, and changing the positioning angle seemed to have no effect on it. However, the sample remained rather small, which means the effect of the tool angle requires further tests.

3.1.3. Adjustments to eliminate continuous chips

After the system was developed to a stage in which it detected continuous chips with sufficient reliability, the development of adjustment features was begun. In order to develop the adjustment features of the system, turning tests were conducted to study the reaction of the system to continuous chips. Based on these observations, the software part of the system was developed. Then, the improvements were tested to ensure their suitability for the system.

During machining, it is possible to adjust the feed (and cutting speed). The depth of the cut is entered into the system before the machining is started. Therefore, it remains constant during the machining within the limits set by the work piece and its form. Continuous chips can be eliminated by selecting the appropriate feed. Continuous chips occur if the feed is too low. The turning tests revealed that when continuous chips began to form, a mere increase in the feed was not enough to eliminate the problem, i.e. break the chip. Instead, increasing the feed without stopping if first often made the situation worse because the continuous chip only became thicker. Thus, the system was adjusted so that the system stopped the feed briefly (< 1 s) when continuous chips were formed. This broke off the chip. Then, the feed was restarted at a higher rate, which normally eliminates the problem. However, if the problem persists, the same course of action is repeated, and the feed is further increased. This greatly improved the reliability of the system, and if the chip detection works, the adjustment is also likely to work.

4. Conclusions

In the system created in this study, the detection rate of continuous chips was 95%. In conclusion, the system works very well with the combination of the tool and work piece material tested. Further studies need to establish how the detection algorithm of continuous chips should be adjusted when different cutting speeds and materials are applied.

The reaction time of the system from the detection of the problem to the adjustment of cutting values should be as short as possible. In the current system application, the long reaction time (5-10 seconds) may prove to be a problem in the turning of work pieces with a short cutting length. In such cases, the system has no time to make adjustments before the next chip, and no optimal cutting values can therefore be found. The feed and the cutting speed have an effect on how long a distance can be cut in a certain time span (reaction time). Especially rough turning would require a cutting length that allows time for adjustments. When the optimal values are determined, the distance in turning no longer has such a great impact. In terms of software and equipment, the reaction time can be reduced, which then relaxes the system requirements for the length of the chip. In the future, systems should be able to enter cutting values directly into the machine control. Thus one would not be as dependent on the original cutting speed, and one could freely choose how much one adjusts the cutting speed.

Wireless sensors would help to install the system on turning machines in production, in which case no inlets, tubes or mounting is required for cables. Acceleration sensors and acoustic emission sensors are attached to the tool holder. In manned production, changing the nose of the tool at certain intervals is easy, and sensors may only be needed in tool holders for rough turning tools. In unmanned production, however, roughing must be continued with a different tool when the nose is worn out. Therefore, also a different tool holder is applied because the tool cannot be rotated automatically. In consequence, unmanned production requires sensors in more than one tool holder.

5. References

1. **Zhou, L., Rong, Y., Li, Z., Yang, J. A.** Development of web-based machining chip breaking prediction systems. -International Journal of Advanced Manufacturing Technology, 2003, 22, p.336-343.
2. **Vica, A.** Simple vision system monitors tools and swarf. -Production Engineering, 1984, 63 (2), p.24-25.
3. **Dornfeld, D. A. and Pan, C. S.** A Study of continuous/discontinuous chip formation using acoustic emission. -Journal of Applied Metalworking, 1985, 4(1), p.8-29.
4. **Sihvo, I., Varis, J.** The wear of single flute gun drill and tool life tests. -Mechanika. -Kaunas: Technologija, 2008, Nr.5(73), p.59-64.
5. **Jawahir, I. S.** A Survey and future predictions for the use of chip breaking in unmanned systems. -International Journal of Advanced Manufacturing Technology, 1988, 3(4), p.87-104.
6. **Andreasen, J.L., De Chiffre, L.** Automatic chip-breaking detection in turning by frequency analysis of cutting force. -CIRP Annals - Manufacturing Technology, 1998, 47(1), p.35-40.
7. **Inasaki, I.** Application of acoustic emission sensor for monitoring machining processes. -Ultrasonics, 1998, 36, p.273-281.

