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A Concept from Sensor to Sustainability in Machining - An Interdisciplinary Approach over a Wide TRL Range

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Abstract. This publication describes a concept that intends to enable an optimization of machining with regard to the balance between criteria related to technology, economy and sustainability. The work is of a discussion nature and intends to provide a framework for further research and development in the area. Previous research and development during the 80's and 90's is presented in general terms and in particular the reasons for its limited success in providing real-time feedback on machining operations are highlighted, despite very large financial investments even by today's standards. Ongoing research worldwide in current process optimization and its associated building blocks will be highlighted, and identified important work is referenced. Below are new conditions that can be linked to both process knowledge and its modeling, as well as new conditions for developing integrated sensors that can handle the extreme environment in and around a processing operation. A previous limiting factor has been signal processing and signal transmission, which with new knowledge and developed technology in the last 10 years provides new conditions for process optimization in real time.The need for new and up-to-date principles for process optimization, which also integrate sustainability issues and environmental impact, has increased in importance in several respects. Important issues such as tool utilization, efficient use of materials and high time utilization have become relevant as these process results control both energy consumption and environmental impact. The geopolitical development linked to the availability of critical tool materials such as cobalt and tungsten also drives research issues that can generally optimize and streamline production processes.Finally, the publication describes the possibility of realizing a real-time feedback and optimized machining that takes into account technology, economy and sustainability, through interdisciplinary research across several levels of technology readiness (TRL). The results are expected to have positive effects on several production factors before, during and after machining. Developed technologies in machining can also make valuable contributions to the development of other products and production processes.

Keywords. Process optimization, machining, sustainability, production rate, manufacturing economics, real-time, feedback, signal processing, modeling, digital process integration, identification blocks.

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1. Introduction

Industry and society face major challenges in terms of resource consumption and achieving long-term sustainability. High and inappropriate resource consumption, in all respects, negatively impacts the environment and limits the prosperity and development of future generations. The need for a more resource-efficient industry with low environmental impact has been drastically accentuated by the current geopolitical situation, including the aftermath of the pandemic. Trade flows and the availability of raw materials and key alloying elements have changed significantly. The stabilizing effect of global trade is no longer valid and common values between trading partners have become increasingly important. These conditions place even greater demands on the efficiency of products and manufacturing processes and the use of materials while optimizing these processes in a conscious and thoughtful way. This work must be done in parallel with the development of products to enable resource-efficient manufacturing based increasingly on reuse and recycled materials. This must be done without degrading the materials in our components in terms of both use and producibility.

Different types of production losses during processing or their consequences contribute significantly to the current high environmental impact in terms of emissions and consumption of different resources such as materials, process additives, energy, production capacity and working time. Increasing material and energy costs and demands for reduced environmental impact mean that the benefits of optimizing manufacturing processes represent a great potential for addressing current and future challenges, which also contributes to increasing our international competitiveness.

Despite very large government research investments already in the 80s and 90s, we have not been able to fully optimize today's very important and central manufacturing processes and associated equipment in real time to prevailing production conditions [1]. A quest for increased sustainability and resource efficiency has also gradually emerged since the 80s but has been strongly accentuated in the last 10 years. Extensive digitalization has been possible alongside the central and value-creating process. Digitization has been successfully carried out in the form of numerical control, automation, quality control, quality assurance and material management, etc.

Manufacturing processes, work materials and production systems need to undergo a more thorough digital integration and optimization, also taking into account current resource consumption and associated environmental impacts. This can be done by adapting the process to controlling factors and prevailing conditions, before, during and after processing. This approach requires the ability to control and optimize manufacturing processes during machining, i.e., to adapt and change the machining process in real time to variations in process conditions related to tools and work materials. Digital process integration of machining processes with the rest of the machine system has been attempted for some time, both in research laboratories and in industry, but has not been successful for a variety of reasons. Significant efforts are currently being made worldwide in this area, including the publication of several reviews [5, 6, 7]. It can be noted that studies that include optimization concerning manufacturing costs, production rate and environmental impact are very few, none of the studied works deal with a balance between different optimization criteria. The focus of the studies is the detection of wear levels and underlying mechanisms. The meaning of optimization is often limited to increasing tool utilization where cutting data is adapted to a given tool life to primarily reduce tool costs. Indirectly affected are the costs of tool failure resulting from rapid wear leading to production downtime. No monitoring systems that allow stress monitoring, monitoring of the tool's main stress or its effective stress have been found in recent references, probably due to a lack of models and measurement systems with the required performance. Studies on the measurement of machine tool motor currents and indirectly power consumption have been carried out regularly since the 1980s. The method turns out to have both advantages and disadvantages. The problem of using cutting fluids is minimized and the signals obtained can be more easily integrated with the machine control system. The main disadvantage that can be identified is the lack of consistency between process behavior and measured variables and its accuracy, especially in finishing. Obtained measurement data is relatively far from the process, which gives low time resolution to detect certain process behaviors. Thermocouples have also been widely used for a long time to identify the process temperature and assess the geometric change of the tool during its degradation. Several studies have been promising where the temperature is measured directly on the cutting tool without intermediate gaps [1]. Measuring the temperature in the tool support anvil or in the tool holder usually gives too low a time resolution [8], especially for tools with low thermal conductivity.

An overall basic view of machining that includes the steps or disciplines required for a conscious process optimization is missing. Many studies are done in dry machining, i.e., where cutting fluid is not used at all. This situation emphasizes the problems that cutting fluids cause in the operation of sensors and associated signal handling and processing. Recently, image processing to determine tool wear levels has dramatically increased in combination with the use of ML techniques and neural networks.

One of the main reasons for the lack of success in the past is the lack of robust sensors and signal transmitting technologies as well as satisfactory process models in combination with optimization principles including sustainability aspects. Current commercial sensor technology cannot cope with the extreme demands and conditions placed on systems for measuring the physical and chemical environment variables in refining processes for regular manufacturing. This situation limits the availability of input data for process models that form the basis for optimization.

New technical and scientific conditions can be identified [2] that can contribute to the successful integration of new sensors leading to an optimization of the manufacturing process with respect to various conscious criteria. The following conditions have been identified:

1. Greater need and increased incentives for resource-efficient and sustainable manufacturing.
2. A new and necessary constellation of researchers is established that can meet all the issues that exist regarding sensors, signal transmission and signal processing and that digital peripheral equipment is available.
3. New conditions exist in nanotechnology that enable the development of integrated robust sensors with great proximity to the process that have good conditions to function under extreme physical and chemical conditions.
4. Models for certain refinement processes and associated manufacturing costs exist today that can form a basis for further development of the current field of science. Current models can partially link controlling factors with process outcomes and results.
5. Knowledge and insight into the possibilities of applying the latest developments in artificial intelligence and machine learning exist. This enables an optimization of the processes against given criteria in real time, where processed sensor signals constitute input to selected optimization criteria.

