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Testing, Modelling and Cost Performance

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Testing, Modelling and Cost Performance

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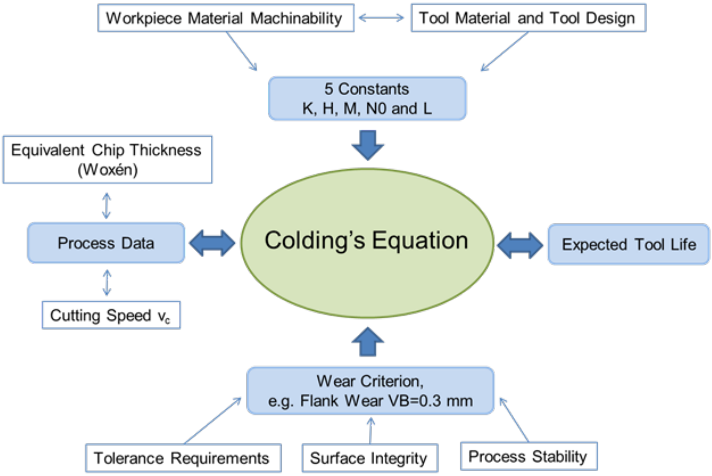

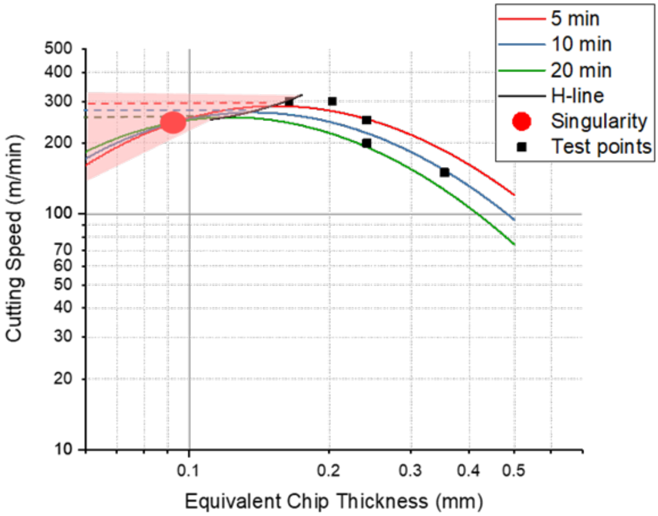

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Tool Life and Cutting Data Modelling in Metal Cutting

– Testing, Modelling and Cost Performance

Tool Life and Cutting Data Modelling in Metal Cutting

Daniel Johansson

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Abstract:

One of the most important production processes in industry is metal cutting. If a product is not a machined metal part, it is likely that the mould, die and tools used to produce the product or parts of the product are machined. The tools, machines and time spent add to the cost of the finished product and both industry and academia spend considerable effort in increasing efficacy and minimizing the environmental impact of these processes.

Models are often referred to both by scientists and industry. These models can help understanding and also predict the outcome of a process and the outcome of intended improvement measures. Models can also be used to minimize empirical testing and “rule of thumb,” thus allowing for shorter lead times and a more reliable production system.

One area of modelling in metal cutting is tool life and wear modelling. Today, tool providers support customers with digital software, suggesting tools for a given operation, process data and expected tool life. To facilitate this support tool life models are used, mainly those based on the Taylor equation and the Colding equation.

This research aims to investigate how one should model tool life for varying cutting data. Empirical data and modern computational power have been used to validate and optimize the process of modelling tool life. Commonly used tool life models have been investigated and the Colding model is suggested for tool life modelling. The process of collecting empirical input data to minimize the time and material consumed have also been investigated.

The author also presents a methodology based on a combination of tool life models and cost modelling as decision support for the selection of tools, workpiece material and process parameters. This approach can be used to minimize tool consumption, time consumption and reduce production costs.

Key words: metal cutting, tool life, tool wear, cutting data, process cost, part cost, Colding model.

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1.1 Selected symbols and abbreviations

a_p	Depth of cut	mm
A_D	True chip area	mm^2
A_e	Theoretical chip area	mm^2
b_e	Theoretical chip width	mm
C_T	Constant in Taylor's tool life equation	-
f	Feed	mm/rev.
H	Colding constant	-
h_e	Equivalent chip thickness	mm
h_m	Chip thickness	mm
K	Colding constant	-
k_A	Cost of tool	€
k_B	Cost of material	€
k_{CP}	Machine cost (running)	€/h
k_{CS}	Machine cost (idling)	€/h
k_D	Salary cost for operators	€/h
L	Colding constant	-
l_{SaD}	Active cutting length	
M	Colding constant	-
m	Exponent in Taylor's tool life equation	-
MRR	Metal removal rate	cm^3/min
N_0	Batch size	units
N0	Colding constant	-
n_{op}	Number of operators	units
p	Exponent in Taylor's tool life equation	-
q	Exponent in Taylor's tool life equation	-
q_Q	Rate of quality losses	-
q_S	Rate of time losses	-

q_{rem}	Rate of remaining time	-
q_{tct}	Rate of tool changes	-
r_{ε}	Nose radius	mm
T	Tool life	min
t_0	Cycle time	min/part
t_e	Tool engagement time	min/part
t_{pb}	Production time per part	min/part
t_{rem}	Remaining time incl. workpiece change and tool transportation	min/part
TL_{act}	Tool life in Coromant turning version 1 tool life model	min
TL_{nom}	Nominal tool life in Coromant turning version 1 tool life model	min
T_{su}	Set-up time per batch	min
T_{tct}	Tool change time	min
t_{tct}	Tool change time per part	min
U_{RP}	Production Capacity Utilization	-
V	Volume of work material to remove	cm^3
v_c	Cutting speed	m/min
vca	Coromant turning version 1 tool life model constant	-
vcb	Coromant turning version 1 tool life model constant	-
vcc	Coromant turning version 1 tool life model constant	-
z	Number of cutting edges per insert	units
ε_{err}	Model error	%
κ	Major cutting angle	degrees

1.2 Acknowledgement

Honestly, it was never my intention to devote four years of my life to investigating tool life models in metal cutting. Once, as I entered the office of Professor Jan-Eric Ståhl as a masters student, the first thing he said to me, looking up from his worn out red leather chair (it should have been retired from service 20 years ago but it is still a trade mark of his office) was, "*(In Swedish) Well, well if it isn't the guitarist from Småland, what can I do for you?*" Considerable amounts of metal, tools and hours on the computer have passed by since that day; but I believe that was the unofficial start of my PhD journey. The reason why I bring up this quote is the question at the end, *"…what can I do for you?"* It is a powerful question.

I would like to thank my supervisors Volodymyr Bushlya and Jan-Eric Ståhl for their support and mentorship. Their efforts and support have far exceeded what I expected.

I would like to thank all my colleagues at the Division of Production and Materials Engineering, Lund University. What we do on a daily basis is teamwork with common goals. I want to give a special thank you to Ville Akujärvi and Oleksandr Gutnichenko for their support in programming. I would also like to thank all the co-authors I have had the pleasure of working with.

Sören Hägglund at Seco Tools AB acted as a mentor for my work. If it was not for his valuable contribution and industrial approach this thesis would not have looked the way it does. Thank you Sören.

My research would not have been possible without financial support from the European Union's Horizon 2020 Research and Innovation Programme under the Flintstone2020 project (grant agreement No 689279) and the Sustainable Production Initiative Cooperation between Chalmers and Lund University. I also want to acknowledge the valuable contributions made by Seco Tools AB, Fagersta.

Finally, I want to thank my family and friends for their support. I would also like to thank my girlfriend Jannike Brandt for putting up with all discussions about metal cutting, and not least, all the metal chips adding to the guitar picks ending up in strange places in our home.

So, four years of investigating tool life models in metal cutting. What I have learned is that all things become fascinating when you dig deep enough into them and still manage to put it into a bigger perspective.

Daniel Johansson

1.3 Abstract

One of the most important production processes in industry is metal cutting. If a product is not a machined metal part, it is likely that the mould, die and tools used to produce the product or parts of the product are machined. The tools, machines and time spent add to the cost of the finished product and both industry and academia spend considerable effort in increasing efficacy and minimizing the environmental impact of these processes.

Models are often referred to both by scientists and industry. These models can help understanding and also predict the outcome of a process and the outcome of intended improvement measures. Models can also be used to minimize empirical testing and "rule of thumb," thus allowing for shorter lead times and a more reliable production system.

One area of modelling in metal cutting is tool life and wear modelling. Today, tool providers support customers with digital software, suggesting tools for a given operation, process data and expected tool life. To facilitate this support tool life models are used, mainly those based on the Taylor equation and the Colding equation.

This research aims to investigate how one should model tool life for varying cutting data. Empirical data and modern computational power have been used to validate and optimize the process of modelling tool life. Commonly used tool life models have been investigated and the Colding model is suggested for tool life modelling. The process of collecting empirical input data to minimize the time and material consumed have also been investigated.

The author also presents a methodology based on a combination of tool life models and cost modelling as decision support for the selection of tools, workpiece material and process parameters. This approach can be used to minimize tool consumption, time consumption and reduce production costs.

Keywords:

Metal cutting, tool life, tool wear, cutting data, process cost, part cost, Colding model.

1.4 Populärvetenskaplig sammanfattning

Svensk industri står för 20 procent av Sveriges BNP, vilket skapar mer än 17 % av sysselsättningen i landet. Utöver detta bidrar industrin med skatteintäkter motsvarande 185 000 arbetstillfällen inom offentlig förvaltning. Tillsammans med de drygt 830 000 personer som har arbete knutet till svensk industri så skapas sammantaget mer än en miljon arbetstillfällen i Sverige (SCB, Teknikföretagen 2019) genom dess verksamhet.

En av de viktigaste produktionsmetoderna inom industrin är skärande bearbetning av metalliska material. Förmågan att framgångsrikt bearbeta dessa material till komponenter som exempelvis kugghjul, ventiler, verktyg och turbinblad är en övergripande förutsättning för vår utveckling och vårt välstånd. Dessa komponenter ingår också i annan tillverkningsutrustning för bl.a. livsmedel, läkemedel, trävaror etc. Skärande bearbetning av metalliska material är en relativt dyr tillverkningsprocess och kostnaden för bl.a. verktyg, arbetstid och maskiner måste till slut slås ut på varje enskild tillverkad detalj. Både akademi och industri arbetar aktivt med forskning och utveckling för att höja produktiviteten och minska resursanvändningen för att möta en alltjämt ökande global konkurrens.

Olika typer av teoretiska modeller används inom skärande bearbetning för att dels öka förståelsen för själva processen och dels för att förutsäga vad som händer i processen under olika förutsättningar. I dag erbjuder flera verktygstillverkare digitala hjälpmedel som kan rekommendera ingenjörer och tekniker val av verktyg och processparametrar för olika applikationer. För att digitala hjälpmedel skall kunna användas på ett värdeskapande sätt inom området krävs bl.a. modeller som kan beskriva verktygets livslängd under olika förutsättningar och vid olika val av processparametrar.

Redovisade resultat i denna avhandling presenterar flera olika modeller för att beskriva verktygens livslängd. Ett resultat från arbetet är att författaren rekommenderar användning av en modell framtagen av Bertil Colding för att uppnå bästa tillförlitlighet.

Avslutningsvis presenteras en metodik där Coldings modell kombineras med en kostnadsmodell som tar hänsyn till kostnads- och prestandardparametrar för analys av utfall för olika val av verktyg och material samt olika val av processdata. Metoden kan ligga till grund för strategiska och hållbara beslut för flera aktiviteter under realisering av en produkt från konstruktionsstadiet fram till reguljär tillverkning.

1.5 Appended publications

This thesis is based on the work presented in the following publications. In the text, these are referred to with Roman numerals **I-VIII**.

I	*Assessment of Commonly used Tool Life Models in Metal Cutting,* Johansson D., Hägglund S., Bushlya V., Ståhl J-E. Procedia Manufacturing, (2017) 602-609
II	*Equivalent Chip Thickness and its Influence on Tool Life,* Johansson D., Lindvall R., Fröström M., Bushlya V., Ståhl J-E. Procedia Manufacturing, 25, (2018) 344-350.
III	*Tool life and wear model in metal cutting, Part 1–Influence of varying flank wear criterion on Colding's tool life equation,* Johansson D., Schultheiss F., Bushlya V., Zhou, J., Ståhl, J-E. In The 6th Swedish Production Symposium, (2014).
IV	*Tool Life and Wear Modelling in Metal Cutting, Part 2— Based on Combining the Archard and the Colding Equations,* Ståhl J-E., Johansson D., Schultheiss F., Zhou J., Bushlya V. In Swedish Production Symposium, 2014. The Swedish Production Academy.
V	*Tool life in stainless steel AISI 304: applicability of Colding's tool life equation for varying tool coatings,* Johansson D., Leemet T., Allas J., Madissoo M., Adoberg E., Schultheiss F. Proceedings of the Estonian Academy of Sciences, 65(2), (2016) 172.
VI	*Sensitivity of Colding tool life equation on the dimensions of experimental dataset,* Johansson D., Hägglund S., Bushlya V., Ståhl J-E. Journal of Superhard Materials, 39(4), (2017) 271-281.
VII	*Selecting Cutting Data Tests for Cutting Data Modeling Using the Colding Tool Life Model,* Johansson D., Akujärvi V., Hägglund S., Bushlya V., Ståhl J-E. Procedia CIRP, 72(1), (2018) 197-201.

VIII *Assessment of Metal Cutting Tools using Cost Performance Ratio and Tool Life Analyses,* Johansson D., Lindvall R., Windmark C., M'Saoubi, R., Can, A. Bushlya V., Ståhl J-E.
Submitted to 29th International Conference on Flexible Automation and Intelligent Manufacturing (FAIM2019).

1.6 Other publications not appended to this thesis

IX *Machinability of CuZn21Si3P brass,* Schultheiss F., Johansson D., Linde M., Tam P. L., Bushlya V., Zhou J., Ståhl J-E.
Materials Science and Technology, 32(17), (2016), 1744-1750.

X *Wear mechanisms of uncoated and coated cemented carbide tools in machining lead-free silicon brass,* Bushlya V., Johansson D., Lenrick F., Ståhl J-E., & Schultheiss F.
Wear, 376, (2017) 143-151.

XI *The influence the uncut chip thickness has on the stagnation point in orthogonal cutting,* Agmell M., Johansson D., Laakso S. V., Ahadi A., Ståhl J-E.
Procedia CIRP, 58, (2017) 13-18.

XII *Comparative study on the machinability of lead-free brass,* Schultheiss F., Johansson D., Bushlya V., Zhou J., Nilsson K., Ståhl J- E.
Journal of Cleaner Production, 149, (2017) 366-377.

XIII *Superhard pcBN tool materials with Ti 3 SiC 2 MAX-phase binder: Structure, properties, application,* Kolabylina T., Bushlya V., Petrusha I., Johansson D., Ståhl, J-E., Turkevich V.
Journal of Superhard Materials, 39(3), (2017) 155-165.

XIV *Tool Wear Mechanisms of pcBN tooling during High-Speed Machining of Gray Cast Iron,* Schultheiss F., Bushlya V., Lenrick F., Johansson D., Kristiansson S., Ståhl J-E.
Procedia CIRP, 77, (2018) 606-609.

XV *Small scale testing of PCD and WC-Co tooling in rock cutting using longitudinal turning,* Johansson D., Hrechuk A., Bushlya V., Mårtensson M., Can A., Ståhl J-E.
Wear 426 (2019): 1515-1522.

XVI *Modelling tool life in high speed machining of AD730®,* Persson H., Johansson D., Chen Z., Lenrick F. M'Saoubi R., Gustafsson, D., Zhou J. M.
Procedia Manufacturing, 25, (2018) 316-321.

XVII *Application of Colding tool life equation on the drilling fiber reinforcement polymers,* Hrechuk A., Johansson D., Bushlya V., Devin L., Ståhl J-E.
Procedia Manufacturing, 25, (2018) 302-308.

XVIII *There is logic in logit – including wear rate in Colding tool wear model,* Laakso S., Johansson D.
Submitted to FAIM 2019, Procedia Manufacturing

XIX *Multi-objective testing of different brass alloy components for DFM,* Laakso S., Johansson J., Johansson D., Schultheiss F., Ståhl J-E.
Accepted for publication CIRP Manufacturing System Conference 2019.