8. **Govekar, E., Gradišek, J., Grabec, I.** Analysis of acoustic emission signals and monitoring of machining proce. -Ultrasonics, 2000, 38, p.598-603.
9. **Dolinsek, S., Kopac, J., Viharos, Zs. J., Monostori, L.** An intelligent AE sensor for the monitoring of finish machining process. -The Second International Conference on Intelligent. Processing and Manufacturing of Materials, July 10-15, 1999, p.847-853.
10. **Stepanov, A.** Adaptive Real-Time Control of Machinery Operation Using Multiple Sensor Inputs. Master's thesis. Lappeenranta University of Technology. Department of Electrical Engineering, 2007.-82p.
11. **Zadeh, L.A.** Fuzzy logic. -Computer, 1988, 21(4), p.83-93.
12. **Dubois, D., Prade, H.** What are fuzzy rules and how to use them. -Fuzzy Sets and Systems, 1996, 84(2), p.169-185.

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RUPIOJO TEKINIMO OPERACIJOS DROŽLIŲ VIJŲ SMULKINIMO IR ŠALINIMO KONTROLĖS SISTEMA

R e z i u m ė

Straipsnyje pateikta prisitaikančioji rupiojo tekinimo operacijos drožlių kontrolės sistema. Drožlių vijos tipas nustatomas akustinės emisijos signalais detalės apdirbimo metu. Sistema valdo drožlių smulkinimą įvertindama jų ilgį ir šalina drožlių vijas stabdydama įrankio pastūmą, o paskui ją vėl įjungdama didesniu greičiu. Kontrolės mechanizmas grindžiamas programinės įrangos ir staklių valdymo įrenginio sąveika. Sistema testuota naudojant dviejų tipų pjovimo įrankius ir ruošinio medžiagą. Ateityje sukurtoji sistema bus tikrinama naudojant daugiau tipų įrankių ir medžiagų. Sistemai vis dar tobulintina greitinant reakciją ir paprastinant jutiklius. Sukurta drožlių vijų smulkinimo ir šalinimo sistema yra svarbus žingsnis automatiškai, nedalyvaujant žmonėms link.

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CHIP CONTROL SYSTEM FOR MONITORING THE BREAKING OF THE CHIPS AND ELIMINATION OF CONTINUOUS CHIPS IN ROUGH TURNING

S u m m a r y

This research project developed an adaptive chip control system for rough turning. Continuous chips are detected with the help of acoustic emission signals during machining. The system monitors the breaking of chips, estimates the length of the chips and eliminates continuous chips if those are formed by stopping the feed and then restarting it at a higher rate. The control mechanism is based on communication between the software and the lathe knob. The system was tested with two combinations of cutting tools and work piece material. In the future, the chip control system should also be tested with more tools and materials. The system still requires development, e.g. to shorten the reaction time and simplify the sensors. The chip control capacity of the system created in this study is an important step towards improving unmanned production.

В. Риинанен, Й. Ратава, Т. Линдг, М. Рикконен, И. Сигво, Й. Леппанен, Й. Варис

СИСТЕМА ДЛЯ КОНТРОЛЯ ИЗМЕЛЬЧЕНИЯ И УДАЛЕНИЯ ВИТКА СТРУЖКИ ПРИ ОПЕРАЦИИ ГРУБОГО ТОЧЕНИЯ

Р е з ю м е

В статье представлена научно исследовательская работа, предназначена для усовершенствования адаптивной системы контроля стружки при грубом точении. Тип витка стружки определяется во время обработки детали при помощи сигналов акустической эмиссии. Система управляет процессом измельчения стружек учитывая их длину, удаляет витки стружек путем уменьшения величины подачи инструмента, после чего ее увеличивает заново. Механизм контроля основан на взаимодействии программного обеспечения с системой управления станков. Для тестирования системы использовались инструменты и материалы заготовки двух типов. В будущем созданная система будет тестироваться при использовании более высокого количества инструментов и разных марок заготовок. Система требует усовершенствования, т.е. ускорения реакции и упрощения датчиков. Созданная система для измельчения и удаления витков стружек является важным шагом к автоматически управляемому производству без участия людей.

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A Sugeno-type fuzzy expert system for rough turning

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A Sugeno-type Fuzzy Expert System for Rough Turning

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Abstract. This work describes a fuzzy expert system for rough turning. In order to automate unmanned turning, safety of the process must be ensured. In addition, any quality requirements should be fulfilled and, within these constraints, productivity maximized. The traditional approach in adaptive control of machining is to keep a measured quantity, such as power, within acceptable limits. However, there have been some studies measuring distinct phenomena in machining and identifying *cutting states* based on the phenomena. By identifying cutting states corresponding to phenomena monitored by human experts, it is possible to construct an intelligent machining system emulating the decision making of a human expert. This paper concentrates on defining the requirements for the inference part of such of an intelligent machining system. This work concentrates on both functional requirements, such as capability to take into account specific cutting states. The existence of process monitoring subsystems which detect and measure the cutting phenomena is assumed. As a result, a Sugeno-type fuzzy control is suggested, and feasibility and the level of completeness of such a system are discussed and issues requiring further study are identified.