Also important for the success of process optimization is the link between technology and economics, which enables real-time automatic decision-making on changes in process data based on pre-established optimization criteria. The link between technology and economics also enables the simulation of cost outcomes for different technological development scenarios. This form of techno-economic simulation provides the conditions for giving the machining processes the right and optimal conditions. This is particularly important when a component undergoes a sequence of processing stations, where, for example, savings in the purchase of materials or savings in the preparation of materials in the foundry are made with the consequence that large cost increases are instead obtained during processing.

Limitations and focus: Below, the work is limited to machining and the present work does not intend to provide any direct technical solutions, but to describe a concept that can provide a framework for technical solutions, from sensors to process optimization and sustainability. Reported work should be seen more as a discussion than a strictly scientific publication that answers a specific research question or proves that a formulated hypothesis is valid. The concept has emerged over a long period of time and is based on many years of accumulated experience in combination with rapid technological development and ongoing global changes and geopolitical potential consequences.

It can be noted that machining is a complex and extremely complicated process with a very large number of input data and variables that may be partly dependent on each other. The outcome of the process in terms of process results is also very large depending on the type of operation and the quality requirements set for the current component to be manufactured. Several of the requirements set for the process can be directly contradictory, which makes it difficult to find optimal technical solutions. Only a very limited part of the total process behavior can today be modeled and described in analytical or numerical form. Current knowledge and technological development in the field of machining does not provide any conditions for creating a digital twin in its literal sense, but only a cluster of well-functioning models that can provide a basis for decisions and optimization combined with real time measurements of relevant variables on the machining process.

2. Sustainability and optimization criteria for machining operations

A developed link between technology and economics has enabled the optimization of machining in terms of manufacturing cost and rate [9, 10]. For a given machining case, it is possible to find mathematically or graphically the relationships between cost and production time. Through the relationship, which consists of about 35 variables and constants, two types of production can be identified, maximum production rate (lowest production time $t_{pb,min}$) and minimum production cost kmin. The relationship can be fully illustrated in a Hägglund graph as shown in **Figure 1**, where the manufacturing cost k is shown as a function of the manufacturing time tpb to produce a component in a batch with N_0 number of parts. In the graph, either the tool life T or the cutting speed v_c is the parameter with constant feed f. The graph can also be produced with the tool life T or cutting speed v_c as a constant where the feed rate f is varied within the intended application range of the tool in question. The choice of the criteria minimum production cost or maximum production rate is traditionally made depending on the company's order intake. If the production capacity limits the ability to deliver, the maximum production rate is chosen, and if there is free capacity and low U_{RP}, the lowest production cost is chosen. In rough machining, it is often possible to vary both cutting speed v_c and feed rate f during an optimization. In this case, the feed is often limited due to the risk of tool failure or plastic deformation. In fine machining where greater demands are made on the quality of the cut surface, only the cutting speed v_c can usually be varied. In this case, the feed rate f is maximized with regard to the current surface roughness requirement.

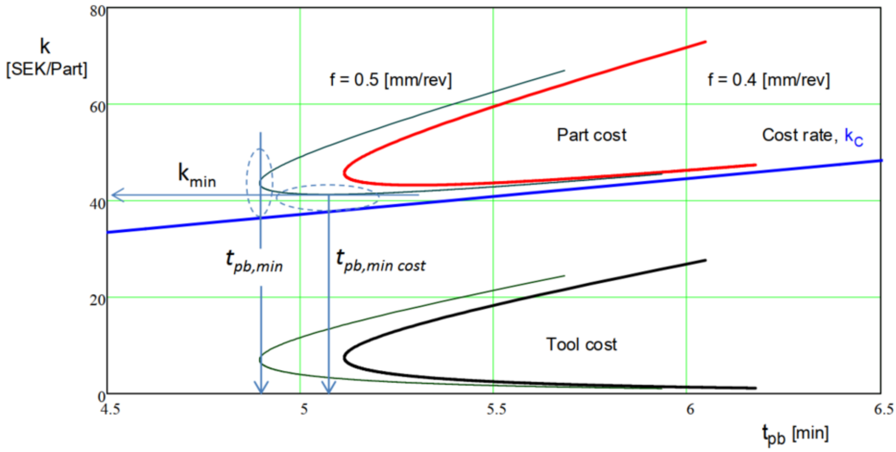

Figure 1. Example of a Hägglund cost and time graph where the part cost k and the tool cost are reported as a function of the production time t_p, (t_{pb}) for two different selected feeds f [9, 10].

2.1 Sustainability as an optimization criterion in machining operations

The optimization of cutting data as above according to **Figure 1** does not take into account the environmental impact in terms of direct or indirect emissions of greenhouse gases (equivalent CO_2), energy and power consumption, material losses in various forms and consumption of critical raw materials (CRM) as well as the use of cutting media and other process additives. In the case that the maximum production rate is prioritized in the optimization, a higher consumption of tools is obtained and generally speaking, more critical raw materials in the form of tungsten and cobalt are consumed at the same time as the maximum power consumption increases and the total energy consumption is reduced. When selecting the lowest manufacturing cost, the opposite occurs: the tool consumption is reduced and the production time increases and the maximum power requirement decreases while the total energy consumption increases.

When considering the environmental impact as well, all environmental impacts must be converted into equivalent releases of CO_2. This calculation is very complex, but quite possible to develop and use in practice. A series of, possibly political, decisions need to be made to optimize the manufacturing process in terms of environmental impact. A central question is how an already made environmental impact should be handled when a technology is used or compared with another alternative technology or process. The concrete question is what weight should be given to existing equipment when assessing a process and its environmental impact. The logical solution in this respect is that the same principles should be used as are used when comparing economic investments made in equipment from a production perspective [11], i.e., the environmental impact should be distributed over all the years of intended use of the equipment, including renovations and updates. This approach differs from the accounting approach based on fiscal depreciation, which does not lead to long-term sustainability and correct production technology assessments.

Significant research and development is required to take full account of the environmental impact of machining processes. The interaction with the contribution of other manufacturing steps to the environmental impact must be taken into account, in the same way as the overall production cost of a component should be taken into account. The total environmental impact of a component must be considered in a coherent way and also include purchase of raw materials.

An optimization of the manufacturing process with regard to all three criteria is illustrated in principle in **Figure 2**. The weight functions x and y describe the influence of each criterion. The choice of x and y is probably a strategic question. With x = 100 %, the best conditions for delivering to customers in the event of high demand are given, with y = 100 % the best economic outcome is obtained as long as the U_{RP} occupancy rate < 100 % and with x = y = 0 %, minimal environmental impact is given the highest priority, which can position the company well in the market. A strategic decision is how the company chooses the weight factors x and y, which can also be a decision taken at board level in the company. This decision can certainly become a topical board issue in an SME that is a specialized subcontractor to a larger industry. It is also not inconceivable that x+y will have to be declared in the future in order to become a supplier to large groups with an environmental profile.