1.7 The author's contribution

I	Johansson was involved in parts of the planning and wrote the major parts of the paper. Hägglund planned the experimental work and performed the tool life modelling.
II	Johansson was involved in planning the work and experimental setup. He also analysed data and wrote parts of the paper. Lindvall and Fröström performed the experimental testing and calculations. Lindvall presented the paper.
III	Johansson performed the experimental work based on planning by Ståhl and wrote major parts of the paper.
IV	Ståhl developed the model and wrote major parts of the paper. Johansson performed the experimental work and presented the paper.
V	Johansson and Leemet performed the experimental work. Johansson analysed the data, modelled tool life and wrote major parts of the paper.
VI	Johansson planned the work, analysed the results and wrote major parts of the paper. Akujärvi developed the script enabling this work.
VII	Johansson planned the work, analysed the results and wrote major parts of the paper. Akujärvi developed the script enabling this work.
VIII	Johansson performed the cost modelling based on Ståhl's models and wrote parts of the paper. Lindvall performed all experimental work. Windmark was heavily involved in planning and writing.

2 Introduction

The industrial revolution is considered the most important event in the history of humanity since the domestication of animals and plants [1]. Our way of life is defined by developments in recent centuries in transportation, agriculture, information technology, medicine etc. resting on the shoulders of industrial production. As the industrial revolution progressed, the development of the mass production of steel followed, and the ability to form steel using machine tools [2]. The global production value of machine tools was estimated to US$81B during 2017 [3] and it has been estimated that over 80 % of all manufactured products have been machined at some point before they are completed [4]. Furthermore, it has been estimated that machining expenditure contributes to approximately 5 % of the GDP in developed countries, while in the EU alone (calculated for 2016 GDP data) it translates to approximately US$1010B per year and in Sweden US$24B [5, 6]. Models to describe, understand, predict and improve metal machining have been used and developed for over a century, and this area of research is still more relevant than ever [7]. As industry is constantly looking to improve its production processes, reduce costs and add value, data is collected at all stages and often analysed using models.

The focus of the work presented in this thesis is the modelling of tool life in metal machining and the use of these models to improve production processes. Mainly, it is the Colding model [8] that has been investigated but other models are also presented.

2.1 Background and objective

When a tool is used to remove unwanted material to produce a desired geometry of a product the tool becomes worn. At some stage the tool is considered worn out and it has to be exchanged [9] and the manufactured part has to carry part of the cost of the worn out tool. If removing material with a higher degree of material removal per time unit, the tool will most often wear faster, and if the material removal rate is decreased the tool will most often last longer [9]. On the other hand, it is not only the cost of tooling that adds to the total cost of the produced part but also to be considered is the cost of machine operator(s), machine time, time lost when changing tools etc. as visualized in figure 2.1. Theoretically, there is an optimal way of producing a specific machined part with regard to the cost of removing unwanted material. Micro-economic models have been developed that can be used in metal cutting to describe the relationship between cutting data, tool life, and processing costs [10]. To use this type of economic model a robust tool life model is needed to feed in information on selected process parameters and their effect on tool life.

The main objective of this work is to investigate different tool life models by using empirical data and modern computational power and software to further improve testing, modelling and the publishing of cutting data. The main aim is to reduce monetary losses due to poor cutting data and tool selection in production and to reduce unnecessary environmental loads, by improving the models being used.

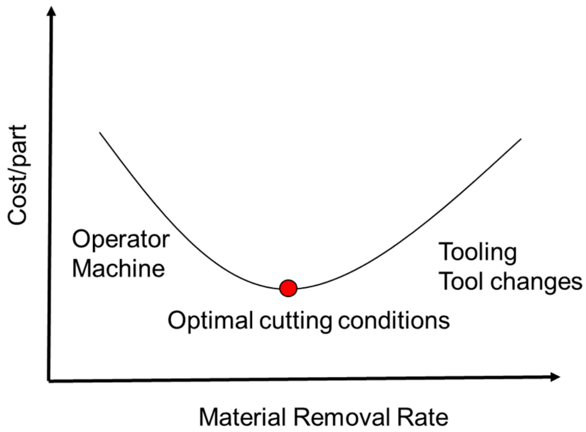


Fig. 2.1: Some factors influencing part cost in machining as a function of material removal rate.

2.2 Hypotheses

The following hypotheses were established for this study:

1. It is possible to investigate the validity and further improve existing models for cutting data recommendation and optimisation using empirical data and today's computational power.
2. Experimental testing and thus consumption of resources can be reduced without loss of accuracy when creating a robust tool life model.
3. Tool life models combined with cost models can be used as cost decision support for selecting tools and optimal cutting data.

2.3 Research questions

Based on the hypotheses presented the following research questions can be formulated:

RQ1. Is it possible to investigate the validity and further improve existing models for cutting data recommendation and optimisation using empirical data and today's computational power for multiple commonly used work materials?

RQ2. How should experimental testing be conducted to ensure an accurate tool life model while limiting the resources required to conduct these tests?

RQ3. How can tool life models be used to assess selection of cutting tools and their performance based on part cost?

2.4 Scope and limitations

The author's ambition is to present theories for tool life modelling in metal cutting for the entire working range of a tool. The theories should also apply to multiple commonly used workpiece materials. Since a considerable number of different combinations of tool material, tool geometry, workpiece material, cutting method etc. exist, it is impossible to validate the theories presented in this thesis, for all combinations. Thus, only selected machining tests and models are discussed and validated. The following delimitations were employed in this research:

- All empirical data used and discussed is based on turning with round or pointed inserts.
- Tool wear is briefly discussed but not studied in this work. Whenever tool life is referred to, the author assumes the existence of a pre-defined wear criteria.
- Work material is also only briefly discussed in this work and empirical data is limited to machining in steel, stainless steel and cast iron. Tool deterioration and the interaction between tool material and workpiece material is not studied in depth.
- Machine limitations such as torque, power and rotational speed constraints are not included in the models presented, nor are vibration, chip formation, shear plane deformation or process dynamics discussed.
- Cost modelling is limited to only one cutting operation. Several cutting operations or machining centres, with the possibility of existing bottle necks or limited machine utilization, are not included in the model presented.

2.5 Outline of the thesis

The outline of the appended publications is presented in figure 2.2. The outline is not in chronological order but rather in a logical order. Some of the work has been done in parallel, and some work published later during the PhD work, should we now know with more acquired knowledge, have been performed at an earlier stage. The author's aim is that chapter three and four should stand by themselves, not only as a report of previous work in the area and work conducted by the author, but more importantly should be seen and serve as a guide to tool life modelling.

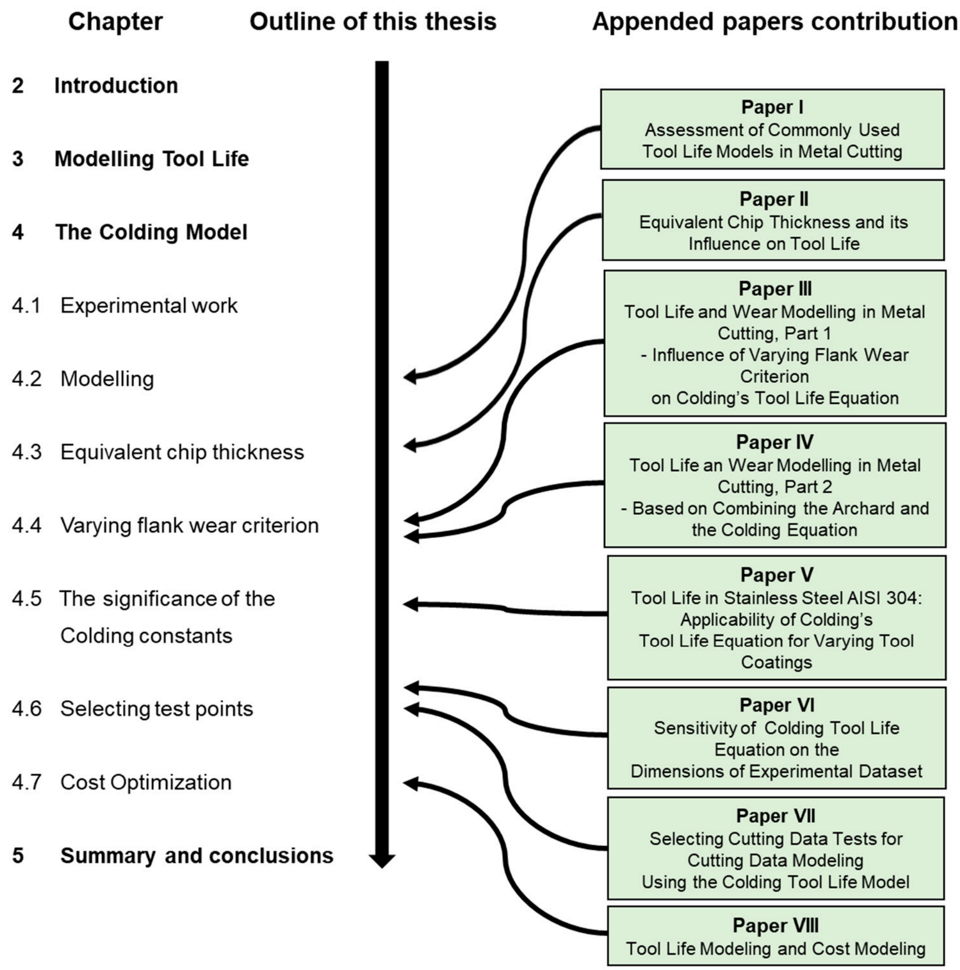


Fig. 2.2: Outline and contibution of the appended publications.

3 Modelling tool life

Two basic aims of modelling machining processes can be distinguished:

- Modelling as an engineering necessity.
- Modelling as a scientific challenge.

Still, the primary aim of any modelling in machining operations is to develop a predictive capability for machining performance, in order to facilitate the effective planning of machining operations to achieve optimum productivity, quality and cost [11].

The earliest known work is that of Taylor, in which Taylor and his colleagues studied machining in a workshop environment to gain a greater understanding of the machining process. This pioneering work set the stage for research in machining processes up to today. Taylor noted that sub-optimization and "rule of thumb" hindered development in machine shops and published guidelines for use in workshops, based on systematic experiments. Some of these guidelines could be presented in mathematical expressions such as the Taylor equation. This equation relates cutting speed and tool life in machining carbon steel with high speed steel tools [9].

Five different types of models are used in the modelling of metal cutting: analytical, numerical, empirical, soft computing and hybrid models, see figure 3.1 [7]. Each type of model has its advantages and disadvantages when used to represent and, more importantly in industrial applications, optimize cutting processes. As new types of models have been developed, previous models are most often not obsolete. Today all types of models can be found in use in academia and industry and new models are constantly being added to the available tool box.

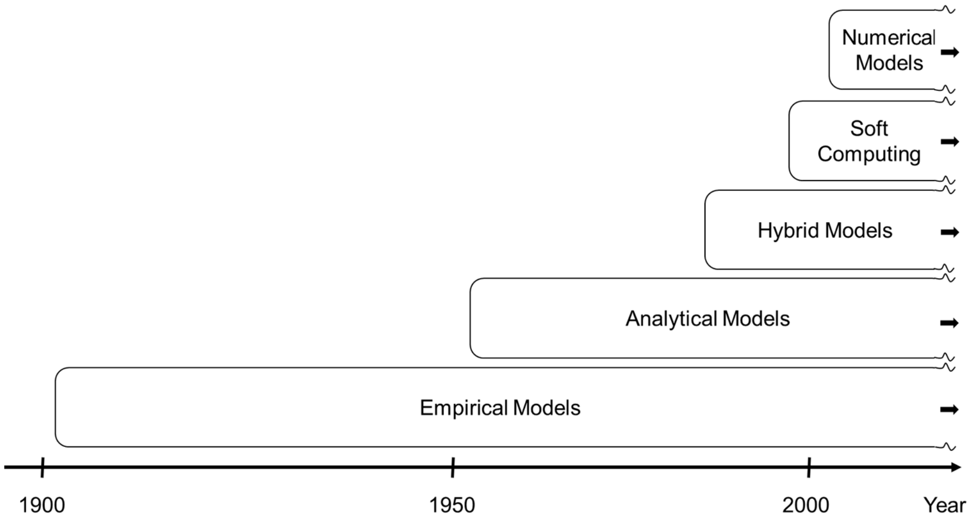


Fig 3.1: Models used in wear and tool life modeling of metal cutting [9, 12-15].

3.1 Metal cutting

The cutting process according to Ståhl [16] may be defined as:

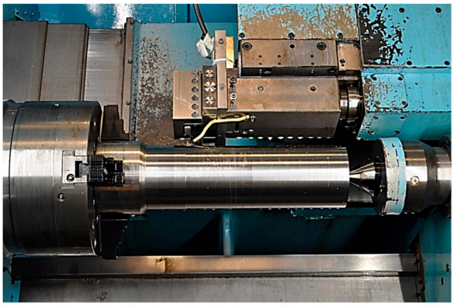
> "Cutting processes are characterized by use of a cutting edge that creates deformations leading to parts that are removed from the workpiece being severe from it in the form of chips."

Metal cutting, as we recognise it today, started around 1900 with machine tools with their own individual electrical power source and the development of High-Speed Steel (HSS) and later Hard Metal (WC-Co) and tool coatings. Along with the development of more efficient cutting tools, the machines have evolved with more advanced computer-controlled control systems and later integration of the product development and design phase into the production process, through the introduction of Computer Aided Manufacturing (CAM). Today, industry is moving towards a higher degree of digitalization of interconnecting machines, warehouse management, logistics, sales etc. with the aim being to further optimize production [17].

Machining processes can mainly be divided into several methods such as turning, milling, drilling, boring, shaping, broaching and reaming. Depending on the method, one or several cutting edges are engaged to work on the workpiece material, continuously or intermittently. Nevertheless, from the perspective of the cutting edge all cutting methods are equivalent with varying geometries and loads. The work presented in this thesis focuses on longitudinal turning due to its relatively simple geometries, while avoiding the challenges of measuring when using rotating tools. The results and discussions presented here can, with a decent amount of care, be extrapolated to other machining methods.

Machining processes are based on individual cutting edge(s) locally shearing the workpiece in such a way as to remove chips. For turning, figure 3.2, the main factors governing Metal Removal Rate (MRR) are the cutting speed v_c, feed f and depth of cut a_p, Eq. 3.1. Cutting speed v_c, feed f and depth of cut a_p are generally referred to as cutting data. When machining a part, a pre-defined amount of material should be removed producing a part within given tolerances and quality demands. The cutting data, giving the MRR, will thereby govern the time needed to complete each machining operation(s), known as cycle time t_0.

$$a_p \cdot f \cdot v_c = MRR \qquad 3.1$$



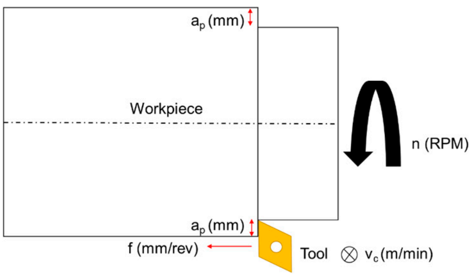


Figure 3.2: Left side of the figure presents a typical setup in a lathe and the right side of the figure presents the parameters v_c, a_p, and f.

In addition to cutting data, figure 3.3 presents several different distances and angles needed to fully define any turning operation.

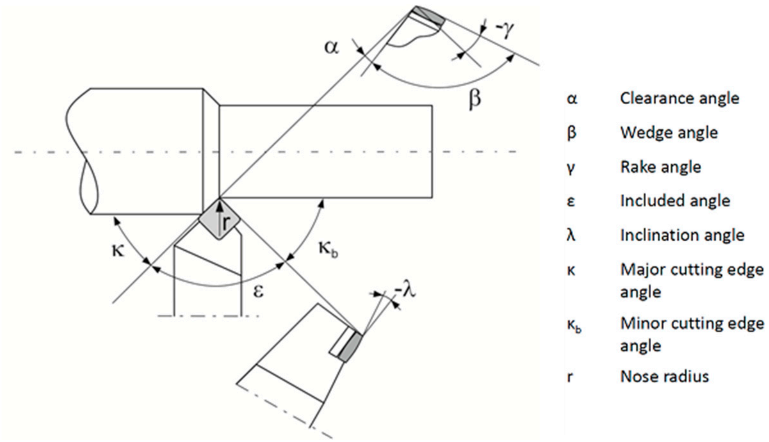


Figure 3.3: Commonly used dimensions and angles for describing the tool geometry in relation to the workpiece during conventional turning operations, adapted from Vieregge [18] as later published by Ståhl [16].

3.2 Machinability

For those working with metal cutting, machinability is a commonly used and understood concept. Still, it is rather hard to define in quantitative terms. Ståhl [16] defines machinability as:

> "The behaviour of the workpiece material during the cutting process and the effect this has on the process results obtained."