Introduction

The traditional approach of adaptive control of turning relies on applying control to maintain a measured parameter constant or within specified limits. Other major vectors of applying intelligence to an online turning process are different process monitoring applications, such as tool wear monitoring. In this study, process monitoring systems are considered to be classifiers assigning a *cutting state* for the process; in the most elementary case, *cutting is possible* and *cutting is not possible*. A single state-based system can monitor multiple states, such as by Tangjitsitcharoen and Moriwaki. [1]

It is possible to further expand this way of thinking. Excluding non-technical factors, we may consider the actions taken by a human machinist taking care of an online CNC turning process as monitoring the process, and adjusting feed rate or cutting speed override if necessary. If a sufficient number of the cutting states can be automatically identified and the knowledge of the current cutting state is combined with feedback (control), it is then possible to make an expert system which emulates a human operator. The benefit of such of an expert system is that not only the bad cutting conditions are taken into account, but the system can take advantage when the cutting state is better than expected.

There are examples of this methodology being applied to adaptive control of the same two cutting parameters as adjusted by human operators. In this study, the following cutting phenomena and their respective control actions respective to feed rate and cutting speed are taken into account, beginning from the ideal case where no error states are detected. In the absence of errors, cutting parameters are kept as they are.

Monitoring cutting stability at high levels of power usage and feed rate is the closest example to traditional adaptive feed rate control. If there are no strictly cutting or quality related problems but the full capacity of the lathe is not yet in use, the system should take advantage of the situation in attempt to increase material removal rate. *Inefficient cutting* is an error state where the consumed power is low while there are no other problems. The state where the power consumption of the lathe is at unsafe levels is *too high power*. These states should be mutually exclusive. Feed rate is used to control the level of power consumption. [2]

Different states of tool wear can be identified, such as in the study of Balazinski et al. [3]. Maintaining a predictable tool wear rate is important, especially in unmanned cutting. Since tool wear is more heavily dependent on cutting speed than feed rate, it seems logical to control it by adjusting cutting speed. If *tool wear rate is too high*, cutting speed needs to be decreased and if *tool wear rate is too low*, cutting speed may be increased.

Chip control is crucial to the safety of the machining process. As the *chip length* increases, it becomes more and more difficult to efficiently and safely remove cut chips from the machining cabinet. If the chip does not break at all (*continuous chip*), it may get entangled to the tool holder, part, or other objects. Suitable chipping is commonly achieved by selecting suitable tool geometry, but there are examples of detecting chip length and using active control to maintain chip control. According to Ryynänen et al. [4], *long chip length* can be eliminated by increasing feed rate and *continuous chips* should be cut by setting feed rate briefly to zero before increasing it.

On the opposing end of the scale, cutting instability at high feed rates seems to correlate with lathe power consumption [2], a function of both feed rate and cutting speed. As cutting speed is used to control tool wear rate, only feed rate can be decreased if cutting instability is detected.

Regenerative chatter appears on ill-supported workpieces or tools. There is some evidence that regenerative chatter may be suppressed by selecting a suitable spindle speed. [5] Required cutting speed may be calculated as a function of current surface radius and spindle speed. This adjustment may result in issues with tool life and therefore, require modifying the feed rate to compensate. Chatter mitigation by spindle speed control departs from the idea of imitating a machinist, as detecting the chatter frequency and setting correct spindle speed may both be beyond the human capabilities.

With the exception of power consumption, cutting states are not mutually exclusive and several may appear at once. All the cutting states shall have a membership value in the unit interval, 0 meaning total absence and 1 full presence. Further study of detecting the cutting state is omitted. We concentrate on adaptive control based on the mentioned cutting states and actions using a Takagi-Sugeno type fuzzy system [6] capable of applying results from earlier studies into a unified system.

The Inference System and Rule Base

A Takagi-Sugeno system has rules of form "if x is A then y = f(x)", i.e. the output (conclusion) is a function of the inputs (and possibly other parameters). The output of each rule is crisp; the output of the system is calculated by assigning each rule a firing strength as a weight (often dependent on the inputs) and taking the weighted average of individual outputs. Importantly, the Takagi-Sugeno system is flexible and computationally efficient.