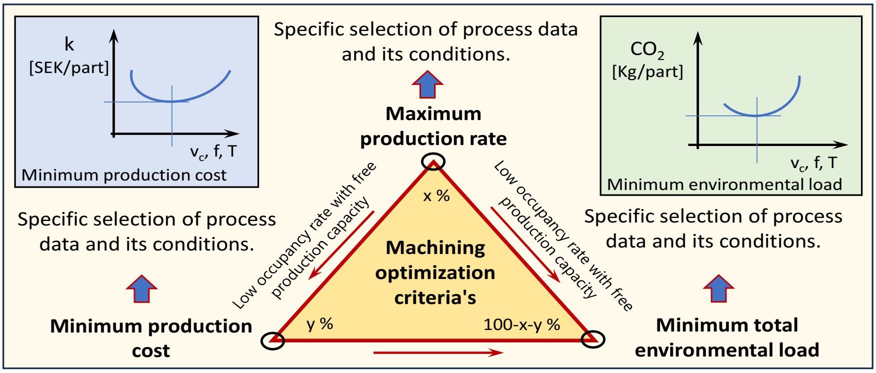

Figure 2. The balance or trade-off between the optimization criteria of maximum production rate, minimum production cost and minimum environmental impact.

2.2 Sustainability and production efficiency in machining operations

Until the 1990s, the manufacturing industry did not fully realize that sustainability and production efficiency went hand in hand. This view has drastically changed in a positive direction, e.g., through increased raw material and energy costs and through regulatory instruments. The introduction of the producer responsibility law has had a major impact on increased recycling in different sectors. An important insight is that an increased production time is also an increased environmental impact, e.g., through extra consumption of energy in various forms per manufactured component or product. A component that does not meet the set quality requirements and must be discarded is both lost production time and lost working material that must be reprocessed once again, partly illustrated in **Figure 3**, where different result parameters are illustrated that depend on each other and affect the environmental impact of the process.

A high production rate without scrap and a minimum of material waste are therefore important performance parameters for achieving sustainable manufacturing. To achieve sustainable and efficient machining, it is of utmost importance to adapt tools, work materials and process data to each other during production planning. However, this assumes that material selection and tolerances etc. are well adapted for high producibility. From a sustainability perspective, the production preparation is required to fully take into account:

- Time efficiency linked to planned production time.
- Workpiece material efficiency in process.
- Tool and tool material efficiency, also with respect to CRM.
- Process energy efficiency.
- Efficient use of process additives.
- In overall minimum process environmental load för manufacturing a component.

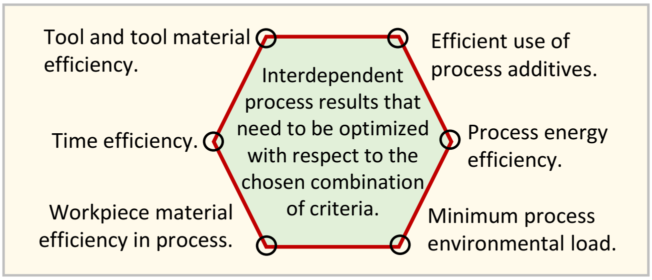

Figure 3. Performance and result parameters related to environmental load (ER), there the result parameters are depending on one or more factor groups related to machining.

3. Factor groups and performance parameters in machining

A very large number of factors affect the output of a machining operation, which can be grouped into factor groups from A to G (Tool A, Work material and starting material B, Process and process data C, Personnel and organization D, Wear and maintenance E, Special factors F and Peripheral equipment G). The output of the machining process can in turn be subdivided into quality outcomes (Q), stoppages and disturbances (S), production rate (P) and environmental and recycling parameters (ER). The factors can individually or in combination control the output parameters of the machining process (Q, S, P and ER). A further complicating factor is that the factors can be interdependent to varying degrees. The dependence between factors (factor groups), process behavior and performance parameters is studied in a PSM, Production Performance Matrix.

3.1 Monitoring, control and optimization of performance parameters

In monitoring, control and optimization of machining, information and data from individual factors and measured quantities in the process are combined to predict and optimize outcomes in performance parameters as shown in **Figure 4**.

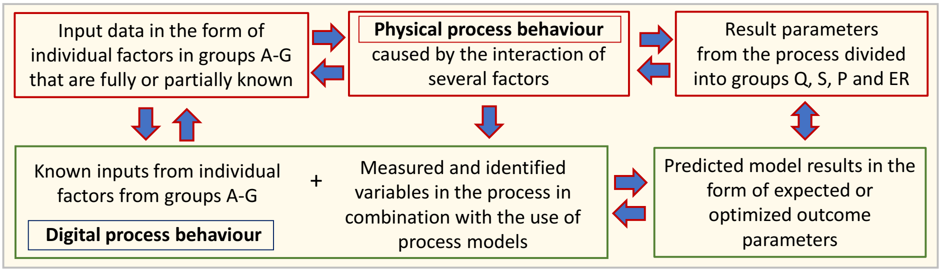

Figure 4. Relationship between factors and performance parameters (process outcomes) and how this can be optimized by measuring and identifying variables in the process that become input to process models.

The optimization of the result according to the previous section is done by changing the input factors in line with the chosen optimization criteria.

3.2 Examples of performance parameters in machining

Machining has a large number of different types of operations that have different requirements for the performance parameters associated with groups Q, S, P and ER. Below are examples of individual performance parameters from each group.

Obtained quality with respect to quality (**Q**):

- Surface integrity, roughness, residual stresses, structure and chemistry.
- Surface roughness with respect to e.g., R_a, R_z and R_{max}.
- Geometric accuracy with respect to shape and dimensions.
- Geometric accuracy with respect to burr formation and tool exit damage on the workpiece.
- Damage and effects on the workpiece related to chip forming and chip management.

Obtained stops and disturbances with respect to productions stops: (**S**):

- Set-up time (T_{su}) and Tool change time (T_{tct}).
- Tool failure and the risk of tool breakage and/or rapid plastic deformation.
- Maintenance of machine tools or other peripheral equipment.
- Other causes of stops and loss of production e.g., related to clamping and fixtures.

Obtained production rate or cycle time with respect to (**P**):

- Tool life T and type of tool degradation and degradation rate for a given tool life criteria.
- Nominal Metal Removal Rate, MRR in [cm^3/min] for different selected tool life.
- Nominal Surface Generation Rate, SGR in [cm^2/min].
- Engagement distance e_T in [km] with respect to selected tool life criteria T in [min] or produced chip volume in [cm^3].