Ståhl's definition can be considered as a holistic view of machinability, whereas Shaw and Cookson [19] lists three main aspects of machinability related to the behaviour of the tool and the workpiece interaction; tool life, surface finish and power to cut. A fourth and fifth parameter, chip control and environmental factors could also be added and aspects of machinability is presented by Ståhl [16] as:

- Tool deterioration.
- Surface quality and surface integrity.
- Energy consumption and cutting forces.
- Chip form and chip behaviour.
- Environmental factors.

It can be seen that it is not only the workpiece material that is in focus with regard to machinability, but also the tool material, tool geometry, cutting data, machine setup etc. and how these factors cooperate, which define good or poor machinability. Furthermore, machinability must be considered in relative terms, good or poor as compared to a different existing or future process. Nevertheless, the link between tool life and machinability is, and has, eluded researchers in metal cutting for decades [20-26].

3.3 Tool deterioration

Tool deterioration is caused by the loads acting on the tool and influencing the tool properties, hence the tool's ability to withstand the acting loads. A tool can either deteriorate in an unpredictable manner leading to a catastrophic failure [27] or in a controlled predictable manner. Unpredictable tool deterioration should, if possible, always be avoided and the work presented in this thesis focuses on predictable wear. Figure 3.4a shows predictable wear with flank wear, notch wear, crater wear and figure 3.4b shows an unpredictable tool failure wherein parts of the tool are lost.

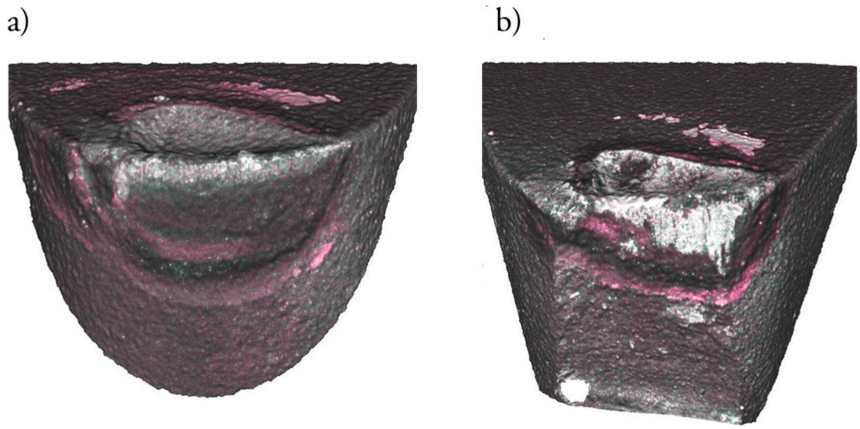


Figure 3.4: Worn Cubic Boron Nitride (pcBN) tool after machining stainless steel 316L taken using Alicona Infinite Focus 3D microscopy. a) Predictable wear b) unpredictable tool failure.

Tool deterioration is a complex process, wherein several different wear phenomena or mechanisms occur simultaneously. As wear progresses, the loads acting on the tool also change and it is not uncommon that the loads on the tool decrease as a Built Up Layer (BUL) forms on the tool edge, changing the geometry for some part of the tool life. It has also been reported that for some cases a Tool Protective Layer (TPL) can form, thus prolonging the tool life [28]. As wear progresses, loads acting on the tool increase and the tool wear rate increases. According to Ståhl [29] tool deterioration is the sum of mechanical loads, thermal loads, tribological loads, and chemical loads, figure 3.5.

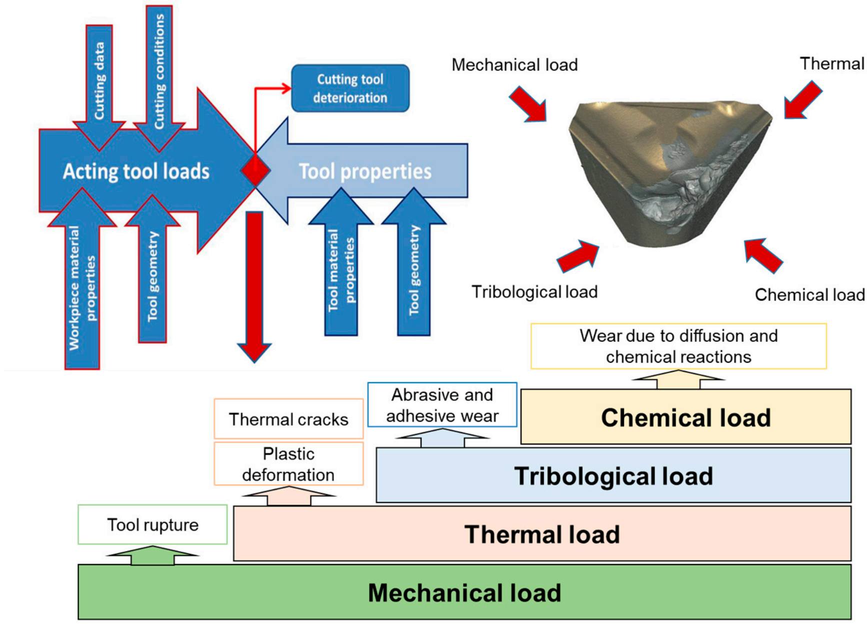


Figure 3.5: Cutting tool deterioration adopted after Ståhl [29].

Several different types of wear have been reported in literature and have been compacted into figure 3.6 adopted after Schultheiss [30].

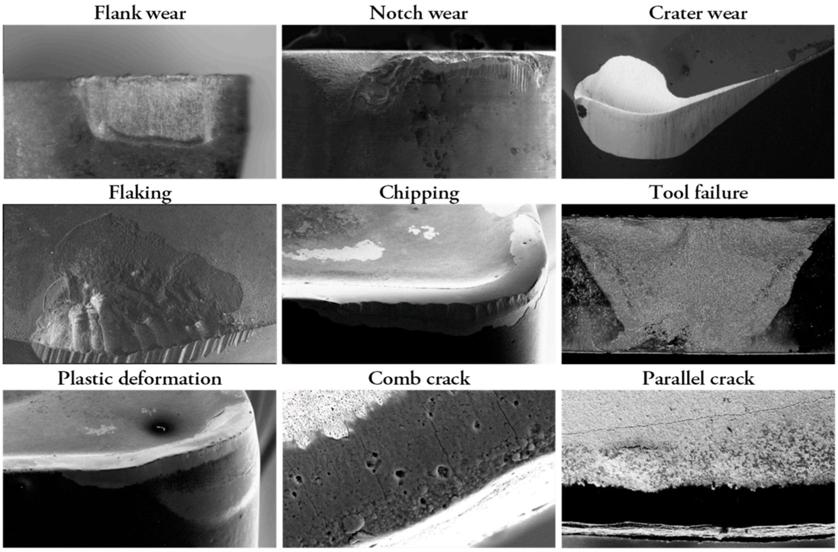


Figure 3.6: Different types of tool deterioration adopted after Shultheiss [30].

3.4 Machining economy

The manufacturing cost of machined parts is determined by several different aspects, such as the material removal rate, tool costs, tool life, machine costs, set-up time and tool changing time, equipment handling time, personnel costs, facility costs, downtimes, quality rejections, wastes, and speed losses [10]. There are different approaches to calculating the manufacturing costs of machined parts, dependent on the level of detail and area of use. In Shaw and Cookson [19], Gilbert´s model from 1952 is presented, providing a method for economic estimations of machining based on direct labour and machine costs, tool changing costs, and tool costs per part. A broader perspective of the manufacturing costs, also involving system costs and performance related cost, is presented in Colding [31]. The estimation approach was later developed to include more detailed information with regard to the machining process and is presented in [10].

Modelling costs can be used as decision support for machining strategies. And comparative studies to evaluate cutting tools and selected cutting data are extensive and, include among others [9, 31-33]. Windmark et al. [34] present a principle on a general Cost Performance Ratio (CPR) assessment, incorporating an extensive cost model including several performance parameters for the evaluation of equipment investments. This model served as the foundation for the development of the Tool Cost Performance

Ratio model presented in this thesis. Equation 3.2 presents the cost performance ratio related to direct part cost and equation 3.3 presents the cost performance of the factor group investigated (e.g. machining centre, operator cost or tool cost) [34]. Where CPR_k is the direct quote between the reference part cost k_{Ref} and the new part cost $k_{sys:X}$ with the new conditions (new technologies). The cost performance ratio CPR_{FG} is the quote between the cost for a specific Factor Group (workpiece material, tooling, machine tool etc.) for new condition $k_{FG:X}$ and the cost for the existing reference Factor Group $k_{FG:Ref}$ for a cost neutral situation when both have the same cost ($k_{Ref} = k_{sys:X}$).

$$\mathrm{CPR}_k = \frac{k_{Ref}}{k_{sys:X}} \qquad where\ k_{sys:X} = k_{known} \tag{3.2}$$

$$\mathrm{CPR}_{FG} = \frac{k_{FG:X}}{k_{FG:Ref}} \qquad where\ k_{FG:Ref} = k_{sys:X} \tag{3.3}$$

3.5 Why model tool life?

Cutting data and tool life can be optimized with two specific aims: to maximize MRR or minimize part cost. Therefore, when optimising cutting data one should always ask in what respect it should be optimized. Figure 3.7 illustrates how tool life modelling can be used from design to production and its value helping with decision making.

Design	Production planning	Ramp up	Production
Selecting design and workpiece material for production realization. Selecting optimal production methods and expected cycle times and expected production cost.	Selecting tools, tool setup, machining center, automation and production location. Initial starting point of cutting data and time balancing of the production.	Tuning the cutting data and tool life for optimal conditions.	Batch optimization and tool change optimization. Adjustments for workpiece material variations. Reducing quality losses and selecting improvement initiatives.

Figure 3.7: Different areas from design to production where tool life modelling can be used as decision support.

Modelling cutting data and tool life to maximize MRR has been discussed by Taylor [9] and later by Colding [8], who also included feed and depth of cut as parameters. The method is based on balancing MRR, tool wear and the time it takes to exchange the worn-out tool using empirical based models.

Modelling cutting data and tool life for minimizing cost is far more complex. A large number of factors has to be taken into consideration and a control volume has to be clearly defined. Hägglund [32] has presented extensive work in this area presenting a cost graph for minimizing costs including fixed and variable costs from the cutting process, directly during cutting and indirectly when the tool needs replacement. Factors such as costs based on hourly rate, tool and tool replacement costs, energy costs, machine tool maintenance costs, machine tool depreciation, operator and supervisor salaries, coolant media costs etc. are all affected by the cutting data selected. The methods and models presented by Hägglund also deal with constraints such as RPM, surface finish, torque and power constraints. Ståhl et al. [10, 35] has presented a model for optimizing cutting data with regards to costs, also taking into account losses such as rejections, downtimes and production rate.

When modelling tool life and cutting data one should always consider the main aim of the modelling when selecting a modelling approach. Some typical examples are:

- Presenting cutting data of a portfolio of tools in catalogues or digital software.
- Optimising cutting data.
- Understanding the influence of different workpiece material selection.
- Comparing different tools with regard to cost and performance.
- Balancing tool changes.
- Analysing data from previous production to predict future outcome.
- Academic interest in a deeper understanding of the cutting process.

3.6 Physics-based models

The physics-based analytical methods and models developed provide a strong foundation for quantitative modelling of machining processes. Typical use is in predicting cutting forces, chip geometry, tool-chip contact length, average stresses, strains, strain-rates and temperature modelling. One disadvantage of the analytical models is that they are often limited to 2-D analysis although some 3-D models exist [7].

Wear has been described by the Archard wear equation, and is based on sliding wear based on the theory of asperity contact [12]. A more complex model has been developed by Usui and Shirakashi [13] which also takes into account chip formation and cutting forces. Although these models are based on actual physical parameters, experimental data is needed and so the models can be considered hybrid models based on one or more experimental constants. Figure 3.8 presents Usui and Shirakashi's prediction system for crater and flank wear.

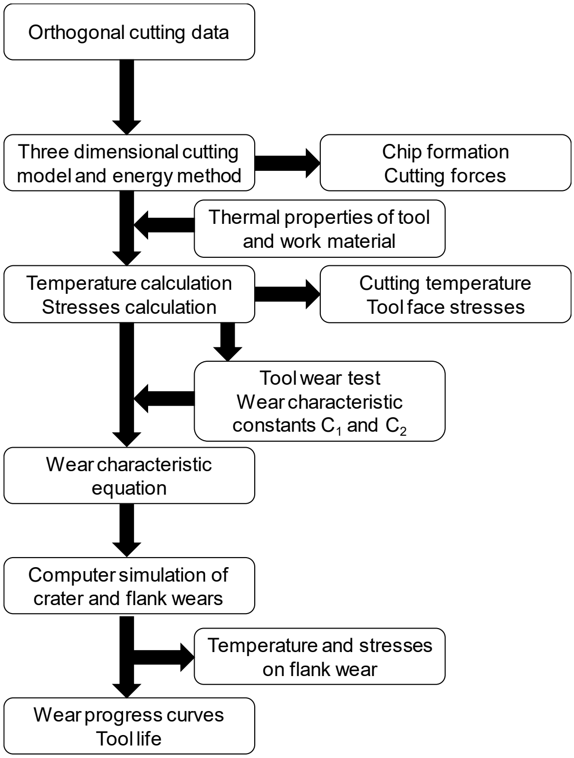


Figure 3.8: Prediction system of crater and flank wear in Usui and Shirakashi's study [13].

Huang et al. [36, 37] published a methodology to analytically model flank wear and crater wear rate, as a function of tool/workpiece material for finishing hard turning using Cubic Boron Nitride (pcBN) inserts. The models proposed are based on the sum of the contribution from abrasive, adhesive and diffusion wear, although five calibration constants are needed and derived from empirical tests of the varying cutting conditions. The benefit of the analytical models is that they connect to physical tool degradation phenomena but this also serves as a disadvantage as wear degradation is a complex phenomenon and each model becomes limited to a specific machining case.

3.7 FEM

Since the introduction of the Finite Element Method (FEM) in the 1970s, many attempts have been made to model the metal cutting process. The largest beneficial factor of the method is that it is non-destructive and theoretically no experimental testing is needed. Still, as of today, experimental testing plays an important role in FEM when verifying models and modelling results [38].

Some pioneering work of FEM simulations of metal cutting was performed by Usui and Shirakashi [39, 40] and Klamecki [41]. Typical areas of FEM modelling are: predicting forces, chip geometry, stresses, strain, strain-rates and temperatures [7]. Some work has been done with regard to tool wear [15, 42, 43]. The singular largest limiting factor reported in such work is the computational power and time required to perform these analyses. Laakso et al. [44] successfully investigated the tool edge deformation mechanisms in the initial stage of cutting. The study was limited to a fraction of a second of the initial cutting, showing the limitations for modelling longer cutting processes of several minutes or more. Still, FEM will likely be a powerful future tool in tool life modelling as more research is done and computational power increases. Klocke et al. [45] suggest that due to the very long simulation time, tool wear modelling using FEM may not be appropriate but that analytical or hybrid solutions might be sought.

3.8 Empirical models

Empirical tool life models have been used extensively to model tool life and cutting data due to the complexity of the cutting process. The advantage with these models is that no physical understanding of the wear mechanisms is needed. The models are based on cutting data and tool life and their relation to a set of constants, figure 3.9. This allows for fast computing compared to FEM and soft computing models. This advantage can be used in software published by tool manufacturers, in which the end user can select a work material and a cutting method and the software will rank all available tool selections and recommended cutting data with regard to MRR or production costs [32]. The greatest disadvantage with these models is the cost of experimental testing. For each tool and workpiece material combination, several tool life tests have to be performed. A wear criterion has to be selected, such as flank wear VB = 0.3 mm and the tool is then tested with fixed cutting data parameters until the wear criterion is reached and the tool life is recorded. As the complexity of the models is increased, and the number of model constants are increased, more testing with a larger sets of test points is required. The minimum number of tests needed is equal to the number of model constants included in the tool life model.

