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INTERPRETATION OF CUTTING ABILITY

BÉLA MÉSZÁROS[1]* AND BALÁZS MIKÓ[1]

1 Institute of Mechanical Engineering and Technology, Óbuda University, Bécsi u. 96/B, Budapest, 1034, HUNGARY

Cutting ability shows how well and economically a material can be machined by cutting. The term is widely used in manufacturing, but there is no agreed, precise definition, usually reflecting the direct interests of the user. It is considered to be a property related to the properties of the material, but there is no generally accepted parameter for measuring it. It is not only influenced by the physical and mechanical properties of the material, but also by the material and design of the cutting tool, the cooling, the stability of the machine tool and the cutting parameters used. Cutting ability can be assessed by various quantitative and qualitative characteristics that apply to the tool, the workpiece and the process. The aim of this article is to present various interpretations of cutting ability, to classify and investigate the parameters that influence cutting ability and characterize it, and to present a methodology for the development of qualitative and quantitative metrics.

Keywords: cutting process, cutting performance, multi criteria decision making, cutting ability

1. Introduction

In manufacturing technology, cutting ability is a frequently used concept, the term is widely used in manufacturing, but there is no accepted, precise definition; it usually reflects the direct interests of the user. It is considered a property related to the material properties, but there is no generally accepted parameter for measuring it [1],[2].

Cutting ability depends not only on the physical and mechanical properties of the material, but is also influenced by the tool material, the cutting parameters, the cooling conditions and the stability of the machine tool used. Therefore, cutting ability can be understood as the result of the whole production process and not only as a characteristic of the material.

The concept of cutting ability is important in many aspects and can be used in many areas. In the design process, a material must be selected that can withstand the stresses and strains of operation, while at the same time not causing difficulties in the production and machining of the part. In the manufacturing process planning phase, it is necessary to determine the technological parameters that allow the task to be carried out with the necessary precision and economy. In the development of a cutting tool, we want to measure the efficiency of production by comparing different tool designs and technological variants.

The aim of the research is to investigate and systematise metrics of cutting ability, and to investigate the applicability of various data analysis procedures. The aim of the paper is to classify several interpretations of cutting ability, to systematise the factors determining and influencing cutting ability, to present the applicable procedures to develop an evaluation system.

2. Parameters influencing and characterising cutting ability

Cutting ability can be understood in several ways. On the one hand, cutting ability is a set of properties that indicate the efficiency and effectiveness of the machining process, and on the other hand, cutting ability can be connected to the parameters that determine the machining process. These characteristics can be quantitative or qualitative parameters.

The cutting ability can be defined from the perspective of the result, which characterises the effectiveness of the machining process (*Figure 1*). What happens during the machining process, and what can be measured and tested during or after the production? The phenomena that occur during the machining process can be divided into three groups. Together, these parameters determine cutting ability, and their analysis can be used to make an informed assessment of whether a given material can be machined well under the given conditions.

The first group contains characteristics related to the machining process. These are the cutting force [3]-[5], the force components [6], their ratios, the power

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*Correspondence: meszaros.bela@bgk.uni-obuda.hu

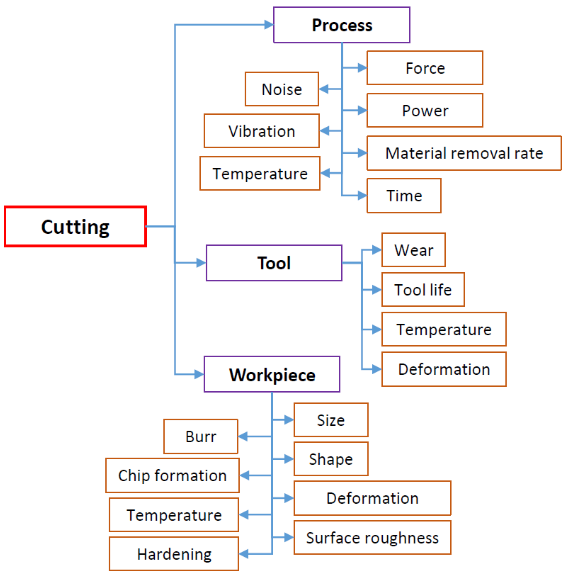


Figure 1: Characterizing parameters of cutting ability

requirement of cutting, the vibrations generated, the acoustic emission [7] and the production time. The second group includes tool-related phenomena.