Obtained losses and environmental loads of different kind respect to (**ER**):

- Scrap rate (q_Q) and workpiece material losses (q_B) and recycling material losses (q_{BR}).
- Stop rate (q_S) and process losses due to non-added value time (q_{rem}, q_{tct} and q_D).
- Speed loss rate (q_P).
- Energy or power consumption in [kWh/h].

- Consumption of process additives in [kg/h].
- Direct ($q_{CO2,D}$) and indirect ($q_{CO2,ID}$) generation of CO_2 in [kg/h].

More or less all of the specific performance parameters described above give rise to production costs that affect a company's competitiveness and its contribution to environmental impact and long-term sustainability. Some of the performance parameters are easier to influence than others.

4. Modeling and optimization of machining operations

It is of great importance to optimize the process not only during machining but also before and after machining. One of the most important parameters is the variation in workpiece machinability between batches and between individual components within the same batch. These properties are largely governed by specifications of purchased materials and requirements of previous operations such as castings and forgings. A consideration of the contribution of different factors to the process behavior and associated production outcomes must be made before processing begins. Factors with a large influence on the production outcome that cannot be influenced during processing must be dealt with prior to the start of processing. There is then a more or less limited number of performance parameters that may be possible to control and change in real time during processing. Against this background, unambiguous relationships and models must also exist or can be developed that describe the factors' influence on the process behavior and its relation to the desired result parameters.

4.1 Variations in performance parameters and their consequences

Variations in the machinability of the workpiece are the most common cause of unwanted deviations in the machining result. The concept of machinability is relatively well defined and includes 5 groups of criteria as follows:

- Tool degradation and tool life.
- Cutting forces and energy consumption
- Chip shape including burr formation
- Obtained surface character including surface roughness.
- Working environment and environmental impact.

There are also other process-related variations that can give rise to problems related to quality, stops and disruptions, speed and environmental impact. This also includes personnel and organizational factors related to e.g., action plans and procedures.

4.2 Opportunities for monitoring, control and optimization

By adapting the process to the prevailing circumstances regarding the machinability of the work material, the processing can be optimized and lead to better efficiency regarding the above-mentioned performance parameters according to **Figure 5**, which can be seen as a subset of **Figure 4**. Variations in the machinability of the workpiece, which have so far increased with the increased proportion of recycled material, contribute to undesirable variations in process results. Selected cutting data is no longer optimal with regard to these new conditions. A new optimization must therefore be made. This optimization can be done during ongoing processing or in connection with the standstill between the respective processing. This reasonably assumes that the material in the same batch has the same machinability and that there are no variations between and in the relevant blanks. Otherwise, an optimization must be made during ongoing processing to obtain a sustainable use of tools and work materials.

Experience from completed processing and its adaptation and corrections made according to **Figure 5** can be utilized and analyzed for future corresponding processing.

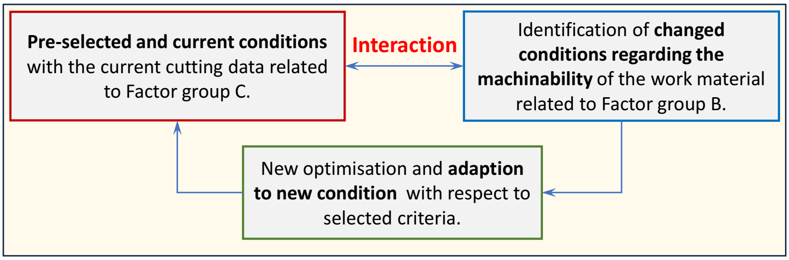

Figure 5. Adaptation and optimization of the machining process to changing conditions regarding the machinability of the work material.

There is particularly great potential in terms of developing improved specifications and requirements for the work material. Documented knowledge and experience may well influence and accelerate the introduction of sustainable and circular recycling of metallic materials when the associated problems are clarified.

4.3 Process engineering models and required measured quantities

In order to make timely adjustments and corrections to the treatment process, both qualitative knowledge and experience and process models must be used to make informed decisions in an efficient and sustainable direction. Models to describe the outcome of the performance parameters, directly or indirectly, must be available. These models require that included variables or parameters can be measured or otherwise determined so that the outcome of the model in question can form the basis for a proactive decision. Below are three examples of typical cases where measures may be relevant:

1. The cutting data shall be adapted to the actual machinability of the material so that the tool is used as efficiently as possible with respect to the established optimization criteria.
2. The cutting data shall be adapted to ensure that the remaining life of the tool results in a tool change after completion of the machined component.
3. High cutting loads in terms of mechanical and thermal loads shall be identified and the cutting data shall be adapted so that tool failure or plastic deformation can be avoided and an optimum load level obtained.

What is to be measured and identified in the cutting process fully determines which variables are to be measured and correlated to one or more result parameters. These can be measured directly, or indirectly via some quantity that correlates or partially correlates with the sought variable. The result parameters of the cutting process are often over-determined and can arise from different combinations of variable values and factors. An example of this is the tool degradation level where e.g., an increased cutting force level or increased power output can be caused by different geometric changes on the tool or by an increased cutting resistance of the work material. A major source of error in this context is variations in the working mode, particularly in the rough machining of cast and forged parts. It is also common for the tool to change its geometry on both the chip and drop sides. The geometric change on the drop side increases the cutting forces while the change on the chip side reduces the cutting forces by increasing the positive chip angle. This relationship can be addressed by studying the load distribution on the tool.

The load distribution can be determined during processing by using identification blocks where the cutting forces are measured and later analyzed, for example as shown in **Figure 6**. Identification blocks are based on a short sequence of well tested changes in the cutting data while measuring the variable of interest. An identification block shall be designed so that it does not adversely affect the processing result. The change in the cutting data and its direct correlation to the variable of interest provides information on the searched result parameter (function). In this way, the load distribution on the tool can be identified and a degradation factor for the tool can be calculated. The degradation factor describes an overall picture of the total load situation of the tool and describes the overall load change on the tool. The degradation factor can in many cases be directly correlated to the tool's wear criterion and tool life. The use of a degradation factor is appropriate to use if the geometric change of the tool due to degradation occurs primarily on the release side of the tool. A model to describe the load distribution on the tool is therefore necessary.

Example of steps in an identification block to estimate the flank wear VB_e of the tool: Theoretical chip thickness h_1 is varied in at least three steps. → The changes in the cutting forces are identified and modeled. → The intercept force coefficients D_2 and C_2 are calculated. → Tool equivalent flank wear VB_e is calculated and estimated with known model. → The remaining engagement time $t_{e,rem}$ until the tool life criterion is estimated based on the known model.