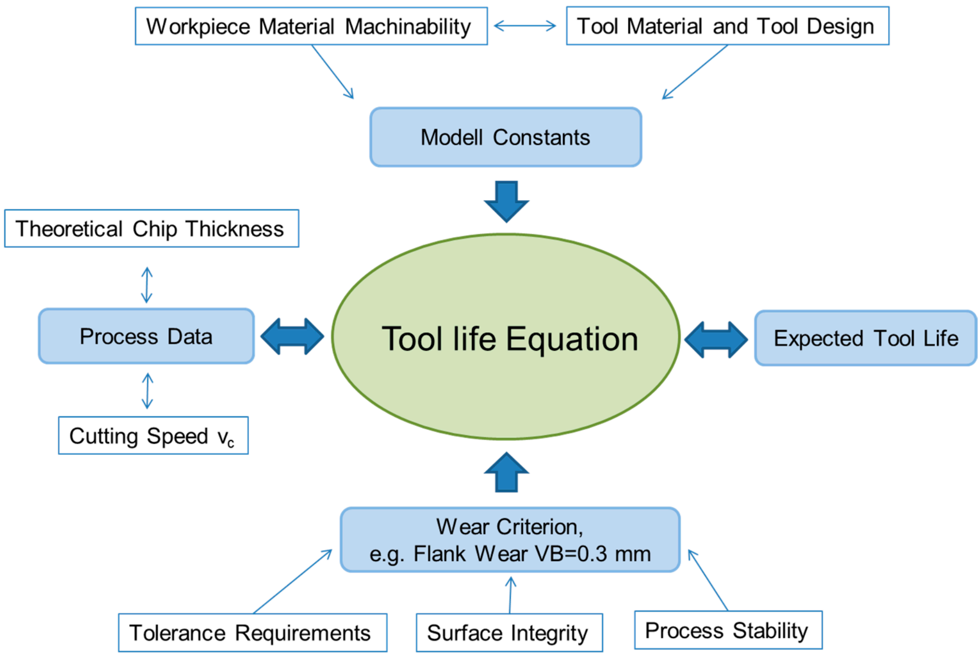


Figure 3.9: Schematic view of a tool life modell and how it connects cutting data and tool life.

As the selected wear criterion is fixed, the model output will only state the engagement time when the tool is expected to have reached the selected wear criterion but the model will not give any indication about how the wear developed over the course of its use, as compared to a tool wear model, figure 3.10. It has also been reported that it is difficult to use empirical models when two or more types of wear are present in one test series, depending on the cutting data selected. Persson et al. [46] machined a nickel-based superalloy using pcBN tools and reported several wear phenomena such as flank wear, crater wear, notch wear, chipping and fracture. When modelling using the Colding model a large model error of 17 % was reported when all empirical tool performance test points were included in the model.

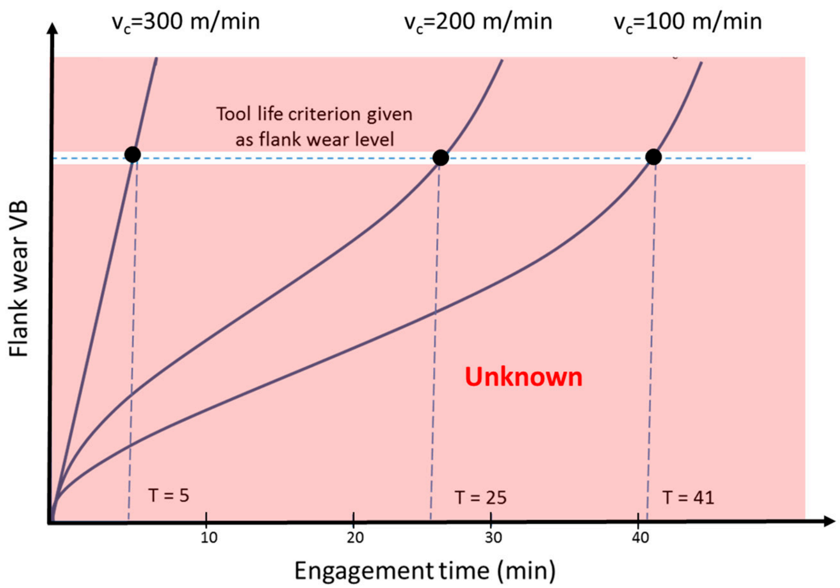


Figure 3.10: The output of a tool life model will only state the engagement time when the tool is expected to have reached the selected wear criterion but the model will not give any indication about how the tool's wear developed over the course of its use.

Taylor's Equation for Tool Life Expectancy, formulated by F. W. Taylor 1906 [9], provides a good approximation of tool life T for varying cutting speed v_c. The Taylor equation is presented in equation 3.4 where v_c is the cutting speed, T is the expected tool life and m and C_T are constants derived from empirical testing.

$$v_c \cdot T^m = C_T \qquad 3.4$$

When examining tool wear for a specific metal cutting process, cutting speed v_c will be the most influential factor while the applied feed f will be of less importance to the tool life. The depth of cut a_p will only play a minor role in the tool wear, as the load is distributed over a larger part of the tool but load per unit length will be approximately the same [32]. One issue with the simplified Taylor equation is that when f and a_p are changed the Taylor curves start shifting clockwise or counter- clockwise according to figure 3.11.

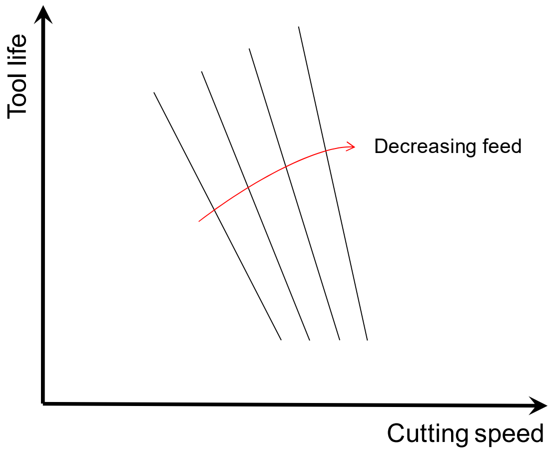


Figure 3.11: The influence of decreasing feed on the Taylor curves with a fixed depth of cut.

To allow for a better tool life estimation, a number of suggested extensions to the Taylor equation have been published [47-49]. Two of the extended Taylor models used, take into account the varying equivalent chip thickness h_e or feed f and depth of cut a_p by adding two more constants, p and q, are presented in equation 3.5 and 3.6.

$$v_c \cdot f^p \cdot a_p{}^q \cdot T^m = C_T \qquad 3.5$$

$$v_c \cdot h_e{}^p \cdot T^m = C_T \qquad 3.6$$

where equivalent chip thicknesses h_e as defined by R. Woxén [50], is a function of feed f, depth of cut a_p, major cutting angle κ and the nose radius of the tool r_ε, equation 3.7. The definition of equivalent chip thickness h_e is further discussed and more accurately defined in section 4.3.

$$h_e \approx \frac{a_p \cdot f}{\frac{a_p - r(1-\cos\kappa)}{\sin\kappa} + \kappa \cdot r_\varepsilon + \frac{f}{2}} \qquad 3.7$$

Another possible tool life equation, not commonly used in academia but still used in industry, is the Coromant turning model version 1, equation 3.8.

$$v_c = 10^{\frac{vca*f^2+vcb\cdot f+vcc}{\left(\frac{TL_{act}}{TL_{nom}}\right)^m}} \qquad 3.8$$

Where *vca*, *vcb*, *vcc*, and *m* are constants and TL_{act} is the given tool life for a predefined wear criterion. TL_{nom} is the nominal tool life predefined by the user. The feed *f* can be replaced with the mean chip thickness h_m, equation 3.9, to account for varying major cutting angle κ or equivalent chip thickness h_e, equation 3.10, as defined by Woxén.

$$v_c = 10^{\frac{vca \cdot h_m{}^2 + vcb \cdot h_m + vcc}{\left(\frac{TL_{act}}{TL_{nom}}\right)^m}} \qquad 3.9$$

$$v_c = 10^{\frac{vca \cdot h_e{}^2 + vcb \cdot h_e + vcc}{\left(\frac{TL_{act}}{TL_{nom}}\right)^m}} \qquad 3.10$$

where the chip thickness h_m is defined as a function of the feed *f* and the major cutting angle κ, equation 3.11.

$$h_m = f \cdot \sin(\kappa) \qquad 3.11$$

The Colding equation, published by Colding [51], is like the pioneering work by Taylor [9], essentially based on empirical curve adjustments made between tool life and cutting data, equation 3.12. Colding [52] published an earlier version of this model based on 9 constants but concluded that the amount of experimental work for this model was too high in comparison to the advantages of a more complex model. The Colding equation based on five constants can be regarded as an extension of the Taylor equation which can be clearly observed in studies of Lindström's reformulation of the Colding equation [53].

$$v_c(T, h_e) = e^{\left[K - \frac{(\ln(h_e) - H)^2}{4 \cdot M} - (N0 - L \cdot \ln(h_e)) \cdot \ln(T)\right]} \qquad 3.12$$

The Colding equation is based on five constants *K*, *H*, *M*, *N0*, and *L* where cutting speed v_c is a function of tool life *T* and equivalent chip thickness h_e. The Colding equation can be rewritten as a function of tool life *T*, according to equation 3.13

$$T(v_c, h_e) = e^{\left[\frac{K - \ln(v_c) - \frac{(\ln(h_e) - H)^2}{4 \cdot M}}{N0 - L \cdot \ln(h_e)}\right]} \qquad 3.13$$

3.9 Soft computing models

Soft computing shares a common benefit with empirical modes, in that limited physical understanding of the wear processes is need. But soft computing differs from conventional models in that it is tolerant of imprecision, uncertainty, partial truth and approximation [54], making them appropriate for solving highly nonlinear multidimensional engineering problems. Major soft computing techniques applied in metal cutting are neural networks, fuzzy sets, genetic algorithms, simulated annealing, ant colony optimisation and particle swarm optimisation [55].

Several authors, among others [56-60], have used soft computing to estimate tool life and/or tool wear in turning. Ezugwu et al. [57] managed to predict tool life in turning grey cast iron within an error of 20 % only using 25 tool performance data points. Several works, among others [61-63], are based on online monitoring using sensor measuring vibrations, sound, torque, power. These types of models can be of help in monitoring an existing production system but are of no use in recommending cutting data during design and production planning.

Process optimisation, which is closely linked to tool life, has been investigated by several authors [64-67]. One issue with these models is that they require large sets of data, which comes at a great cost if no prior production exists. If an existing production is in place, an issue is the risk and costs involved with collecting data for varying cutting conditions in an existing production.

3.10 Conclusion on existing tool life models

As is evident in the previous introduction of analytical, numerical, empirical and soft computing tool wear and tool life models, empirical models are very much the work horse of tool life modelling. When trying to answer RQ2 and RQ3 it is evident, according to table 3.1, that empirical models have some major advantages.

Table 3.1: A conclusive table of capabilities, limitations, advantages and disadvantages for different approaches to modelling tool life.

	Analytical	Numerical	Empirical	Soft computing
Capabilities	Wear modelling [7, 68].	Visualising and creating deeper understanding of the wear process [7, 38].	Recommending cutting data and tool selections. Optimizing cutting data and tool life [9, 52, 69].	Analysing existing process data and optimizing existing production [7, 55].
Limitations	Mostly limited to wear progression in specific case-studies [7].	Material model, friction models, chemical diffusional interaction models, temperature models [7, 38].	Valid only for the experimentation work included. No possibility to vary tool wear criterion [70].	Give no physical understanding of the processes. Valid only for the experimental data included in the model [7, 55].
Advantages	Selecting varying wear criteria and connects with physical properties [7, 71, 72].	None or limited experimental work needed [7].	Practical, fast and direct estimations. Industry-relevant. Can be used without full understanding of the tool deterioration phenomena [32].	The possibility to process large data sets drawing conclusions from existing data [7, 55].
Drawbacks	Lack of basic understanding of tool deterioration and the tool/work material interaction [7].	Long computation time, lack of basic under-standing of tool deterioration and the tool-work material interaction [7, 38, 44].	Extensive experimentation, time consuming and costly [7, 73].	Need for extensive empirical data [7, 55, 74].

If one aims to create a database with tool life models to predict tool life, recommend cutting data and predict part cost for several different tools and work material combinations, while these models should work as decision support in design, production planning, production ramp up and production (according to figure 3.7), some crucial factors need to be taken into account:

- The amount of experimental testing should be as minimal as possible to reduce costs and resources.
- A low calculation time is required to quickly facilitate an end user with output data.
- The model must handle all possible combinations of cutting data within its working range.
- The model should not require a full evaluation of all wear degradation mechanisms acting on each tool material and workpiece combination as this is still not fully scientifically understood.

- The type of model used should be valid for a dominant part of existing cutting operations and workpiece materials.

Based on the literature reviewed table 3.2 can be used to select the type of models to investigate when aiming to answer RQ1, RQ2 and RQ3.

Table 3.2: A table to support the decision on type of model to use when answering RQ1, RQ2 and RQ3.

	Analytical	**Numerical**	**Empirical**	**Soft computing**
Number of tool life tests	Low	Low	Medium	High
Low calculation time	Yes	High	Yes	Yes
Large range of cutting data	Theoreticly yes	Yes	Yes	Yes
Requires no evaluation of wear degradation mechanisms	No	No	Yes	Yes
One model fits all	No	No	Yes	Yes

4 The Colding model

In the thesis presented, the main work focuses on the Colding tool life model which is motivated in **paper I** and section 4.2.4. For further discussions, an introduction to the model, experimental work and modelling associated to the model is needed. Figure 4.1, based on figure 3.9 in section 3.8, presents a schematic view of the Colding model.

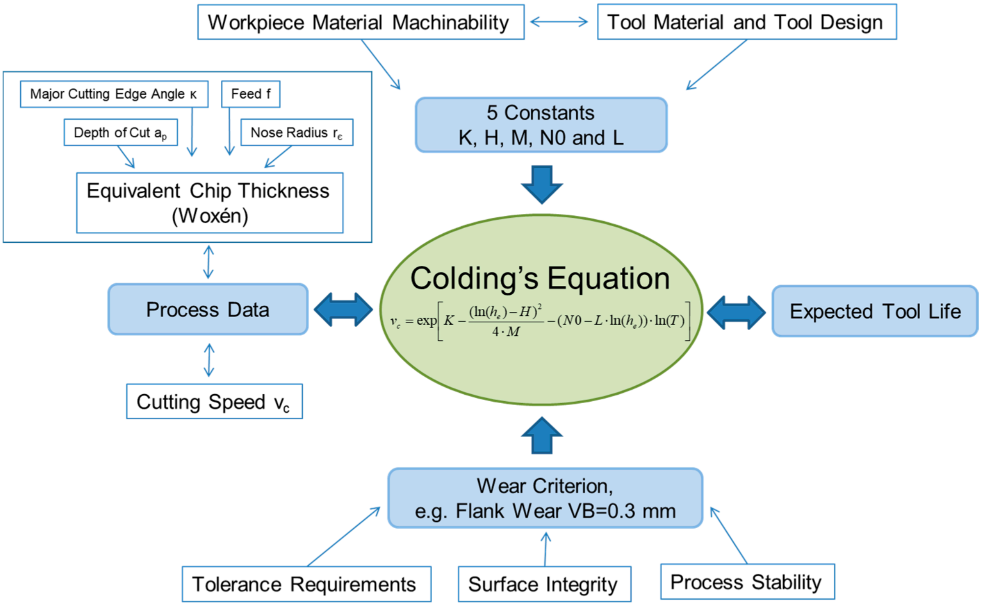


Figure 4.1: Schematic view of the Colding model and how it connects cutting data and tool life.

For any given tool life the suggested cutting data can be calculated or vice versa using the model with its five model constants derived from experimental testing.

4.1 Experimental work

The planning and execution of the experimental work is crucial to create an accurate Colding model. Today's solvers based on the least squared method [75, 76] are very effective and will most often give "a" result but not necessarily a "good" result when curve fitting. The author cannot stress enough the importance of well conducted experimental work and planning in tool life modelling, as well as careful thought when analysing results. It might also be tempting to extrapolate results but this should be done with great care, or preferably, not at all.

One should note that both the Colding model and the Taylor models are only valid in the part of the cutting regime where the relation of log(T)-log(v_c) is linear (free-cutting), figure 4.2. This is also the regime where the tool is being used in an industrial manner. If speed or feed are low the main wear pattern will be linked to the appearance of built up edges BUE. If the selected cutting data is high, temperature will be higher than the tool can withstand and the tool will plastically deform. Further discussions on planning experimental work and selecting test points are discussed in **paper VII** and section 4.6.2.