The wear patterns on the tool, the wear rate [8],[9], the tool life [10]-[12], the tool deformation and the tool temperature are the parameters that can be investigated. The third group of parameters is the workpiece characteristics. The accuracy of the resulting surface can be investigated in several aspects, such as dimensional accuracy [13], shape accuracy [14], or different parameters of surface roughness [15]-[17]. The temperature of the workpiece [11], the variation of material hardness [8], residual stress, the rate of line formation, and the shape and size of the resulting chip [9],[18] can be measured.

Cutting ability can also be considered in terms of the parameters that determine the process, i.e. what are the "given conditions"? The factors that determine a machining process can be grouped into four categories (*Figure 2*). The first category is material properties. These include the composition of the material and the chemical composition (alloys) [2], the mechanical properties of the material, such as tensile strength, yield strength, hardness, or the anisotropy and inhomogeneity of the material [4],[9],[12]. The second group is the set of cutting tool characteristics, tool material, coating, size, edge design, edge geometry [19]. The third group is the set of cutting parameters: cutting speed, feed rate, depth of cut, width of cut. The fourth group is the parameters describing the technology. This includes the machine tool design and condition, the workpiece and the tool clamping method used, the clamping device, type of cooling material [9],[10],[20],[21], application, and tool path layout. The cutting ability is determined by the combination of these factors.

Cutting ability is the result of the whole manufacturing process, not just a characteristic of the raw material. Thus, for the purposes of cutting ability testing, we must distinguish between

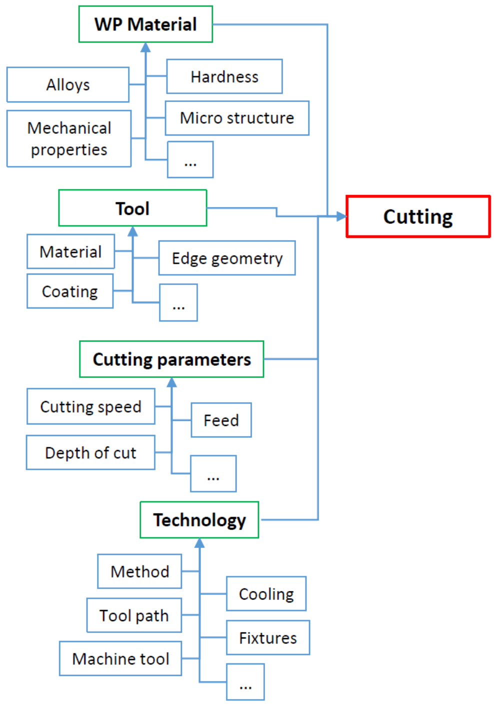


Figure 2: Influencing parameters of cutting ability

- the cutting ability of the material, which refers to the properties of the material,
- the cutting ability of the cutting process (process cutting ability), which characterises the efficiency of the technological process, and
- tool cutting ability, which describes the performance of the tool.

By classifying the measurement data according to the purpose of the investigation, the cutting ability of several elements of the technology can be evaluated.

3. Cutting ability index

To measure cutting ability, cutting ability indices are used, which can vary depending on the application and the information available (*Figure 3*).

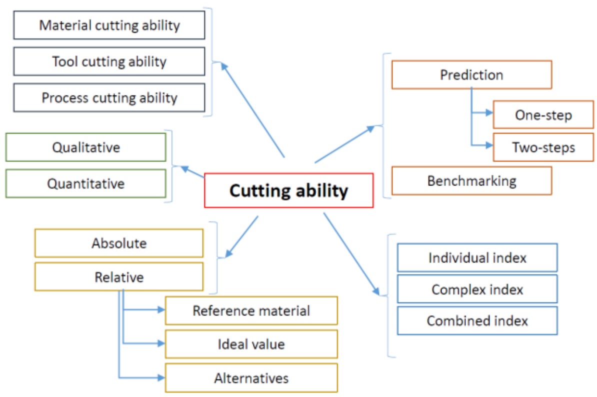


Figure 3: Classification of cutting ability index

The parameters that determine the machining process can be used to predict cutting ability, i.e. to give an estimate of cutting ability based on an analysis of material–tool–machining parameters–process conditions or a subset of these. This approach is well-suited for process design or material selection. In contrast, the cutting ability index can be used to evaluate the cutting ability of a given manufacturing task and thus can be used to compare technological developments and tool designs.