In this study, the conditions for each rule are of form "if cutting is in this state, but not in these states", which can be modeled with the firing strength of a rule. The fuzzification for the inputs of the system is by necessity done by (or at least highly dependent of) the modules detecting and measuring the cutting states. Therefore, a more detailed description is omitted in this study. The control system is divided into two subsystems: One single-output-single-input (SISO) system controlling continuous chip breakage and a multiple-input-multiple-output (MIMO) system controlling cutting speed and feed rate. The fuzzy operators are defined such that the *and* (Eq. 1) and *not* (Eq. 2) operators are:

$$a \wedge b = \min(a,b) \quad (1)$$

$$\neg a = 1 - a \quad (2)$$

The single input for the system controlling the breaking of continuous chip is the appearance of continuous chip, which is signaled by the *long chip* parameter $x_1 = 1$. Essentially this system is merely a crisp trigger for the control action. For the MIMO system, the coefficients of polynomial output functions can be collected (Eq. 3):

$$C_h = \{c_{h,i,j}\}_{9\times 11}, h \in \{'f', 'v'\}, i = 1, 2, \dots, 9, \quad j = 1, 2, \dots, 11 \tag{3}$$

and weights w_f and w_v are collected as row vectors. The outputs u_f and u_v of the system can be computed as a weighted average of individual outputs (Eq. 4). x^* is a column vector of inputs and parameters (Eq. 5):

$$u_h = w_h(C_h x^*)/\sum w_h, \quad h \in \{'f', 'v'\} \tag{4}$$
$$x^* = [x_1, x_2, \dots, x_8, f_c, v_c, v_{stable}]^T \tag{5}$$

There are five fuzzy inputs required by the feed rate control (x_1 to x_5): long chip, inefficient cutting, too high power, cutting instability and *tool wear rate very high*. The last one refers to the situation where cutting speed has been increased in an attempt to stabilize regenerative chatter. In addition, we need to know the crisp input f_c, *current feed rate*. The cutting speed control requires inputs (x_6 to x_8) tool wear rate is low, tool wear rate is too high and chatter. For cutting speed control, two crisp inputs are needed: v_c, *current cutting speed* and v_{stable} (*chatter-*)*stable cutting speed*. Weights $w_{f,j}$ and $w_{v,j}$ (for feed rate and cutting speed) and functions for outputs $u_{f,j}$ and $u_{v,j}$ (similarly) are defined for each rule *j* below (Eqs. 7 - 26). If a weight or output is not defined, it is zero. The coefficient of the crisp input ($c_{f,i,9}$, $c_{v,i,10}$ or $c_{v,i,11}$) relevant to the rule is one (omitted).

The first rules (Eqs. 6 - 9) help stabilize the system when there are no problems detected.

$$w_{f,1} = \neg x_1 \wedge \neg x_2 \wedge \neg x_3 \wedge \neg x_4 \wedge \neg x_5 \tag{6}$$
$$w_{v,1} = \neg x_6 \wedge \neg x_7 \wedge \neg x_8 \tag{7}$$
$$u_{f,1} = f_c \tag{8}$$
$$u_{v,1} = v_c \tag{9}$$

The feed rate related rules react to presence of long chips (Eqs. 10, 11), low or high power (Eqs. 12 - 15), cutting instability (Eqs. 16, 17) and very high tool wear rate (Eqs. 18, 19) as described in previous section. Reacting to long chip (x_1) has priority over other problems, followed by tool wear rate control (x_5) and prevention of the onset of cutting instability (x_4):

$$w_{f,2} = x_1 \tag{10}$$
$$u_{f,2} = c_{f,2,1}x_1 + f_c, \quad c_{f,2,1} > 0 \tag{11}$$
$$w_{f,3} = x_2'' \wedge \neg x_4 \wedge \neg x_5 \tag{12}$$
$$u_{f,3} = c_{f,3,2}x_2 + f_c, \quad c_{f,3,2} > 0 \tag{13}$$
$$w_{f,4} = x_3 \wedge \neg x_1 \tag{14}$$
$$u_{f,4} = c_{f,4,3}x_3 + f_c, \quad c_{f,4,3} < 0 \tag{15}$$
$$w_{f,5} = x_4 \wedge \neg x_1 \tag{16}$$
$$u_{f,5} = c_{f,5,4}x_4 + f_c, \quad c_{f,5,4} < 0 \tag{17}$$
$$w_{f,6} = x_5 \wedge \neg x_1 \tag{18}$$
$$u_{f,6} = c_{f,6,5}x_5 + f_c, \quad c_{f,6,5} < 0 \tag{19}$$