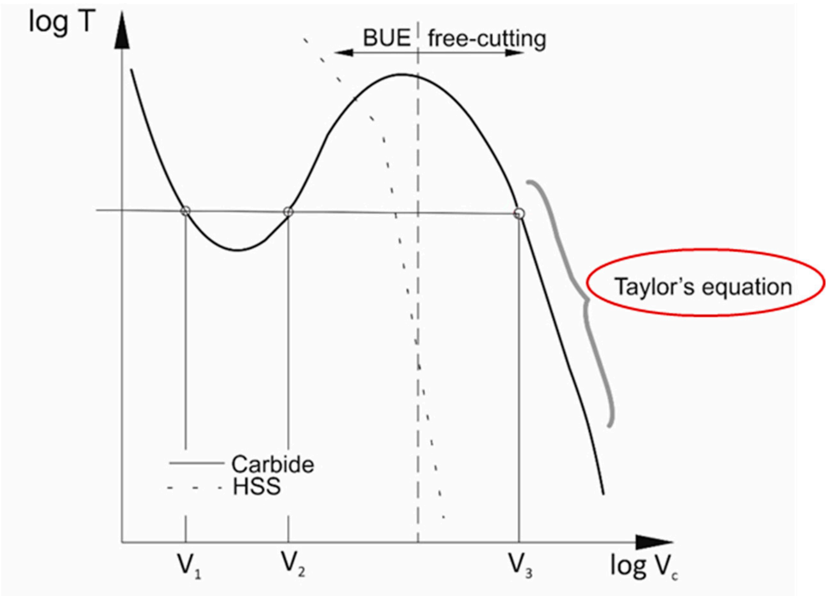


Figure 4.2: A schematic T-v_c diagram shown for cemented carbide and for high speed steel HSS tools, respectively, where a straight line in a double-logarithmic plot is displayed [16].

4.2 Modelling

Solving the constants for the Colding model can be done analytically for 5 test points with specific interrelations, selected in two h_e pairs and one central point as suggested by Colding [77]. By using "what-if-analyses tools" as suggested by Hägglund [78] the selection of test point can be chosen more freely and the number of included experimental tests can be increased. The author has investigated the solvers in Microsoft® Excel®, PTC® Mathcad® and MATLAB® by MathWorks® using experimental data concluding that all programs provide equivalent results and model errors.

Example of data input based on 5 tests for determining the Colding constants using Mathcad® is presented in figure 4.3.

$$h_e = \begin{pmatrix} 0.354 \\ 0.241 \\ 0.203 \\ 0.241 \\ 0.164 \end{pmatrix} \quad v_c = \begin{pmatrix} 150 \\ 200 \\ 300 \\ 250 \\ 300 \end{pmatrix} \quad T_{30} = \begin{pmatrix} 10.37 \\ 19.10 \\ 2.73 \\ 4.21 \\ 3.45 \end{pmatrix}$$

A B C

Figure 4.3: Example of data input based on 5 test machining AISI 4340 for determining the Colding constants, h_e (Colum A) is the equivelent chip thickness given in mm, v_c (Colum B) is the cutting speed given in m/min, T_{30} (column C) is the time given in min machined when reaching the level of tool wear VB = 0.30 mm.

The evaluation of the model and the validity of the calculated constants K, H, M, $N0$, and L is based on the mean linear error ε_{err} in %, according to equation 4.1, between experimentally attained $v_{c,exp}$ and modelled cutting speed $v_{c,mod}$ for each test. It is important to note that errors and deviations from the empirical testing and measurements will also affect the model error.

$$\varepsilon_{err} = \frac{100}{n} \cdot \sum_{j=1}^{j=n} \left| \frac{v_{c,\exp_j} - v_{c,\mathrm{mod}_j}}{v_{c,\exp_j}} \right| \qquad 4.1$$

4.2.1 Presentation of the model

When presenting the result of a Colding model this is most commonly done in a Colding diagram, cutting speed v_c as a function of equivalent chip thickness h_e, or a Taylor diagram, tool life T as a function of cutting speed v_c. These plots are presented in figure 4.4 based on the data presented in figure 4.3.

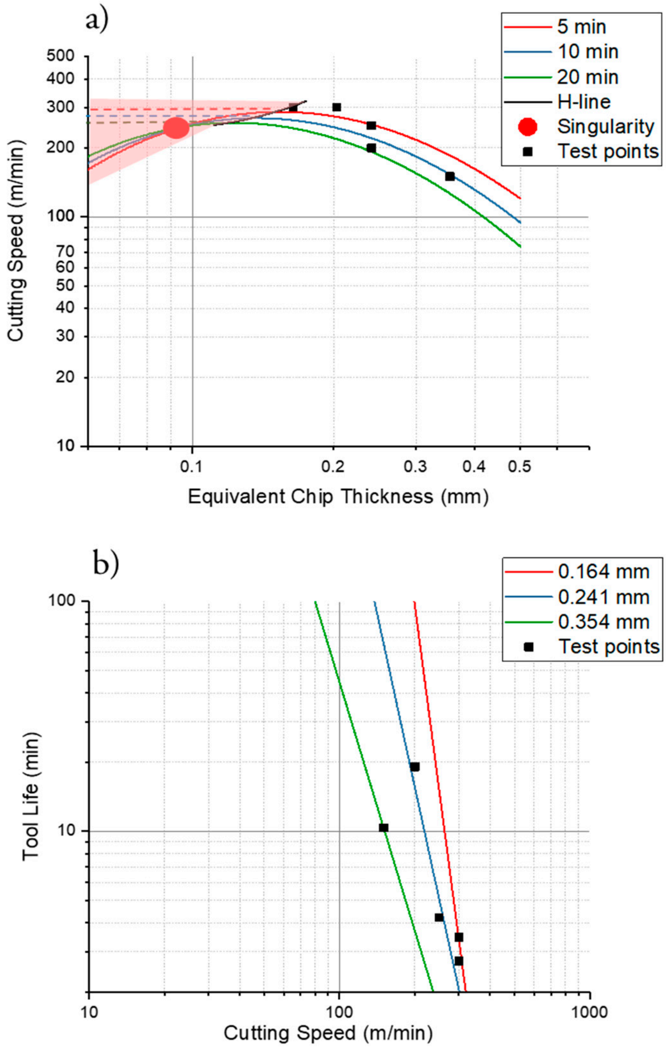


Figure 4.4: a) The Colding graph based on 5 test machining AISI 4340, b) the corresponding Taylor graph.

4.2.2 Colding H-line

The Colding H-line connects the top point of all tool life curves as shown in figure 4.4a. On the left side of the H-line (marked with shaded red) the model will give a lower v_c for a decreased h_e. This can be troublesome and therefore it is not uncommon to extrapolate data as straight lines from the given highest cutting speed, as suggested by Hägglund [32], shown with dotted lines (- - -) in figure 4.4a, in this work defined as Colding levelled. **Paper I** further discusses the accuracy of levelling the Colding model. The H-line is mathematically defined as equation 4.2:

$$\ln(h_{eH}) = H + 2M \cdot L \cdot \ln(T) \qquad 4.2$$

4.2.3 The singularity

The Colding equation contains a singularity, shown in figure 4.4a (●). In the singularity the tool life is undefined for the given h_e and left of the singularity the curves are reversed. This implication can be solved by either putting constraints on the constants or by using a levelled Colding, introduced in the previous section. Most often the singularity is outside of the cutting regime where the tool is used and therefore does not affect the end user. However, if there are physical phenomena that can be connected to the singularity, it is not fully understood. One physical explanation of the relevance of the singularity could be the presence of a Tool Protective Layer (TPL) [28, 79]. The workpiece material reacts with the environment to form a protective layer in the cutting zone protecting the cutting edge, hence relative high tool life can be found. Hägglund [32] mentions that in occasional conversations with Colding, Colding stated that he believed the singularity to exist but never showed any data to support the claim. It is the author's belief that the singularity can be connected to TPL but further investigations are needed. Figure 4.5 is an example of relative long tool life measured when machining AISI 4340, suggesting the presence of a TPL.

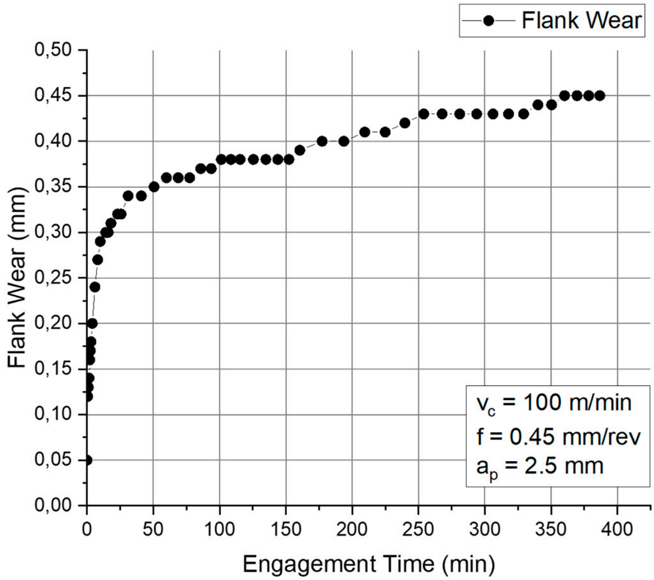


Figure 4.5: The wear of a cemented carbide insert when turning AISI 4340, v_c = 100 m/min, f = 0.45 mm/rev and a_p = 2.5 mm. Possible presence of a TPL protecting the tool.

4.2.4 Taylor vs. Colding

In order to investigate the accuracy of previously introduced tool life models section 3.8, listed in table 4.1, experiments were performed, **paper I**.

Table 4.1: Tool life models investigated.

Model	Eq. no.	Base	Number of constants
Taylor	3.4	-	2
Extended Taylor	3.5	f, a_p	4
Extended Taylor	3.6	h_e	3
Coromant turning ver. 1	3.8	f	4
Coromant turning ver. 1	3.9	h_m	4
Coromant turning ver. 1	3.10	h_e	4
Colding	3.12	h_e	5

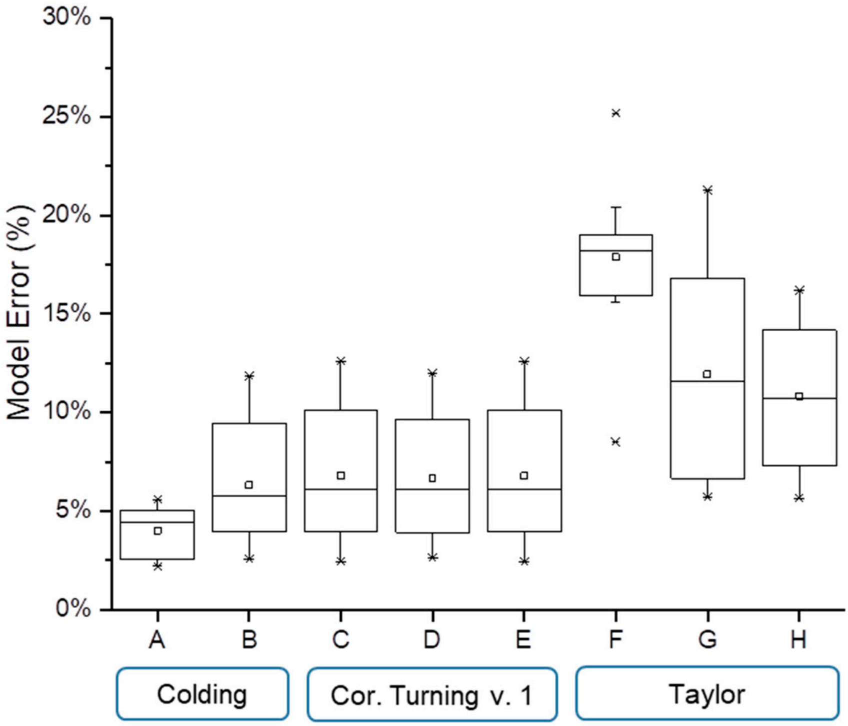
A total of seven different workpiece materials and three different tool grades were evaluated when turning using industry standard coated cemented carbide inserts. Tool grade A being of a wear-resistant grade, tool grade B a medium grade and tool grade C being a tougher grade. C 45E and 42 CrMo4 were tested with all three tool grades A, B and C and the other materials were tested with tool grade A, resulting in eleven different tool-work material combinations. Workpiece material in machining is divided into six different groups according to ISO 513:2004 [80], P (steel), M (stainless steel), K (cast iron), N (non-ferrous), S (heat resistant alloys) and H (hardened steel). Three groups were evaluated: P, M and K. The workpiece materials used are presented in table 4.2.

Table 4.2: Workpiece material evaluated.

Workpiece	Material group
235JRG2	P
16 MnCr 5	P
C 45E	P
42 CrMo 4	P
100 Cr 6	P
X5 CrNi 18 9	M
EN-GJS-500-7	K

Five or more tests were performed for each workpiece and tool material combination by varying cutting data, covering a range of cutting data suitable for the tool geometry and chip breaker. The ratio between the tool nose radius r_ε and depth of cut a_p was held constant in this series of testing. A wear criterion was chosen, such as maximum flank wear VB_{max} = 0.3 mm. The cutting data as well as the time the tool was engaged with the workpiece until reaching the wear criterion were recorded. The tool was removed from the tool holder and the attained wear was measured using an optical microscope.

Figure 4.6 presents the model error in a box plot using different commonly used tool life models for the 11 sets of workpiece and tool material combinations. The best performing model in this investigation with the lowest mean error as well as lowest dispersion is the Colding model with no limitations. These results suggest not only that the Colding model is a well-suited tool life model but also that the Woxén equivalent chip thickness h_e is a valid model describing the theoretical chip geometry for tool life modelling. This is further proven by analysing the resulting model errors of the extended Taylor models, whereby the extended Taylor based on h_e has lower model errors compared to the extended Taylor based on a_p and f even though the latter introduces one additional model constant.



A) Colding
B) Colding levelled
C) Coromant Turning version 1 with f as base
D) Coromant Turning version 1 with h_e as base
E) Coromant Turning version 1 with h_m as base
F) Taylor
G) Extended Taylor with based on a_p and f
H) Extended Taylor based on h_e

Figure 4.6: Tool performance data from 11 sets of workpiece and tool material combinations modelled using different tool life models A-H with the average model error presented on the Y-axis. The tool life models plotted are A) Colding B) Colding levelled, C) Coromant Turning version 1 with *f* as base, D) Coromant Turning version 1 with h_e as base, E) Coromant Turning version 1 with h_m as base, F) Taylor, G) Extended Taylor based on a_p and *f*, H) Extended Taylor based on h_e. The box plot shows the mean value (□), median (−), first and third quartile as well as the lower and upper adjacent value (⊥,⊤).

4.3 Equivalent chip thickness

One analytical based model that is referred to several times in this work is the equivalent chip thickness h_{eW} defined by Woxén [50], a simplification of the true equivalent chip thickness h_{eT} between the area of the uncut chip A_D and the cutting edge length l_{SaD} of the tool engage with the workpiece, figure 4.7 [32], equation 4.3.

$$h_{eT} = \frac{A_D}{l_{SaD}} \approx \frac{A_e}{b_e} \qquad 4.3$$

For the cutting chip area A_D, Woxén suggested the simplification in equation 4.4 for the active cutting edge b_e equation 4.5, giving the equivalent chip thickness according to Woxén in equation 4.6. The cutting edge length components l_{SaD1} and l_{SaD2} are defined in figure 4.7.

$$A_e = a_p \cdot f \qquad 4.4$$

$$b_e = l_{SaD1} + l_{SaD2} + \frac{f}{2} = \frac{a_p - r(1 - cos\kappa)}{sin\kappa} + \kappa \cdot r_\varepsilon + \frac{f}{2} \qquad 4.5$$

$$h_{eW} = \frac{a_p \cdot f}{\frac{a_p - r(1 - cos\kappa)}{sin\kappa} + \kappa \cdot r_\varepsilon + \frac{f}{2}} \qquad 4.6$$

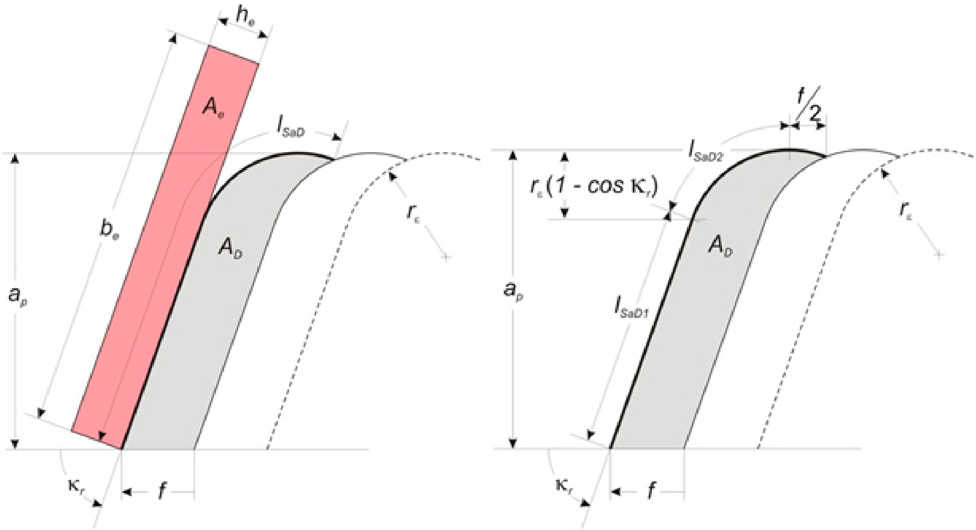


Figure 4.7: Equivalent chip thickness as defined by Woxén, adopted by Hägglund [32].