Cutting ability can be a qualitative or quantitative parameter. For a qualitative parameter, we want to place the process on a scale from "very good" to "very poor". For a quantitative parameter, a numerical value is assigned to the cutting ability. The quality parameter is more difficult to compare; it is subjective and empirical. The quantitative parameter allows easier comparison, is suitable for optimisation, is reproducible, but the method is time-consuming to develop.

Cutting ability can be evaluated on its own, i.e. the process is placed on an absolute scale in terms of cutting ability. It can also be evaluated in relative terms, as a comparison, in relation to something. The comparison can be made to a reference material, to another process variant, or to a set of expected values.

The various individual parameters can be used as quantitative parameters, but this allows only a very one-sided evaluation. Nevertheless, most research evaluates each parameter separately [8],[11].

Complex parameters can be used, combining several effects. The tool life is a parameter that characterises traditional cutting ability and summarises the effects of several factors [10]. Another such composite parameter is the cutting speed for a given tool life (e.g. 60 min), which characterises the machining process through tool wear. A commonly used composite parameter is also the material removal rate (*MRR*, cm^3/min), the amount of material that can be removed in a unit of time [14],[15]. This is a good characterization of productivity; its value depends on the cutting parameters, which are determined by the workpiece material, tool and machine tool properties.

A third option is to evaluate and combine several parameters together to give a more comprehensive picture of cutting ability. The combined evaluation of several parameters allows the combination of conflicting or competing aspects.

The relative cutting ability parameter relates the cutting ability of the material under test to a reference material:

$$CI = \frac{P}{P_{ref}} \cdot 100\ [\%] \qquad (1),$$

CI – Cutting ability index,
P – Investigated parameter,
P_{ref} – Reference value of the parameter.

Several material grades are used as reference materials in parallel experiments. For steels, the most common reference grades are:

- C45 (1.0503; AISI 1045) medium carbon non-alloy steel,
- 42CrMo4 (1.7227; AISI 4140) medium carbon, low alloy, high strength steel [7],
- 10S20 (1.0721; AISI 1108) free-cutting steel,
- x5CrNi18-10 (1.4301; AISI 304) stainless steel [10].

The comparison can be made with an ideal or target value, but this can be problematic to define. For surface roughness, it is obvious to use the manufacturing specification as a target value, but for tool wear or cutting force, this results in an unclear choice.

A third way to generate a relative cutting ability parameter is to compare two or more materials/tools/technology variants. Any one of these elements can be the "reference" element in this case, the order among them is not affected. In this way it is possible to compare different technological variants.

4. Multi-criteria decision making

When considering several individual parameters together, the individual parameters should be combined. Multi-criteria decision making (MCDM) provides tools for this [22]. MCDM requires accurate and reliable data for each alternative and criterion. Several methods can be applied for optimisation of turning processes [23],[24].

The main challenge of the evaluation is that the effectiveness of the cutting process must be evaluated based on competing criteria. Is productivity (MRR), tool wear or surface quality more important? MCDM methods provide a means to evaluate these together.

The simplest way to consider several parameters together is to use the sum or multiplication of their relative values. Since each parameter may be of different importance, it can be taken into account by applying weighting factors. The WSM (Weighted Sum Model) procedure sums the relative values, the WPM (Weighted Product Model) procedure multiplies them:

$$CI = \sum w_i \cdot \frac{P_i}{P_{i\,ref}} \qquad (2),$$

$$CI = \prod \left(\frac{P_i}{P_{i\,ref}}\right)^{w_i} \qquad (3).$$

The TOPSIS method is a MCDM method used to rank alternatives based on their similarity to the ideal solution and their distance from the worst solution. It is widely used in engineering, manufacturing, business and decision analysis. It can also be used in the selection of cutting tools, the determination of cutting parameters, and the joint evaluation of cutting ability characteristics [14],[22].