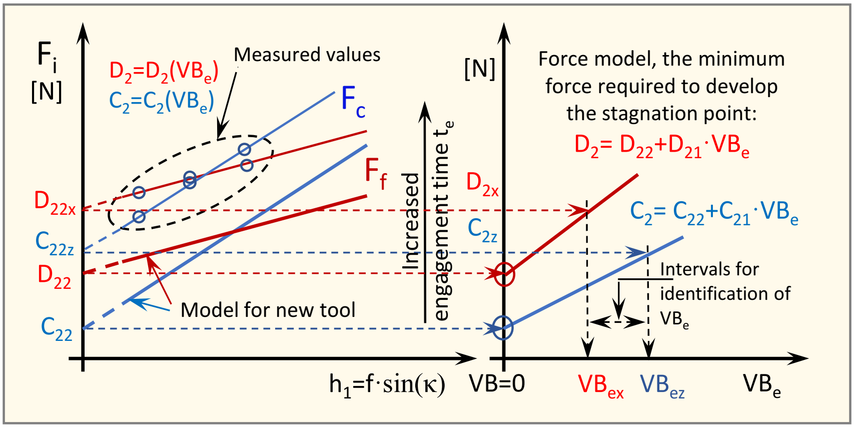

Figure 6. The principle of how an identification block is used, 6 or more measured values are recorded, by interpolation the constants (process variables) C_{2z} and D_{2x} are calculated (left) and by knowing the relationship between the process variables and equivalent flank wear VB_e can be estimated (right).

The geometric change associated with the release side of the tool can be indirectly identified by measuring the process temperature in combination with the movement of the tool. The motion is often determined by measuring accelerations that are filtered and integrated. Through the motion, the damping in the process can be determined in relation to a known reference value. The combination of process temperature and damping can together strengthen the identification of the wear level of the tool. Also in this context, identification blocks can be very useful.

If the risk of tool failure is to be assessed, it is necessary to know the load distribution on the tool and the absolute value of the maximum main cutting force in combination with the current cutting depth a_p and the maximum theoretical chip thickness (h_1), which can be calculated using the selected feed rate f and the current approach angle κ. The main cutting force and current chip area form the basis for calculating the cutting resistance, which in turn is directly proportional to the maximum main stress in the tool (σ_1). The same applies to the effective stress (σ_e) in the tool. Dimensionless stress functions can be determined using linear elastic FEM simulations, which provide an approximate and general description of the global stresses in the tool. The calculation methodology can be used in real time [3].

If the maximum principal stress σ_1 exceeds a certain value, a principal stress rupture of the cutting tool is obtained. In case the effective stress σe exceeds a certain value in combination with the temperature, plastic deformation of the cutting tool is obtained. In very brittle tool materials, a crushing of the tool is obtained, which applies preferably to ceramic-based tool materials. The total load distribution of the tool can be described in a mechanical load diagram as shown in **Figure 7** where the combination of feed force F_f and main cutting force F_c gives different mechanical loads that can correlate to types of tool degradation. However, it should be noted that the relationships are not conclusive.

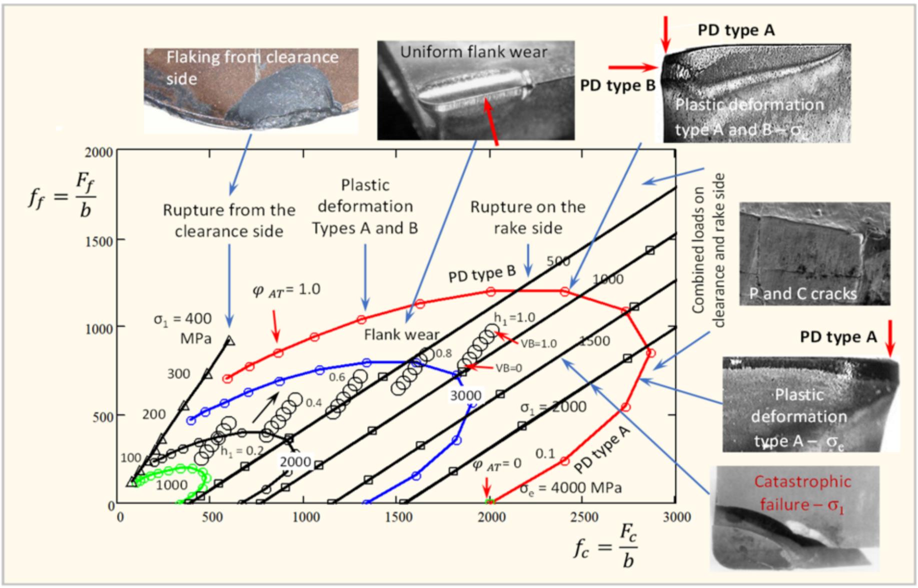

Figure 7. A schematic mechanical load diagram in which areas characterized by the occurrence of specific types of cutting tool degradation can be identified [4].

There are major difficulties in detecting and assessing the risk of principal stress rupture as this requires very high demands on the measurement technique to be used. The cutting forces have to be measured with a high bandwidth so that the load condition at the engagement phase during intermittent machining can be reproduced with correct dynamics and correct phase angles between the cutting force components. In general, the force dynamics caused by the chip segmentation must also be recorded.

In rough machining, cutting force variations should therefore be well reproduced with a frequency of about 10 kHz, which is generally very high for mechanical systems. In these cases, a sampling rate of measurement data corresponding to about 100 kHz is required to well reproduce the actual course of the cutting process. This measurement data can also provide a snapshot of the tool's mechanical load pattern. Examples of measured dynamic cutting forces (F_f and F_c) are exemplified in **Figure 8** together with a load pattern when machining gray iron SS 0125. **Figure 9** exemplifies older cutting force sensors for measuring dynamic cutting forces. These force sensors are very sensitive to the cutting fluids and electromagnetic fields. They work well in a controlled laboratory environment but are still very difficult to use in an industrial environment.

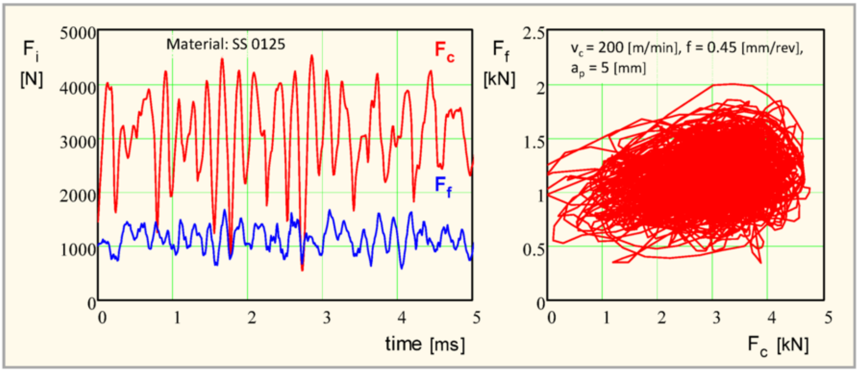

Figure 8. Examples of measured dynamic cutting forces, main cutting force F_c and feed force F_f during rough turning in gray cast iron SS 0125 (left) and corresponding load diagram (right).