The cutting speed related rules manage tool wear rate (Eqs. 20 - 23) and chatter (Eqs. 24, 25):

$$w_{v,7} = x_6 \wedge \neg x_8 \tag{20}$$
$$u_{v,7} = c_{v,7,6}x_6 + v_c, \quad c_{f,7,6} > 0 \tag{21}$$
$$w_{v,8} = x_7 \wedge \neg x_8 \tag{22}$$
$$u_{v,8} = c_{v,8,7}x_7 + v_c, \quad c_{v,8,7} < 0 \tag{23}$$
$$w_{v,9} = x_8 \tag{24}$$
$$u_{v,9} = v_{stable}, \tag{25}$$

The behaviour of the system can be visualized by simulating two opposing-direction rules (such as Eqs. 10, 11 and 16, 17), shown in Fig. 1, and same-direction rules (such as Eqs. 10 - 13), shown in Fig. 2. In the figures coefficients of approximately the same magnitude are assumed; should one coefficient be considerably greater than the other, the control will be slanted towards that control action, but still weighted by firing strengths. The authors' implementation requires significantly less than a millisecond to compute the output, being essentially real-time.

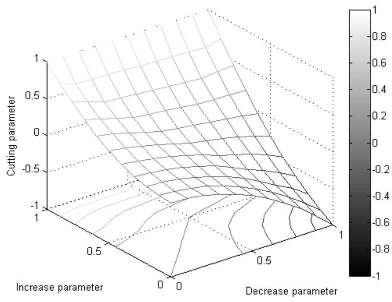

Fig. 1: Two opposing effects.

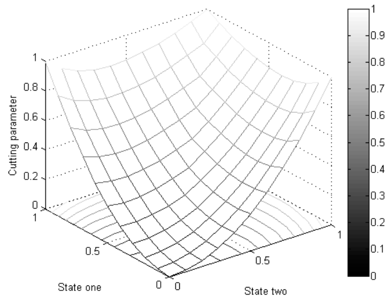

Fig. 2: Two matching effects.

Conclusions and discussion

A fuzzy expert system framework capable of real-time control of turning operations (given information about present cutting states) was formulated. Accurate measurement or good approximation of cutting states is important. Otherwise, it is necessary to maintain a wide margin of safety in case of error. As a benefit, the fuzzy system can manage some uncertainty in cutting state detection.

Selecting the values of the coefficients $c_{v,i,j}$ and $c_{f,i,j}$ depends on the exact case. The step size would be relatively coarse 10 - 20% of the reference value if strictly emulating an human operator using a CNC machine override switch. Experimentation would be needed to discover suitable gain (control action magnitude) for the system.

The inference is very fast. It is expected that the measurement of cutting states does consume the majority of computing time required by a completed system. Future research is needed on rapid detection of the states, though in some cases speed of physical actuation may be the limiting factor.

References

[1] S. Tangjitsitcharoen, T. Moriwaki: Intelligent identification of turning process based on pattern recognition of cutting states. Journal of Materials Processing Technology 192-193:491-496 (2007).

[2] J. Ratava, M. Rikkonen, V. Ryynänen, J. Leppänen, T. Lindh, J. Varis and I. Sihvo: An adaptive fuzzy control system to maximize rough turning productivity and avoid the onset of instability. International Journal of Advanced Manufacturing Technology 53:71-79 (2011).

[3] M. Balazinski, E. Czogala, K. Jemielniak, J. Leski: Tool condition monitoring using artificial intelligence methods. Engineering Applications of Artificial intelligence 15:73-80 (2002)

[4] V. Ryynänen, J. Ratava, T. Lindh, M. Rikkonen, I. Sihvo, J. Leppänen and J. Varis: Chip control system for monitoring the breaking of chips and elimination of continuous chips in rough turning. Mechanika 4(78):57-62 (2009)

[5] Y. S. Liao and Y. C. Young: A new on-line spindle speed regulation strategy for chatter control. International Journal of Machine Tools and Manufacture, 36(5):651-660 (1996)

[6] T. Takagi and M. Sugeno: Fuzzy identification of systems and its applications to modeling and control. IEEE Transactions on Systems, Man and Cybernetics 15(1):116-132 (1985)

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