After normalisation and weighting (e.g. APH or Q-method) of a matrix of individual characteristic values (e.g. roughness, cutting force, material removal rate), the best and worst value of each characteristic shall be selected from the set of values. During normalisation, the value is divided by the root mean square (RMS) of the characteristic. The Euclidean distances (D_i^+, D_i^-) from the best and worst cases are then determined for each

Table 1: Comparison of TOPSIS and ELECTRE methods

Aspect	TOPSIS	ELECTRE
Approach	Distance to ideal/anti-ideal.	Pairwise outranking.
Data	Quantitative, measurable.	Quantitative and qualitative.
Output	Full ranking of options.	Outranked / not outranked.
Strengths	Simple, fast, transparent.	Handles conflict and uncertainty well.
Weaknesses	Poor with conflicting criteria.	Complex, less intuitive.

alternative. The two distance values are used to determine the coefficient of similarity (C_i):

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-} \tag{4}$$

A higher Ci value indicates a better solution.

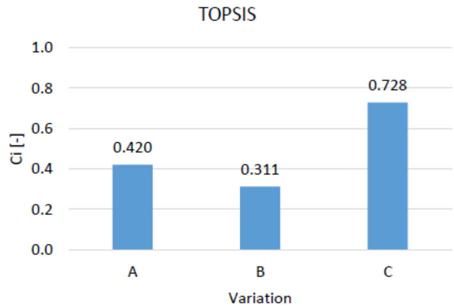
The ELECTRE method (ELimination Et Choix Traduisant la REalité) is a MCDM method developed to support decision-making by considering several, often conflicting, criteria. The basic principle of ELECTRE methods is to design a decision network based on dominance and preference systems to help the decision-maker filter or rank alternatives. ELECTRE is particularly useful when the choice between alternatives is not always transparent or clearly numerical.

In the determination of cutting ability, the use of the ELECTRE method allows the cutting ability characteristics of different materials (e.g. tool wear, surface roughness, cutting force, temperature, tool life, etc.) to be evaluated from several aspects. By comparing different materials and tools, it is possible to determine which parameters can achieve a better machining result, taking into account manufacturing considerations and priorities [25].

Table 1 compares the properties of the TOPSIS and the ELECTRE methods. *Figure 4* shows an example of the TOPSIS and ELECTRE methods with hypothetical data. Three variations of the cutting process are compared based on tool wear, cutting force, surface roughness (Ra) and material removal rate (MRR). Weights are defined; the surface roughness is the most important, and cutting force is the least important. 1/-1 parameters indicate the preferred level of the property: 1 means larger is better, -1 means smaller is better. As the diagrams show, the TOPSIS method provides a more sophisticated result, it can make a difference between cases A and C.

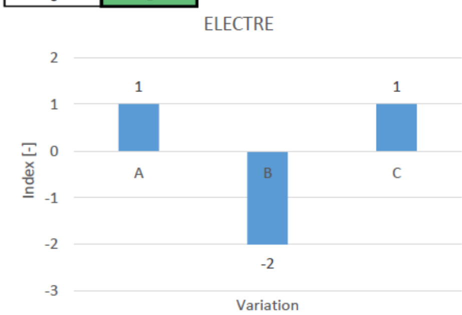
Prioritizing and weighting individual characteristics is also an important task to be solved during the evaluation, which are used by both of the methods presented above. The AHP (Analytic Hierarchy Process) method is particularly well-adapted to problems where

Alternative	Tool wear [um]	Cutting force (N)	Ra (μm)	MRR (mm³/s)
A	120	260	1.6	220
B	150	380	1.5	180
C	230	220	1.3	240
Weight	0.2	0.15	0.35	0.3
Best	-1	-1	-1	1
Linearization				
A	100.0	75.0	0.0	66.7
B	72.7	0.0	33.3	0.0
C	0.0	100.0	100.0	100.0
SQRT(SS)	123.6	125.0	105.4	120.2
Normalization				
A	0.162	0.090	0.000	0.166
B	0.118	0.000	0.111	0.000
C	0.000	0.120	0.332	0.250
A+	0.162	0.120	0.332	0.250
A-	0.000	0.000	0.000	0.000
Ranking				
	Di+	Di-	Ci	
A	0.344	0.249	0.420	
B	0.357	0.162	0.311	
C	0.162	0.432	0.728	



a)