With regard to tool life, this model has worked well in balancing the loads acting on the tool when machining [51, 81]. Hägglund [32] noted two areas for improving the Woxén model:

1. Woxén's model is not defined for round inserts and therefore also not for relatively small a_p using a pointed insert when only the nose of the pointed insert is engaged.
2. Woxén's model is based on a simplification around the nose of the tool, the error by these simplifications is quite limited when $f < r_\varepsilon/2$ and $a_p > 2.5 \cdot r_\varepsilon$.

Hägglund has presented more accurate h_e models solving these issues and has also introduced h_e models dealing with milling. Hägglund's extended simplified versions, used in this thesis, for pointed and round inserts are presented in table 4.3, equations 4.7-4.9, visualized in figure 4.8. Hägglund noted in his work that mathematically correct versions of h_e can be derived but are in practise irrelevant for small feeds f relative to the nose radius r_ε for pointed inserts (or insert diameter d for round inserts) [32].

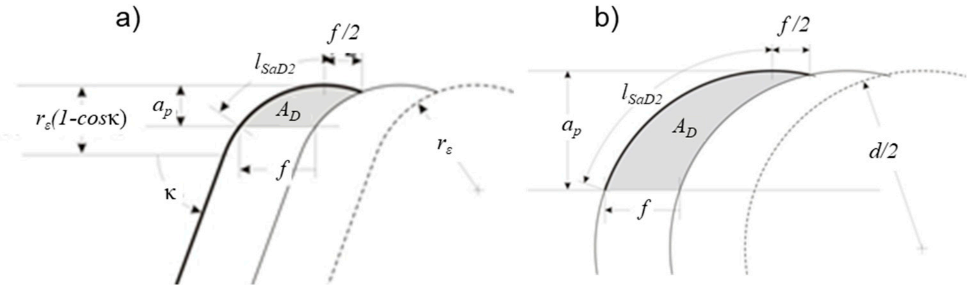


Figure 4.8: a) Pointed insert case 2 with Woxén's simplification using *f/2* for the minor cutting edge, b) round insert with Woxén's simplification using *f/2* for the minor cutting edge [32].

Table 4.3: Applicable h_e equations for round and pointed inserts according to Hägglund [32].

Case	$h_e = \dfrac{A_D}{l_{SaD}} \approx \dfrac{A_e}{b_e}$	**Eq. number**
Round insert $a_p \leq \dfrac{d}{2}$ $f \leq 2\sqrt{a_p(d-a_p)} \leq d$	$h_e \approx \dfrac{a_p f}{\dfrac{d}{2} \arccos\left(\dfrac{d/2 - a_p}{d/2}\right) + \dfrac{f}{2}}$	*4.7*
Pointed insert, *case 2* $a_p \leq r_\varepsilon(1-\cos\ \kappa_r)$ $f \leq 2\sqrt{a_p(2r_\varepsilon - a_p)} \leq 2r_\varepsilon$	$h_e \approx \dfrac{a_p f}{r_\varepsilon \arccos\left(\dfrac{r_\varepsilon - a_p}{r_\varepsilon}\right) + \dfrac{f}{2}}$	*4.8*
Pointed insert, *case 1* $a_p > r_\varepsilon(1-\cos\ \kappa_r)$ $f \leq 2r_\varepsilon$	$h_e \approx \dfrac{a_p f}{\dfrac{a_p - r_\varepsilon(1-\cos\ \kappa_r)}{\sin\ \kappa_r} + r_\varepsilon\ \kappa_r + \dfrac{f}{2}}$	*4.9*

Bushlya et al. [82] has published a h_e model for round inserts where it takes into account that the length of the active cutting edge l_{SaD} should be calculated in three dimensions and not on its projection on the reference plane. The common theme of these models is that they are more or less accurate representations of equation 4.3 and equation 4.7-4.9 have mainly been used in this work.

Bus et al. [81] found a linear relationship of cutting forces and equivalent chip thickness when machining C45N with varying feeds at 180 m/min. The authors concluded that equivalent chip thickness must not be considered to be of purely academic value but rather a basic technological quantity governing the metal cutting process.

It should be noted that by the very definition of equivalent chip thickness a variety of chip geometries will render the same h_e values, figure 4.9. According to the definition of the Colding equation for modelling tool life and using equivalent chip thickness a variety of f and a_p keeping h_e constant should give constant tool life T.

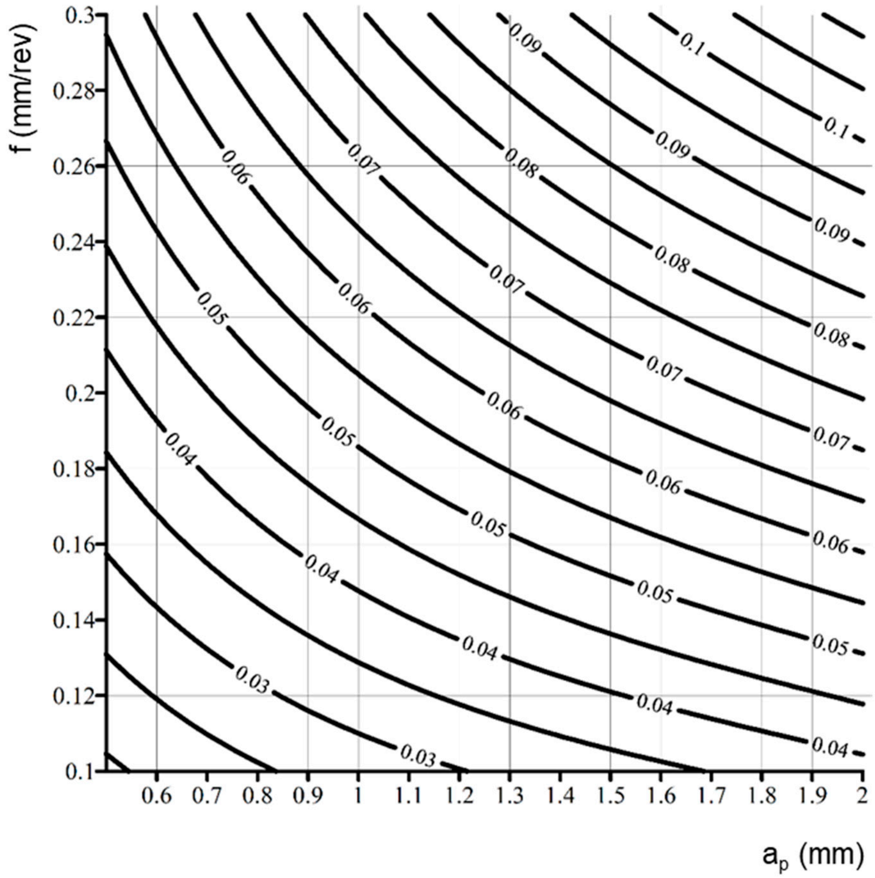


Figure 4.9: Equivelent chip thickness h_e for varying combinations of f and a_p for a round tool insert with a diameter d of 12.7 mm.

In **paper II** testing was done by longitudinal turning using coated CNMG120408 inserts, with r_ε = 0.8 mm machining AISI 4340. Tool holder DGLN3232P12-M with 50 mm tool overhang, and κ = 95° was used. The machining was done in dry conditions. The machine, used for the data collection, was an SMT SAJO 500 Swedturn, NC-turning machine [83].

Tool wear was measured with an Olympus SZX7 stereo microscope. The tool life criterion was selected to flank wear VB_{max} = 0.3 mm. The tested cases are for h_e = 0.12 mm (case 1) a medium fine chip breaker was used, and for h_e = 0.26 mm (case 2) a medium chip breaker was used. The result of the testing is presented in figure 4.10.

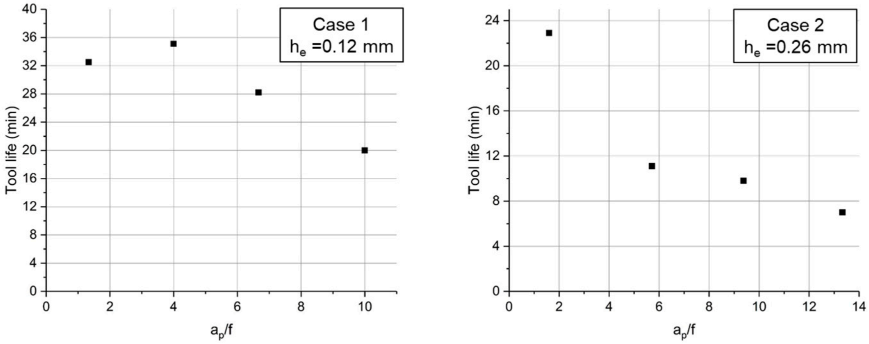


Figure 4.10: Tool life at the wear criterion VB = 0.3 mm for constant h_e while varying f and a_p [83].

The result is troublesome if the h_e model is expected to be a technological quantity governing tool life. It is possible that the h_e model is not valid for large ranges of a_p/f but still is a valid model when used within reasonable limitations. Several previous publications have used h_e successfully when modelling tool life [8, 32, 46, 51, 70, 71, 84, 85].

4.4 Varying flank wear criteria

Two major limitations with the Colding model, mentioned in section 3.8, are:

- Not being able to include varying flank wear when creating the tool life model.
- It is not possible to calculate at what time a tool will reach a selected wear level over or under the tested wear criteria.

In **paper III** the Colding constants and the model error were studied when selecting different wear criterion when machining ASI4340 using coated cemented carbide inserts [70]. The Colding constants are presented in figure 4.11 for selected wear criterion VB = 0.1 to VB = 0.6. The higher model error and nonlinear behaviour for several constants for lower wear criteria was believed to be an effect of the tool coating, figure 4.12.

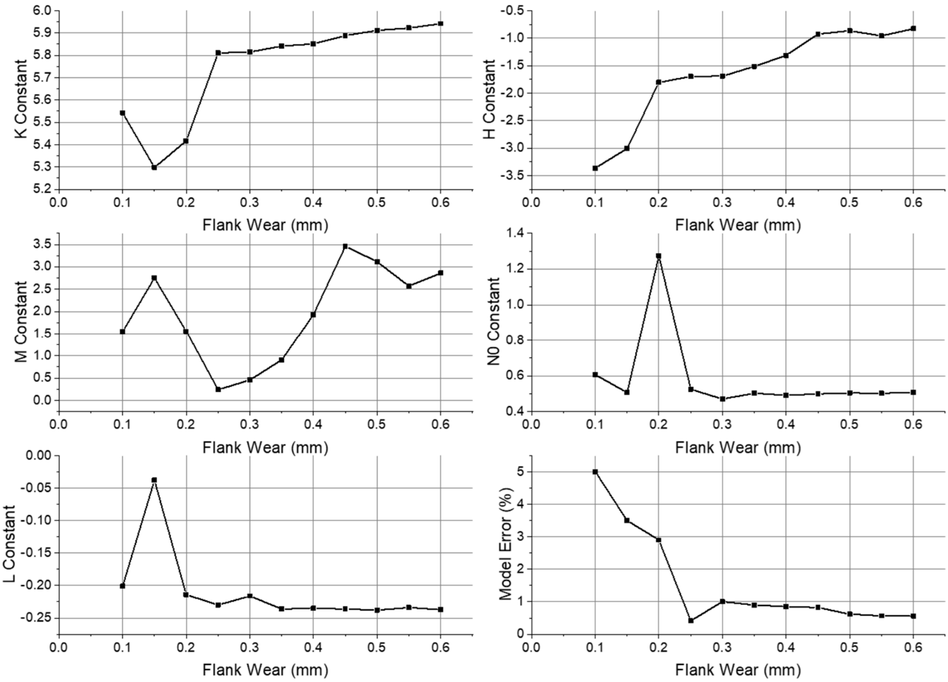


Figure 4.11: The Colding constants and the model error for different selected wear criteria from *VB* = 0.1 (mm) to *VB* = 0.6 (mm) when machining ASI4340.

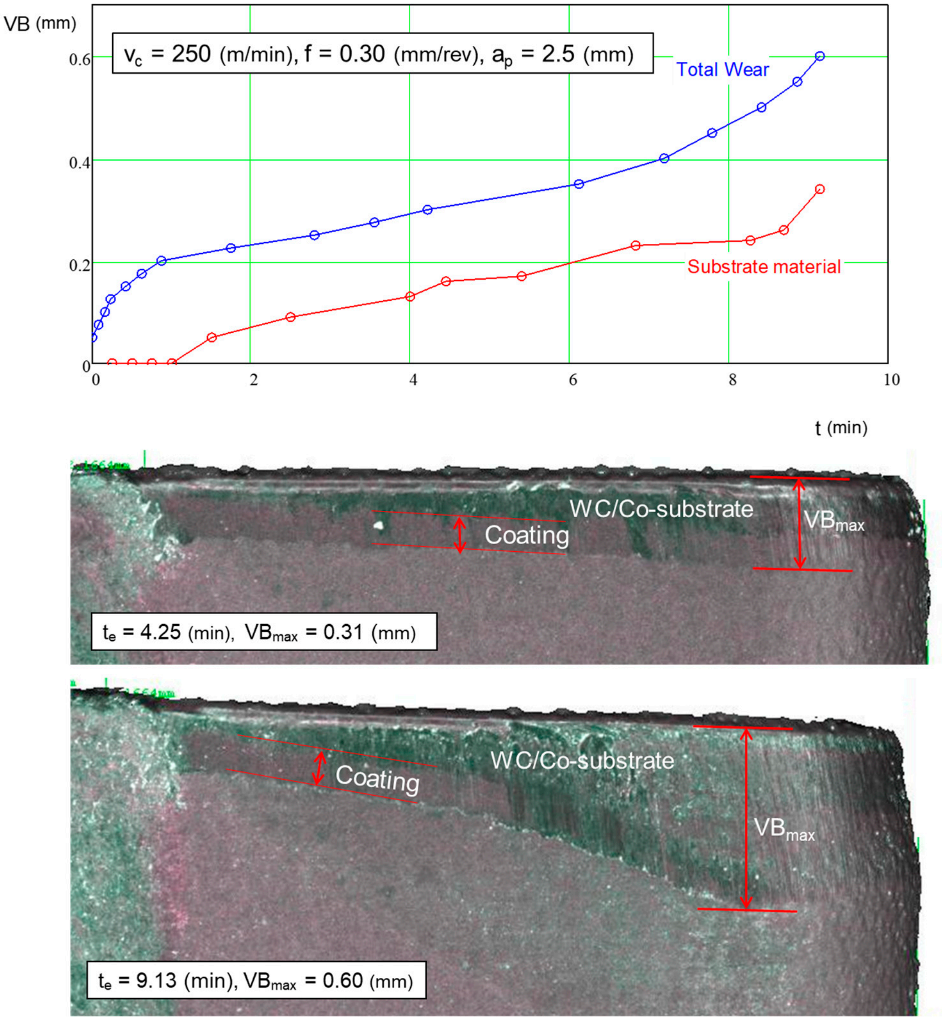


Figure 4.12: The wear development of the tool coating and the substrate material when machining ASI4340 with coated cemented carbid inserts.

One solution to solve varying wear criteria is to extend and combine the Colding model with the Archard wear function [12] discussed in **paper IV**. Figure 4.13 and equation 4.10 present the Ståhl et al. [71] version of Archard's wear function that also takes into account the cutting geometry of the tool and of changes in the cutting forces present in the wear process [16, 85].

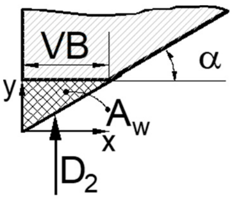


Figure 4.13: An idealized view of the cutting geometry for a cutting process, the directions of the coordinates which are shown, the components of the cutting force VB producing flank wear being indicated.