When assessing the risk of plastic deformation of the tool, a significantly lower sampling rate is required compared to detecting the risk of principal stress rupture. This is because plastic deformation of the cutting tool occurs relatively slowly, on a scale of tenths of seconds as opposed to principal stress rupture which occurs on a scale of tenths of milliseconds. Some tribological conditions in contact surfaces can be identified by sound and acoustic emission (AE). Early on, AE was used to detect cracking, which has also been tried in the machining field to detect cracking and breakage in cutting tools.

The chip formation process including chip forming and chip breaking greatly complicates the ability to detect damage to the tool. This condition is particularly accentuated when machining brittle work materials where cracking is a significant part of the generation of short chips. Changes in sound or AE signal are obtained when the contact surfaces between cutting tool and workpiece change. However, the relationships between tool wear development and obtained signals are often diffuse and not always clear. Power and torque measurements are possibly the most common way to identify undesirable events in the cutting process. Power measurement is hampered by the idle energy consumption of the equipment and has low time resolution and low sensitivity. Torque measurement can provide better performance than power measurement, depending on how close to the process the torque can be measured.

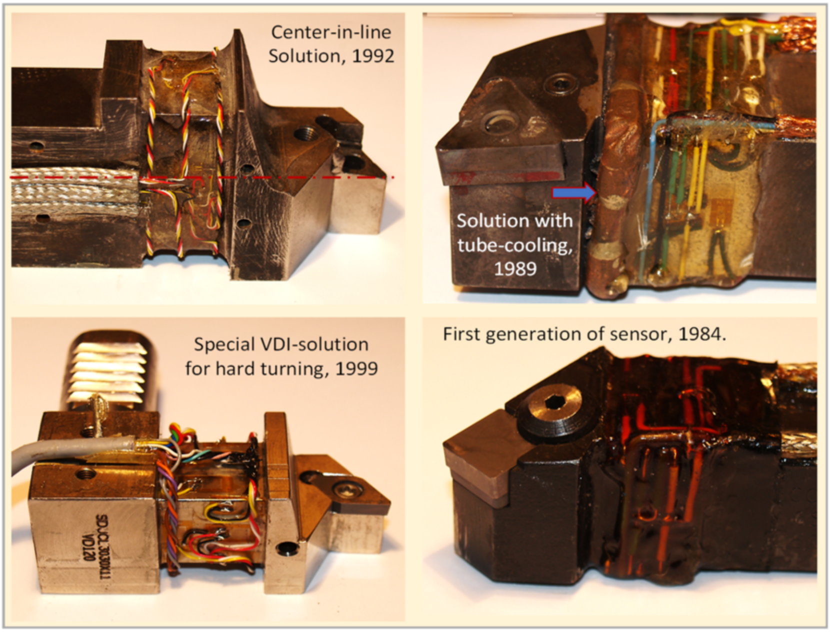

Figure 9. Example of a force sensor for measuring dynamic cutting forces with a relatively high bandwidth, developed at Lund University between 1984 to 1999.

5. Sensors and signal processing for machining optimization

The above examples are based on the assumption that the following can be measured in the cutting process:

- Static and dynamic cutting forces.
- Tool temperature and its temperature distribution.
- Acceleration, movement or dynamic position of the tool.
- Airborne sound measurements with microphones.
- High frequency acoustic emission (AE).
- Power and torque measurements associated with different spindles of the machine tool and its different feed directions.

Regardless of what is being measured, the location of the sensors in relation to the process will determine the accuracy of the measured quantity and its time resolution.

5.1 Development of robust sensors and encoders for machining applications

Widespread implementation of sensors directly into harsh and hard to access industrial environments such as machining has been an ongoing scientific and technological goal for many years [1] but has still not occurred. One reason for renewed optimism is the significant progress in micro and nanofabrication which has occurred in the last decade [12-26]. Exact bottom-up synthesis is now possible for a wide range of electronic materials with varying properties and top-down lithography has evolved not only in terms of miniaturization (which is well publicized [17]), but also in regard to the creation of a wide variety of 1D, 2D and 3D structures [12-22]. Metal droplet seeded or selective area growth using Chemical Vapor Deposition (CVD) methods makes it possible to form extremely well-defined compound structures with electrical device properties in specific locations even hidden from line-of-sight of the CVD tool [12-14]. **Figure 10** shows a CVD furnace with accessories designed to deposit a variety of functional materials, including insulators, hard coatings, semiconductors or thermal alloys. The chamber, seen in the center, is where the tools are placed and subjected to controlled heating and infusion of precursor gases, which react to form uniform thin-film coatings tailored for improved tool performance. In-fact metal patterns can be used to control synthesis as they change the local chemical environment, as have recently been shown [5]. These methods have been further combined with advanced lithographic structuring and fabrication of advanced layered structures in 3D combining many different types of materials [16, 17, 18].

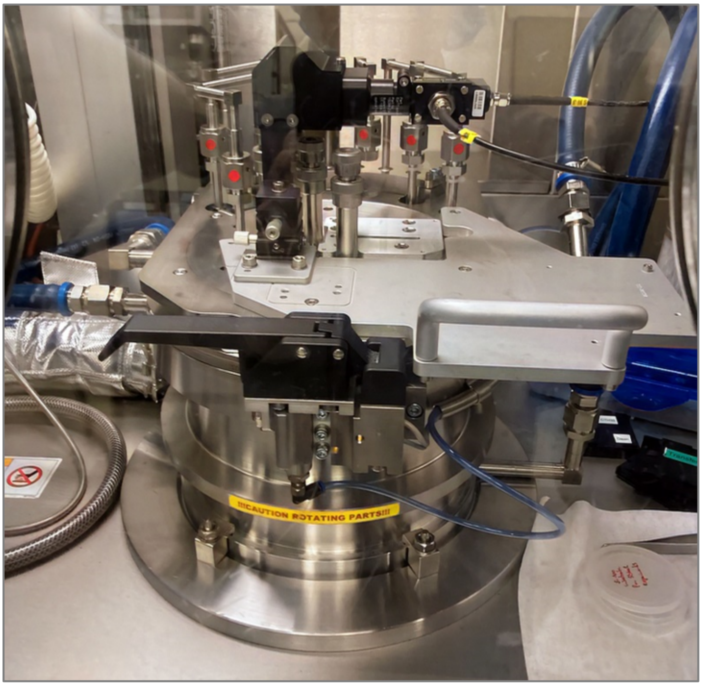

Figure 10. Research CVD-furnace used to produce different types of functional materials, including functional coatings that can be used for sensors.