Alternative	Tool wear [um]	Cutting force (N)	Ra (μm)	MRR (mm³/s)
A	120	260	1.6	220
B	150	380	1.5	180
C	230	220	1.3	240
Weight	0.2	0.15	0.35	0.3
	-1	-1	-1	1
Linearization				
A	100.0	75.0	0.0	66.7
B	72.7	0.0	33.3	0.0
C	0.0	100.0	100.0	100.0
Concordance matrix				
	A	B	C	
A		0.65	0.2	
B	0.35		0.2	
C	0.8	0.8		
c*	0.50			
Discordance matrix				
	A	B	C	
A		0.33	1.00	
B	0.75		1.00	
C	1.00	0.73		
d*	0.80			
Outranking matrix				
	A	B	C	out
A		1	0	1
B	0		0	0
C	0	1		1
in	0	2	0	
Ranking (out-in)				
A	1			
B	-2			
C	1			



b)

Figure 4: Example: a) TOPSIS method b) ELECTRE method

the evaluation criteria can be organised in a hierarchical way into sub-criteria. AHP models a decision problem through a four-stage process of (1) hierarchical structuring of the problem, (2) data input, (3) estimation of relative weights of the evaluation criteria, (4) combining the relative weights to obtain an overall evaluation of alternatives (criterion aggregation) [22]. The method is suitable for weighting individual influencing and characteristic parameters [19],[25].

In determining cutting ability, the Q-method can be used to prioritise and weight those aspects that are important in the assessment of cutting ability (e.g. surface quality, tool wear, cutting force, cost, etc.). The involvement of various manufacturing experts (technologists, engineers, machine operators) can be used to identify which factors are more important in practice. The Q-methodology is a method combining qualitative and quantitative elements, which is mainly used to map subjective opinions, attitudes and preferences. The method consists of participants ranking items from a pre-defined set of statements (Q-samples) on a scale (e.g. least to most characteristic) to produce a Q-score. Statistical analysis of the Q-sorting (e.g. factor analysis) can be used to identify groups of similar opinions and, on this basis, to determine the dominant viewpoints. The method is useful when a structured, comparable analysis of the opinions of different experts or stakeholders is required [26].

5. Cutting ability models

Based on the experimental results, a model can be built to describe the relationship between input (influencing) and output (characteristic) parameters. The model can be used for prediction and process optimisation [14],[27].

Predictive models can be built based on the parameters that determine cutting ability. This requires understanding the effect of certain parameters on cutting ability and establishing a relationship between the values of the characteristics and cutting ability. The predictive model can be a one-step model, where the cutting ability index is determined directly from the influencing factors. The model can be a two-step model, where the process characteristic parameters are predicted in a first step and then the cutting ability index is determined based on these parameters. In model building, several methods can be used to determine the relationship between input and output parameters.

Multivariate linear regression (MLR) is a statistical method that examines how several independent variables (e.g. material properties, process parameters) influence the value of a dependent variable (e.g. machining performance, tool wear). Assuming a linear relationship between the dependent variable and the independent variables, the weight values of each independent variable are determined from the data collection during model fitting [21]. Its main strength lies in its simplicity and interpretability: each coefficient directly indicates the effect of a cutting parameter, making it useful for deriving engineering knowledge and validating experimental hypotheses. However, MLR assumes linearity and additivity of effects, which limits its accuracy when machining processes exhibit nonlinear behaviour, such as complex tool-workpiece interactions, thermal effects, or vibration.

The use of artificial neural networks (ANNs) avoids one of the limitations of regression models, which is the need to compose the mathematical function. ANNs are able to identify complex, nonlinear relationships between process parameters and output characteristics. Based on large amounts of experimental data, neural networks are able to learn the relationships between these parameters and then provide accurate predictions for new cases [3],[15],[16]. In the case of cutting ability, artificial neural networks can be used to estimate the value of each characteristic parameter, i.e. to predict the output value based on each input variable. On the other hand, it can also be used for direct estimation of cutting ability, if such data are available.

ANNs are data-driven models that can learn nonlinear and high-dimensional relationships without making explicit assumptions about the underlying process. They are particularly effective in assessing cutting ability under changing or dynamic conditions, where multiple parameters interact in complex ways. ANNs generally achieve higher predictive accuracy than MLR, but require larger data sets, more computational power, and careful tuning. This is because their “black box” nature reduces their interpretability.

Fuzzy logic inference can also be used to determine cutting ability, as there are many uncertainties and non-linearity in the machining process. Traditional mathematical models are often not able to accurately describe the factors influencing cutting ability, as these are not always definitive (e.g. "good", "medium", "poor" cutting ability). Fuzzy logic allows the translation of expert knowledge and experience into mathematical models and thus build a flexible decision-making system [7],[13].