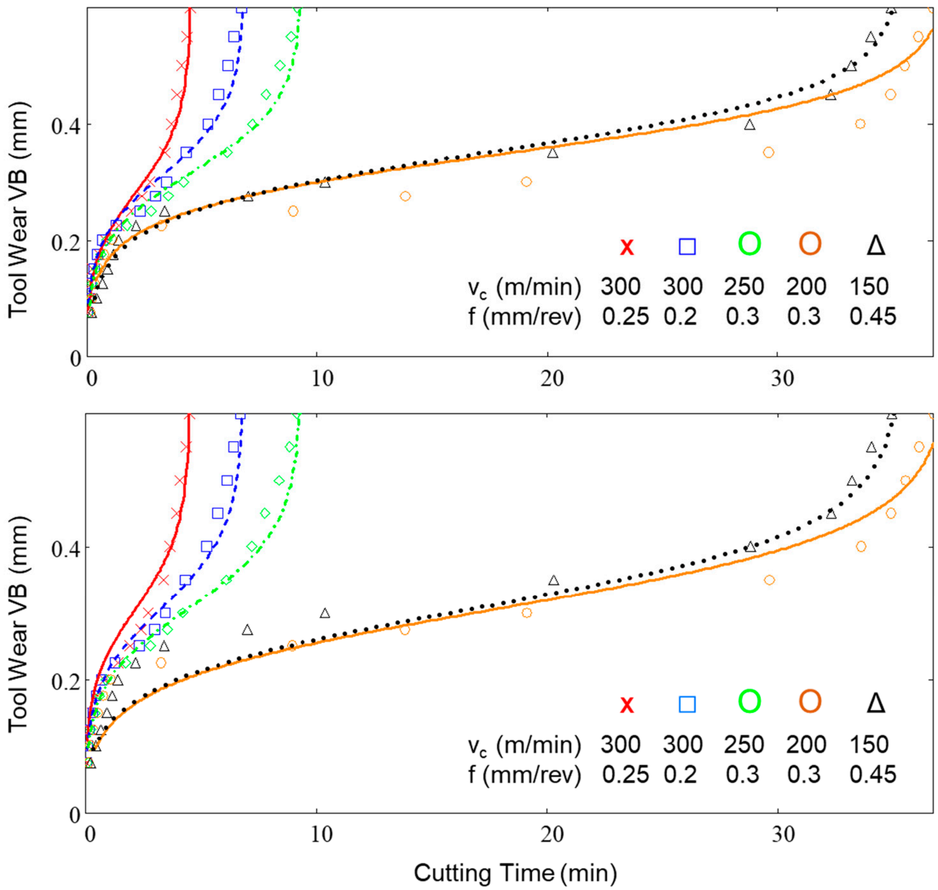
$$k_0 = \frac{D_{21} \cdot VB + D_{22} \cdot ln \dfrac{D_{22} + D_{21} \cdot r_\beta}{D_{22} + D_{21} \cdot VB} - D_{21} \cdot r_\beta}{\dfrac{D_{21}^2 \cdot v_c \cdot 2 \cdot t_e}{b \cdot tan\alpha}} \qquad 4.10$$

Where t_e is engagement time (min), v_c cutting speed (m/min), VB flank wear (mm), D_{21} and D_{22} cutting force components (N), k_c a wear function constant and r_β the edge radius. Equation 4.11 presents a combined Archard Colding model.

$$v_c = \frac{d_{21}(VB_T - r_\beta) + d_{22} \cdot ln \dfrac{d_{22} + d_{21} \cdot r_\beta}{d_{22} + d_{21} \cdot VB_T}}{\dfrac{T_{AC} \cdot 120 \cdot d_{21}^2 \cdot k_{0AC}}{\tan\left(\dfrac{\pi \cdot \alpha}{180}\right)}} \qquad 4.11$$

When using the combined Archard-Colding model, cutting forces are needed from the experimental testing. Laakso et al. [86] suggested a novel approach where no force components are required based on the logit function, presented in equation 4.12, that was widely used by Joseph Berkson in statistics [87]. Figure 4.14 presents the results when applying the methodology suggested by Laakso et al. on the tool performance data presented in **paper III.**

$$f(x) = log \frac{x}{1 - x} \qquad 4.12$$



Figur 4.14: Logit tool wear model with Colding's tool life equation for AISI 4340. upper) individual fit, lower) general fit [86].

The model has a good performance if the fit is done to the whole data set or individual data sets with different cutting parameters. The logit model brings the benefit of including the full representation of the experimental data in the model, instead of only the selected limiting wear, and this is achieved by including only two additional model constants [86].

4.5 The significance of the Colding constants

The Colding model is based on five unique constants with no reported physical connection to the metal cutting process. Each constant will significantly change the curves and contribute to the fitting of experimental data.

4.5.1 K constant

Figure 4.15 visualizes the function of the *K* constant. When the *K* constant is increased the recommended cutting speed is increased and the curves are lifted upwards. The global maxima of the Colding curve for a tool life of 1 min is $v_c = e^K$. A higher *K* value in the Colding model will mean better machinability in the sense that the tool can be run with higher v_c while still maintaining the same tool life.

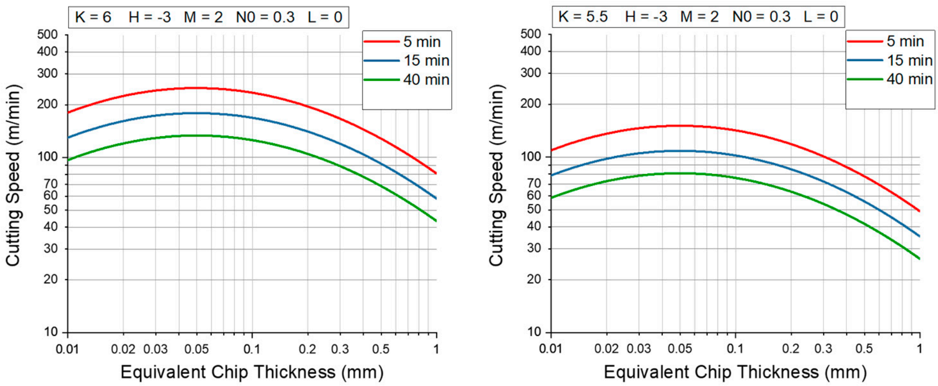


Figure 4.15: The impact of the K constant on the Colding model.

4.5.2 H constant

The *H* constant will shift the Colding curves horizontally to the left when decreased, visualized in figure 4.16. The equivalent chip thickness at the global maxima for a tool life of 1 min is $h_e = e^H$. A Colding model with a higher negative value on the *H* constant will be more sensitive to an increase in h_e. Also, the global maximum will be shifted to a smaller value of h_e.

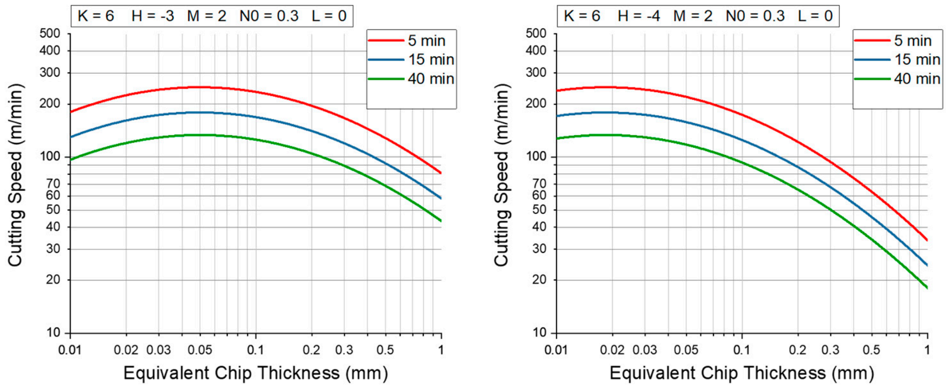


Figure 4.16: The impact of the H constant on the Colding model.

4.5.3 M constant

The M constant, visualized in figure 4.17, will form the curvature of the Colding curves. If M is negative the curves will be inverted pointing upwards and for $M = 0$ the curves will be represented as straight horizontal lines. A Colding model with a lower M constant will be more sensitive to an increase in h_e with regard to tool life.

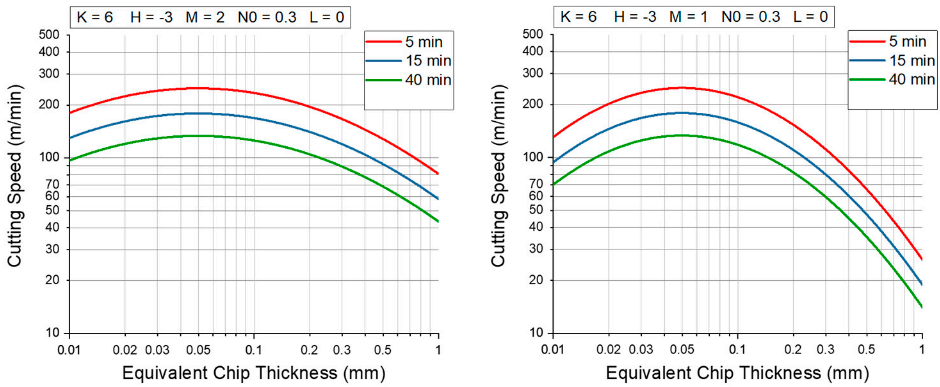


Figure 4.17: The impact of the M constant on the Colding model.

4.5.4 N0 constant

The functionality of the *N0* constant is visualized in figure 4.18. A decrease of *N0* will tighten the gap between the curves. A Colding model with a lower value of *N0* will be more sensitive to change of cutting speed with regard to tool life.

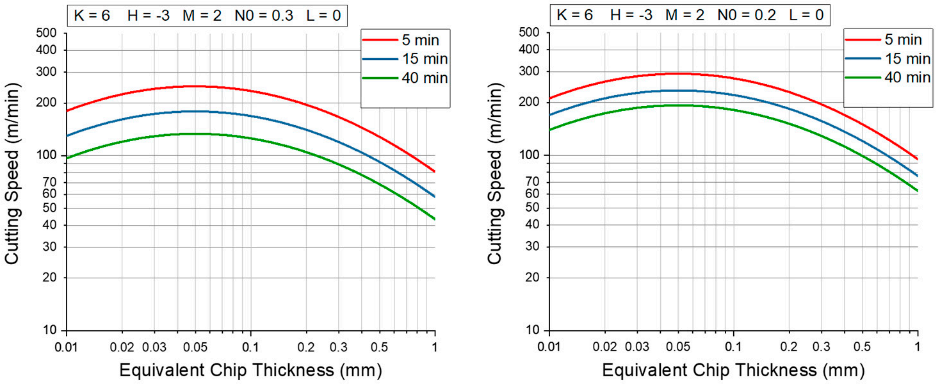


Figure 4.18: The impact of the *N0* constant on the Colding model.

4.5.5 L constant

The functionality of the *L* constant is visualized in figure 4.19. When $L \neq 0$ the constant introduces a singularity to the Colding model, previously discussed in section 4.2.3.

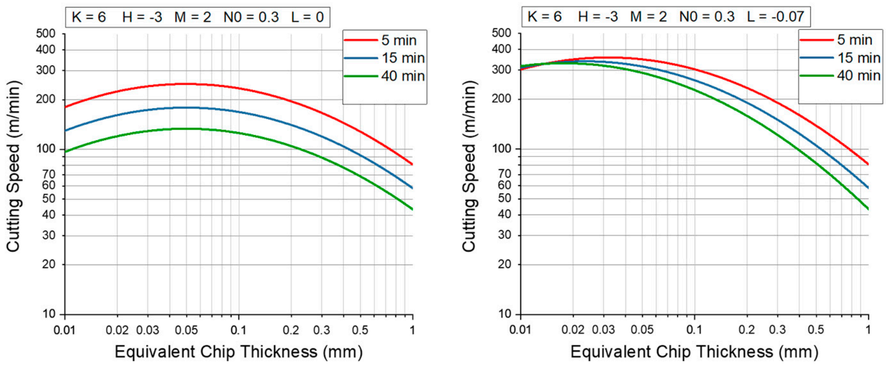


Figure 4.19: The impact of the *L* constant on the Colding model.

4.5.6 Statistical analysis of the Colding constants

Colding equation is an empirical model with five coefficients – an assessment of statistical relevance of the coefficients and their confidence intervals in the scope of real cutting data for studied workpiece materials is of vital importance in order to validate the suitability of the model.

To verify the ability of the Colding models to predict tool life, statistic characterization was performed with empirical data using ANOVA® in the MATLAB® environment. The 22 tool performance data points presented in **paper VI** and **paper VII** [73, 88] were used in this study. Using such a small dataset for computation will affect the precision and accuracy of the ANOVA® analysis, preferably a larger dataset should be used. Unfortunately, the cost of collecting data did not allow for a bigger dataset in this study. The results of the modelling are presented in table 4.4.

Table 4.4: Statistic characterization perfomed using ANOVA® for 22 tool perfomance datapoints.

Term	Estimate (with 95 % confidence)	SE	t-Stat	p-value
K	6.388 (6.119, 6.656)	0.10452	59.72	3.0071e-17
H	-1.813 (-2.295, -1.331)	0.25663	-5.6024	8.5901e-05
M	0.704 (0.5175, 0.8904)	0.16214	3.1874	0.0071384
N0	0.3875 (0.2344, 0.5407)	0.10996	4.2966	0.0008688
L	-0.1521 (-0.2865, -0.01768)	0.09594	-2.5092	0.0261330

RMS Error: 0.222
R^2: 0.842
F-statistic vs. zero model: 471
p-value = 3.28e-14

Figure 4.20a presents a 3D plot of log(v_c-h_e-T), 4.20b the residual of log(T) in the log(v_c-h_e)-plane, 4.20c Plots the residuals for log(T) as a function of the fitted log(T) value and 4.20d a surface approximation of log(T) in the log(v_c-h_e)-plane. Figure 4.21 presents the tool life model in 3D (v_c-h_e-T).

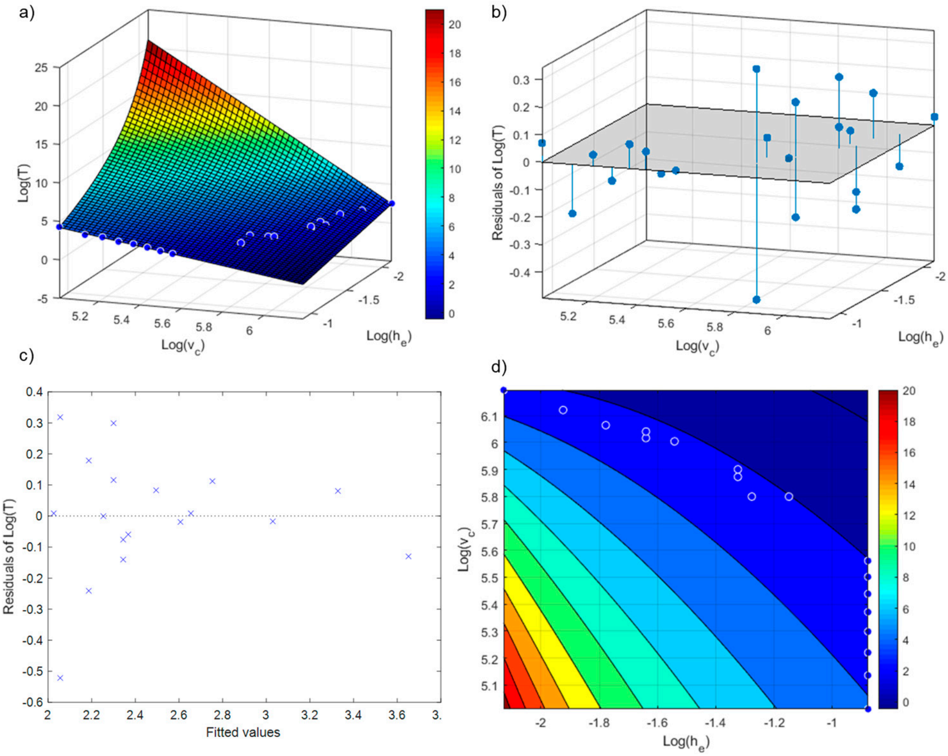


Figure 4.20: a) presents a 3D plot of log(v_c-h_e-T) b) the residual of log(T) in the log(v_c-h_e)-plane, c) plots the residuls for log(T) as a function of the fitted log(T) value and d) a suface approximation of log(T) in the log(v_c-h_e)-plane.

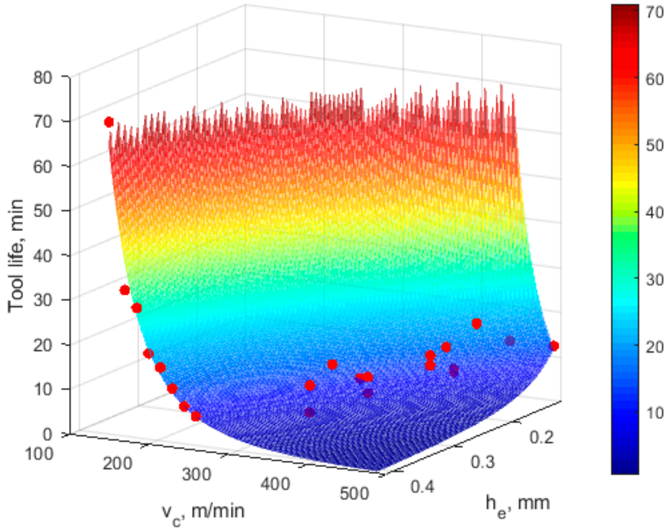


Figure 4.21: The Colding model in 3D in v_c-h_e-T.