In these methods combinations of layer-by-layer etching and deposition are used in combination with various types of masking both using polymers as well as shadow masks. Often the manufacturing is combined with advanced characterization using both electron microscopes and synchrotron-based X-ray studies [19-22]. This makes it possible to do intelligent choices when developing a new fabrication process and not rely on trial-and-error. With so many possible routes for nano and microstructure formation this is an important step as the development of fabrication strategies is a time-consuming affair. An interesting development is the ability to create patterns on curved surfaces by initially fabricating devices on a flat standard substrate, embedding them in an organic transport layer, which is then released from the original substrate and transferred to the machining tool [23, 24]. The polymer layer will then fold around the machining tool in 3D. Subsequently, the organic material layer can be removed by chemical treatments or heating in a reactive atmosphere and the device will adhere to the underlying substrate via heating and/or adhesion layers. Such contact deposition has the advantage that the functional structures can be made under optimum conditions as the growth substrate will strongly influence the final structure. Thus, a flexible and non-invasive production is possible, that can also be fast. It depends on the device structure being flexible, here it can be noted that nanostructure will often be rather flexible due their reduced dimensions [44]. **Figure 11** show a bisected view of the metal cutting tool post Wire Electrical Discharge Machining (W-EDM) process, illustrating the precision cutting capabilities (a) and an internal cross-section of the cut tool revealing the intricate metal patterns created using UV lithography, serving as precursors for thin film sensor integration (b) and finally a high-resolution microscopy image highlighting the fine details and the superior resolution of the UV lithography-imprinted metal patterns, essential for the functionality of thin film sensors (c).

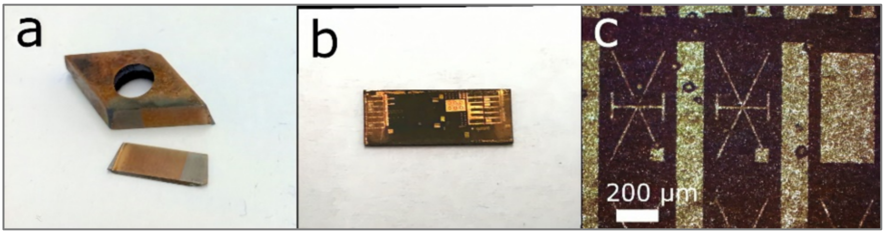

Figure 11. Example of a cutting tool that is sliced (a), a manufactured UV lithography pattern with sensor properties (b) and a magnification of a produced film-sensor (c).

Deep reactive Ion Etching is technique that allows the formation of very thing high aspect ratio channels that can be used for wiring or sensors in a range of materials [25]. Also, fluid flow assembly can be used to guide functional device structures to the correct position using chemical specificity or electrophoresis [26]. For the specific implementation of sensors in machining and on steel, micrometer scale structures have been fabricated using various basic lithography and growth techniques that have been previously implemented for semiconductors indicating the high potential for transference of knowhow between the sectors [28-33]. Further complex integration into composites has been done [34] and sensors for harsh environments have been explored [35]. One of the powerful features of nano/micron fabrication is the ability to create several sensors or even sensor arrays in the same printing cycle. This is highly advantageous as it will make the eventual signal interpretation more robust and potentially contain considerably more information [36, 37].

While most nano and microstructures are inherently excellent sensors due to their small volume and large contact area this is not enough to qualify as a useful in a real application. Here both sensing of the relevant signal, transmission of the signal to the external world and the interpretation of the signal, in the presence of noise, fluctuations and actual functional connection to the relevant physical property at the relevant place in space, must be taken into consideration. An important further consideration for successful implementation of micron/nano sensors in industrial products and production is the direct connection to the actual industrial processing and models of these. While much work on sensors, for example for machining, deals with the measurements of physical parameters such as temperature these works often lack the direct connection to the implementation in the manufacturing process and the additional requirements and constrains this sets. A direct comparison between the requirements for sensing based on models of industrial production, including their environment impact, with what capabilities can be physically realized with nanofabrication is crucial. For both technology/research fields the parameter space for possible developments is huge, but only where there is a reasonable probability that they will overlap is it worth researching. Additionally, a continuous collaboration is needed as both industrial production models and physical sensor systems and signal interpretation can be modified to find the optimum solution. Here continuous modelling using input from ongoing experiments is important as this will further act to reduce the parameters spacing for time consuming fabrication development.

For the specific case of machining, a central challenge lies in sensing and hence understanding the conditions (such as temperature, pressure, and vibrations) at the local point where the cutting tool interacts with the material to be machined. As an example, a parameter such as temperature changes very rapidly and non-linearly away from the contact point, hundreds of degrees within a few hundred microns [32], making measurements close to the contact point essential. Thus, the sensor has to function near the cutting zone that can reach temperatures above 1000 ºC and which is also under considerable mechanical stress and experience vibrations. For both technology/research fields the parameter space for possible developments is huge, but only where there is a reasonable probability that they will overlap is it worth researching. Finally, communicating the signal to the exterior world is a challenge. An example is that the contact point where the cutting occurs is often obscured both by the tool and tool piece as well as liquids administered during the machining making remote optical diagnostics difficult. Finally, while most micro and nanofabrication methods have been developed for planar homogeneous surfaces, such as Silicon wafers, tool surfaces will usually be rougher, curved and consist of a complex elemental composition and crystal structure.

Overall, promising sensor options are based on either electrical or optical signals, here we focus on sensor capabilities embedded in the tools. External sensors, such as cameras, can be easier to implement and need no modification of the tools, but has significant limitations due to e.g., poor optical access. For temperature measurements sensing can be accomplished electrically via integrating a thermocouple inside the tool or printed on the tool. Alternatively infrared radiation from the tool can be measured via optical fibers embedded in the tool. These different approaches have different challenges, but reasonably successful cases have been demonstrated [33]. Further miniaturization can help make these methods less invasive to the tool and the use of combinations of bottom-up and top-down approaches can be helpful. For measurements of vibrations (and pressure) both electrical and optical sensing again appear as viable options. Piezoelectric materials can be used to gauge both vibrations and larger pressure changes while optical reflection has been used to monitor vibrations.

5.2 Sensor design and signal transmission

Some of today's available sensors have a strong temperature drift, which is why they cannot be placed too close to the process without a well-functioning cooling system. Another significant problem with measurements in the cutting process is its difficult environment in terms of cutting fluids, sharp and heavily deformation-hardened chips and severe electromagnetic interference. The electromagnetic interference comes from the machine itself but also from other equipment. By increasingly integrating sensors in tools, tool holders or other machine equipment, the above-mentioned problems can be reduced, but new challenges will arise. A final consideration in the sensor design is the need for local filtering, interpretation, amplification as well as subsequent transmission of the signal. Here edge computing close to the actual sensor should be considered [38, 39]. Already performing a first filtering and interpretation of the signal locally close to the sensor can allow for a more simplified and amplified signal to be transmitted out. The ability to actually transmit the signal out from the active area should not be underestimated as a significant challenge that must be thought out together with the sensor design. Here local electronics that can work in high temperature conditions and which have high structural stability is of relevance. This leads to materials such as GalliumNitride compounds which can work at elevated temperatures, have a high melting point and are mechanically robust [30, 31, 32]. Further, these materials are already used in the semiconductor industry for high power and optical applications and suggested as vibration sensors for harsh environments [41, 42].