If the individual values of each influencing factor can be related to the cutting ability, a predictive model can be constructed. In the case of steels, limit values can be defined for the alloys and mechanical properties, which are suitable for the combined evaluation of the fuzzy method. It is difficult to fit individual properties of the tools or the cutting parameters into this model, since they do not determine cutting ability by themselves. The fuzzy method can also be used to assess cutting ability. A qualitative cutting ability value can be assigned to the individual characteristics (roughness, dimensional accuracy, tool wear, burr size, etc.) and their combined evaluation is carried out using the fuzzy method.

The effectiveness of different models can be confirmed by validation methods. The mean squared error (MSE) method is suitable for measuring the accuracy of the estimation, based on the average of the squares of the differences between the estimated and the actual values. The determination coefficient (R^2) shows the explanatory power of the model. K-fold cross validation helps to estimate the generalization ability of a model and avoid overfitting by repeated “model building – testing" cycles. Validation is performed on randomly separated training and testing data [16],[28].

6. Development of cutting ability model

During the model development process, the purpose of the model must be defined, i.e. whether we want to build a predictive or an evaluative model, or whether we want to define quantitative or qualitative values. This basically determines the input parameters of the model. While for a predictive model only the parameters of the machining task can be used, for an evaluative model the parameters measured during or after the process can be used. An important question is what the cutting ability model applies to, the material, the tool or the process parameters.

To develop a model, we need a set of samples that give examples of output and input values. The source of the sample data can be from literature, such as standards, manuals, technical articles.

A set of data obtained from a real production process for a specific manufacturing task, or the results of designed experiments, can provide more specific data. When planning the data acquisition, the availability, accuracy, cost and complexity of each data item should be analysed. The parameters that are important for the specific manufacturing task and the properties that are important to consider need to be investigated. Designed experiments are more expensive, but they can provide the necessary database in a shorter time, with better coverage of the range of variables and possible combinations of values.

Figure 5 shows the development process of the cutting performance evaluation system. The key question in development is therefore what data are available for model building and what type of model is best suited to the development goal.

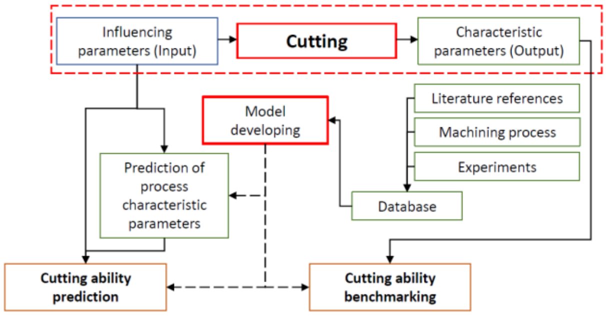


Figure 5: Development process of cutting ability evaluation model

7. Summary

Cutting ability in manufacturing engineering technology is an almost self-evident but difficult-to-define concept that measures the efficiency and adequacy of the machining process.

Our research aims to investigate different interpretations of cutting ability, to study the parameters influencing and characterising cutting ability, to implement and compare the methods used in the evaluation.

Based on our research, we found that cutting ability is the result of the whole manufacturing process, not just a characteristic of the raw material. Thus, for the purposes of cutting ability testing, we must distinguish between

- the cutting ability of the material, which refers to the properties of the material,
- the cutting ability of the cutting process (process cutting ability), which characterises the efficiency of the technological process, and
- tool cutting ability, which describes the performance of the tool.

We conclude, in order to create a cutting ability index for an evaluation system:

- A distinction must be made between parameters that affect cutting ability and parameters that characterise cutting ability.
- It is not possible to characterise cutting ability by a single parameter, but it is advisable to characterise it by evaluating several parameters together.
- The development of evaluation models should take into account the purpose of the model. The model can be a predictive model to support the process of technology planning decision making, or a benchmarking model to help evaluate different process variations to support manufacturing process improvement or tool development.
- The complex relationship between the many parameters that can be used in the evaluation and the cutting ability requires the use of artificial intelligence methods for more reliable models.

In further research, we will develop predictive and comparative models based on machining experiments to compare the applicability of each evaluation and weighting method. The experiments focus on side milling technology in the case of different grades of tool steels. An important aspect of the development is to integrate the opinions of industry engineers in the area of machining and tool development into the models.

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