5.3 Signal processing for machining optimization

After sensor local signal handling, amplification, resampling and filtering, the signal transmission itself will also contribute with new disturbances and challenges, typically outlier and missing data samples as well as complete structural breaks, which calls for initial careful data cleaning. The resulting cleaned measured time series will generally be of non-stationary and non-linear character buried in high noise levels. Additionally, the noise distributions can be expected to include outliers which typically call for robust techniques in the time series modelling. Such methods can in general be combined with state-of-the-art methods for prediction of temperatures, e.g., finite element analysis and regression analysis [33]. Another challenge is coupling and correlation of measurements. Multi-variate time series, in time and space, can be used for modelling of temperature prediction using modern techniques for robust covariance and cross-correlation modelling. Dimensionality reduction analysis of resulting models and parameters using principal component analysis (PCA) and independent component analysis (ICA) are important approaches. Following the success in image classification, machine learning has naturally gained interest also within classification of machining measurements. For sound and vibration measurements, state-of-the-art techniques extracting time-frequency (TF) domain information are often applied and used as input data. Typical machine learning models in this context are Multi-Layer Perceptron, Convolution Neural Network (CNN), Long Short-Term Memory (LSTM), and transformers. Classification is then generally performed on spectrograms images, obtained from the time series measurements, which allow the rendering of more accurate and richer features from the signals, as the original time domain signal is very noisy and exhibits several non-linearities [33].

In the popular deep learning sub-field, models with many CNN-layers and millions of parameters have been pre-trained using millions of images (e.g., ImageNet and ResNet-50). These pre-trained models are successfully used for different computer vision tasks, such as image classification and object localization in images. However, these pre-trained models are not at all optimal for classification of features from TF images, which are known to have a different structure compared to a general image, with a particular strong dependence between the time- and frequency dimensions. Regardless of this important restriction, the pre-trained deep learning models are nowadays extensively used for sound and vibration classification by adding an extra classifier to be trained for the difference in the TF image characters. In general, a spectrogram image, with additional mel-frequency and log-energy transformations, is used as the input TF image. The hyperparameters, such as e.g., spectrogram window size, hop length and number of mel bands, are always difficult to choose for an optimal performance [46, 47].

A number of challenges arise in the application of pre-trained deep learning models for sound classification: (1) data cleaning and annotation of measurements is time consuming and cannot in general be fully automated, restricting the availability of large data sets; (2) extensive testing is needed to find the optimal choices of hyperparameters, where mistakes lead to insufficient and non-optimal resolution of the TF images; (3) the high noise level of data is in general resulting in degraded information extraction; (4) the interpretation of the performance of the deep learning algorithm, as the importance of the explicit features is in general hidden.

The complete solution to the above challenges are not yet available but a number of approaches can be found. **(1)** Annotation of data often needs to be performed by an expert and to save time and effort in these matters, active learning is a modern strategy for the expert annotation of data. The available techniques rely on algorithms that actively selects informative samples to be labeled by the human expert. An acquisition function is used to score the unannotated data which will then contribute to a faster learning of the machine learning model [48]. **(2)** To avoid the extensive testing for optimal hyperparameters, recent work has proposed the differentiable spectrogram where the window size and hop length are jointly optimized with the model parameters [49]. Avoiding the manual choice of these hyperparameters leads to optimal TF resolution for a specific classification task. Other novel approaches propose the actual transformation from the time series to the TF image to be included in the deep learning model [50]. **(3)** For vibration signals, the frequency variation with time can be expected to be non-linear. The feature extraction of separate condition-related components then calls for TF ridge sharpening techniques [51, 52, 53]. Modern noise robust methods are the multitaper synchrosqueezing wavelet transform and the multitaper reassignment method. These techniques aim is to concentrate the blurry energy to sharper structures, which makes the TF image more interpretable for the human eye. Specific signal models can be incorporated and the methods can be used for optimal feature detection and selection [53]. **(4)** To solve the issue of interpretability and importance of features in deep learning, several recent papers investigate explainable AI (XAI) algorithms. General techniques exist for interpretation of black-box models, e.g., Shapley Additive Explanations (SHAP) and Local Depth-based Feature Importance for the Isolation Forest (Local-DIFFI). Specifically for TF images, there exist a number of popular methods to identify the globally important features and their connection to a specific TF area, e.g., GradCAM and Local Interpretable and Model-agnostic Explanation (LIME) [54, 55, 56].

6. Identified challenges related to the optimization of machining operations

The development of models and techniques to optimize machining with respect to several different criteria has a wide range of challenges, not least linking several different fields of science that need to be integrated and interact. A number of research questions must be answered both at the system level and at the process level. Examples of research questions at the system level are:

- Which variables need to be identified and measured in order to optimize machining with respect to predefined criteria?
- What is possible to measure in the machining process and how can this be correlated to the process behavior and output results relevant for an optimization, see previous section 3.2?
- How can measured variables be correlated, directly or indirectly, to the process models that can be used for an optimization?

- How can the feedback between measured variables and process control contribute to knowledge and experience related to the properties of the work material and its machinability?
- How flexible systems for process optimization can be created and how varied can the processing be in terms of the number of different operations and the number of similar workpieces in terms of batch size?

Examples of research questions that can be linked to technology and process are:

- How should the sensors be integrated and constructed to cope with the current environment in terms of pressure, temperature, tribology but also in terms of chemistry of the workpiece material, chips and cutting fluids?
- How should measurement signals be handled and transmitted taking into account the machine's movement pattern and the current cutting environment?
- How can AI/ML be integrated together with conventional process models to enable data for optimization with respect to different criteria, especially in short-series production with limited data sets and large process variations?
- What additional process models and optimization principles need to be developed to include the environmental impact of machining fully also under different machining conditions?

7. Summary and conclusions

The present paper deals with problems, conditions and new opportunities to optimize machining with regard to several different criteria. In the discussion, the environmental impact of machining has been added as a new optimization criterion. The reported study states that a broad approach is required where several different disciplines interact to succeed in real-time optimization of machining. New and robust sensors are required while new signal management including signal transmission is required, machining models linked to the process and system must be further developed in various respects. The development of nano-sensors, signal transmission technology and ML/AI in combination with a long research tradition in machining provides new and unique conditions to eventually be able to control and optimize machining in real time, which also includes the environmental impact of machining.

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