The following conclusions can be drawn based on this statistical analysis:

- ANOVA* analysis of the Colding model based on the experimental data set of 22 measurements proves a good statistical relevance of the model with 97 % confidence interval.
- All five model constants have a significant impact on the model with a maximum p-value for the coefficient L of 2.6 % at the 5 % significance level.

This study is based on empirical data from machining tests. Errors and descriptions from workpiece material variations, tool variations and measurement deviations when measuring the level of wear etc. will have an effect and are included but considered a known-unknown in this statistical analysis as well as any modelling in this work.

4.5.7 Adjusting the model

A model based on tests in a well-controlled environment with a relative stiff machine setup, tight control of work material quality etc. can give discrepancies between the nominal or recommended data and the actual tool life given in the application at hand. One possibility for describing and handling such a situation is to differentiate Colding's equation with regard to the relatively strong constant K that the equation contains. This enables one to create a new and more adequate tool life model. This methodology can also be used to extrapolate models without extensive testing between closely related workpiece materials within a material group or tools within a group of similar performance and wear behaviour.

Such a differentiation of the Colding model can be derived from equation 4.13.

$$\Delta T = \frac{dT}{dK} \cdot \Delta K \qquad 4.13$$

where ΔK is the change in Colding's constant K corresponding to the error in the tool life time ΔT. If the tool life time turns out to be 3 minutes shorter than was expected, ΔT = -3 minutes. This methodology is a simplification as the five constants in the Colding equation do have some dependency.

Rewriting Eq. 4.13 for ΔK results in equation 4.14.

$$\Delta K = \frac{\Delta T}{\frac{dT}{dK}} \qquad 4.14$$

A derivation of Colding's equation (3.12) with regard to K results in equation 4.15.

$$\frac{dT}{dK} = e^{-\frac{\frac{H^2 - 2 \cdot H \cdot ln(h_e) + ln(h_e)^2 - 4 \cdot K \cdot M + 4 \cdot M \cdot ln(v_c)}{4 \cdot M \cdot (N0 - L \cdot ln(h_e))}}{N0 - L \cdot ln(h_e)}} \qquad 4.15$$

An example of this methodology, **paper V** [89], is given in figure 4.22. Trials were conducted through longitudinal turning experiments while machining AISI 304. Coated cemented carbide cutting inserts were used as study subjects. Tools A, B and C are based on the same substrate material but with three different tool coatings. A full test series to create a Colding model for tool grade A was performed. Two tests were performed for tool grades B and C. One test to establish dT and the new K constant and one test to verify the accuracy of the model for tool grade. The error of the secondary test point was -9.9 % for grade B and -0.6 % for grade C, including the original model error of -3.1 %, presented in table 4.5 [89].

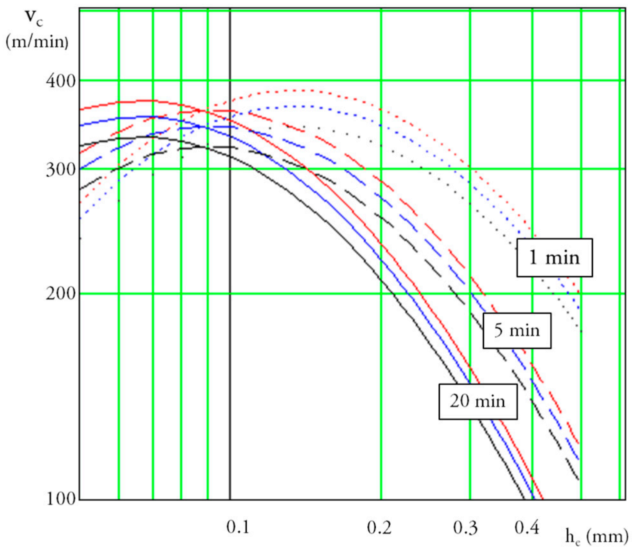


Figure 4.22: Tool A (red), Tool B (blue) and Tool C (black): Cutting speed v_c in relation to equivalent chip thickness h_e for 1(···), 5 (- - -) respective 20 (—) min tool life *T* in log-log scale.

Table 4.5: The error of the secondary test points.

Tool Type	$v_{c, exp}$ (m/min)	$v_{c, mod}$ (m/min)	Error (%)	$v_{c, exp}$ (m/min)	$v_{c, mod}$ (m/min)	Error (%)
A	250	241	3.6	275	284	**-3.1**
B	250	241	3.6	275	302	**-9.9**
C	250	241	3.6	275	296	**-0.6**

4.6 Selecting test points

The Colding model, being an empirical model, will be sensitive with regard to the quality and the size of the dataset included when building the model. One issue with these types of models is the cost involved and the time needed for experimental testing. Therefore, the aim will always be to limit testing if possible, without losing confidence in the model's predictive capacity. Model error is most commonly reported as the linear mean error or standard deviation error when predicting the tool performance points included in creating the model. This creates a bias that needs further investigation.

Two main questions are of interest:

- How many tool performance data points should be included to create a stable model?
- How should these tool performance data points be placed within the cutting data range (max vs. min v_c, f, a_p)?

A clarification and definition of three types of model errors is needed for the purpose of this investigation, visualized in figure 4.23:

- **Approximative error** (green): This is the model error commonly presented for tool life modelling. A number of tool performance tests are used to create a tool life model. This model is then tested on the data used to create the tool life model and the error of how well the model can approximate this data is presented. This is the type of model error that is presented in, for example, **paper I**.
- **Interpolative error** (blue): This error includes one or more tool performance points not included when creating the model but these tool performance data points are within the range of included test points.
- **Extrapolative error** (red): This error includes one or more tool performance points not included when creating the model and these tool performance data points are outside the range of included test points.

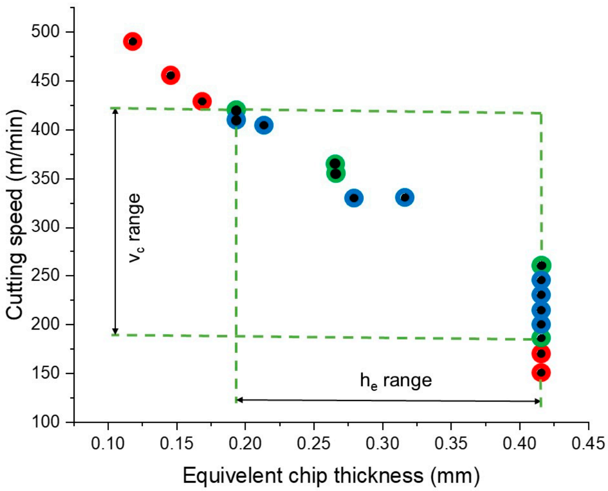


Figure 4.23: Definition of the placemnent of tool perfomance test points used to claculate the model error, approximative (green), interpolative (blue) and extrapolative (red) error.

A total of 22 tool performance data points were included in this study, **paper VI** and **paper VII** [73, 88]. The included data and the experimental testing are presented in the papers.

4.6.1 Size of dataset

Figure 4.24 presents the error distribution when including 7, 10 and 13 tool performance data points. A randomizer was used to randomly select data points and therefore a mix of approximative, interpolative and extrapolative errors is presented. A Colding model was created based on the randomly selected tool performance data points and the model was then tested on the full dataset of 22 test points and the mean linear model error was calculated. This was repeated 1000 times.

It can be noted that, as expected, the distribution of errors decreases as the dataset is increased. When including only 7 data points the majority of the models will have a model error of 2-5 % but still, it is very possible to find combinations of data points creating models with model errors over 10 %.

The data presented in figure 4.25 is based on 4000 randomly created models for each case, 5, 6 and up to 18 data points included in the model based on the experimental dataset presented in **paper VI** and **paper VII** [73, 88].

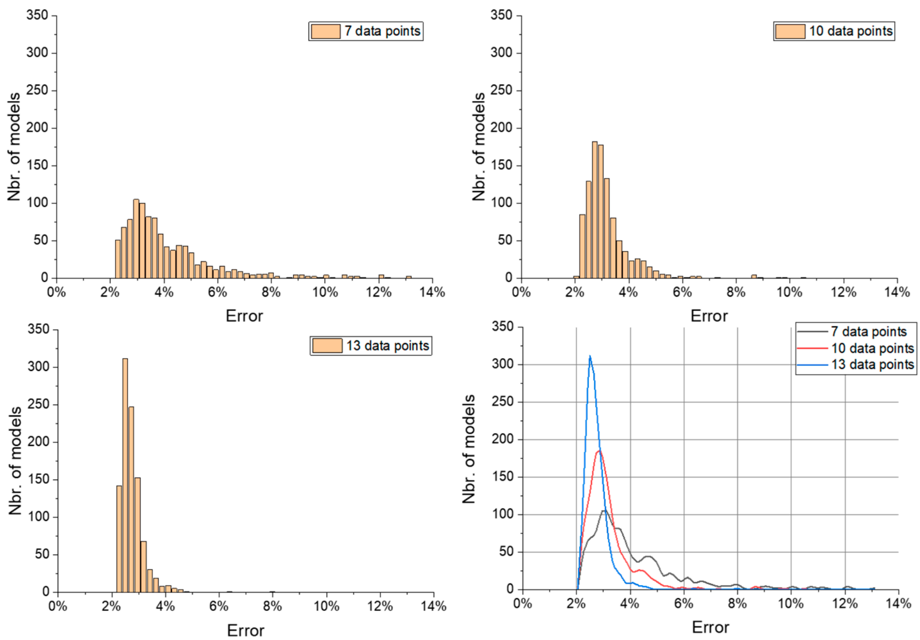


Figure 4.24: The error distribution of approximative, interpolative and extrapolative mean errors for 1000 Colding models based on 7, 10 and 13 tool performance data points.

In figure 4.25 (a-d)) the approximative error (a), interpolative error (b) and the extrapolative error (c) are separated, also the total error when testing each model on all available data is presented (d).

Several conclusions can be drawn from the presented data:

- Figure 4.25 a) The mean model error increases slightly as more tool performance data points are included, as expected. Still, the Colding model can approximate the data points with a low model error less than 3 %. This is the mean model error reported in [70, 84, 89].
- Figure 4.25 b) The mean interpolative error is below 5 % proving that for this dataset the Colding model can predict tool life well within the tested v_c and h_e range. This is the error likely affecting an end user of the model where it is expected that the model, within given boundaries, can predict tool life with reasonable errors for various cutting data.
- Figure 4.25 c) The mean extrapolative error is of limited interest as it is not sensible to predict tool life and cutting data outside the tested range of v_c and h_e. Still, the Colding model does have some extrapolative accuracy hence further proving its capability as a tool life model.
- Figure 4.25 d) the total error is based on a mix of approximative error (a), interpolative error (b) and extrapolative error (c) and it can be noted that the main contribution of model error comes from extrapolation.

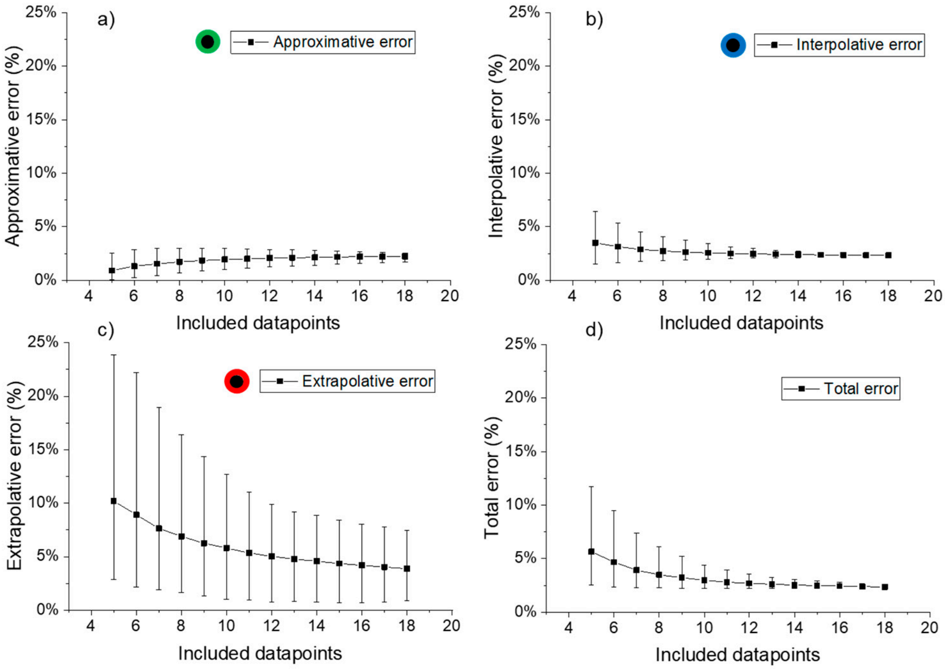


Figure 4.25: The mean approximative error (a), interpolative error (b), the extrapolative error (c) and the total error (d). The error presented (⊥,T) is the 95th percentile.

The presented data shows the importance of including enough data when creating a Colding model to secure the models validity. As this analysis is based on only one dataset general conclusions cannot be made. However, based on this dataset, a large improvement is found with regard to model error when increasing the dataset from 5 data points to 9 data points. Over 13 data points the improvement to the models is minor.

It should be noted that a randomizer was used to select the tool performance data points, which means that the presented total model error, figure 4.25d, is a mix of approximative, interpolative and extrapolative errors. It would be expected that with a more careful selection and placement of the test points, lower model errors could be achieved with smaller datasets, see 4.6.2.

4.6.2 Placement of the test points

The previous section investigated the importance of the size of the included dataset when creating a Colding model. This section investigates the importance of the quality of the included data set. More specifically, how to design the experimental setup when collecting data for a Colding model. The Colding model, based on five model constants, needs a minimum of five tool performance test points to determine its model constants. This investigation is based on how to select five test points out of a dataset with 22 test points while keeping model error as low as possible.

A total of 26,334 combinations of picking 5 data points out of 22 data points can be mathematically obtained. For all these combinations a Colding model was calculated and the mean deviation error (including approximative, interpolative and extrapolative errors) was calculated when testing each model on the full dataset.

With resource efficiency in mind, one should minimize the metal consumed as chips and the time used for testing. Figure 4.26 presents the 26,334 models with the total amount of metal removed during the testing as a function of model error.

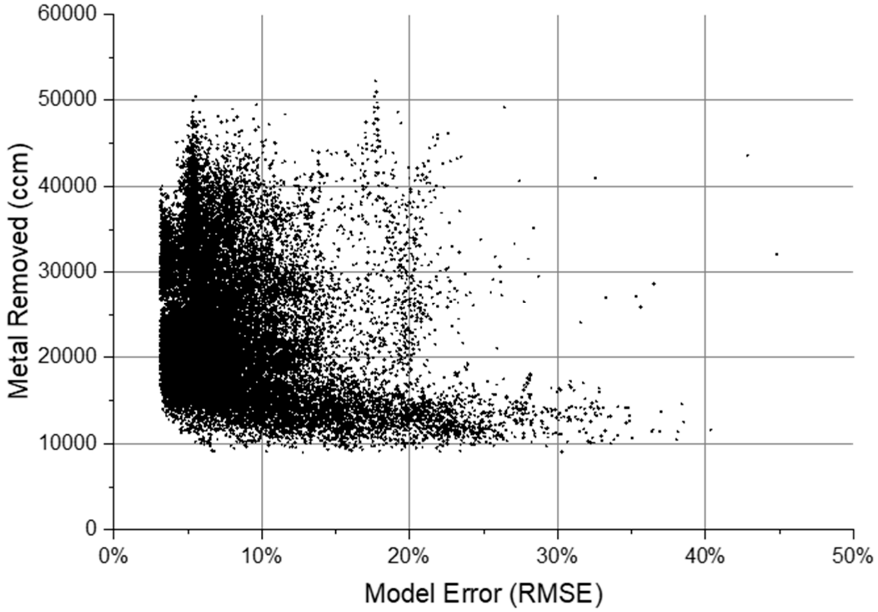


Figure 4.26: 26,334 Colding models plotted (●) where the amount of metal removed during testing is plotted on the Y-axis and the model error (RMSE) is plotted on the X-axis.

The optimal models with regard to workpiece consumption and model error can be found in the lower left corner of the plotted data. When analysing these models in depth there is no clear correlation between models with low model error versus high model error with regard to the amount of metal consumed during testing. Figure 4.27 presents the 26,334 models as a total amount of machining time used during the testing as a function of model error. Also, it is not possible here to distinguish well performing models versus models with a high model error.

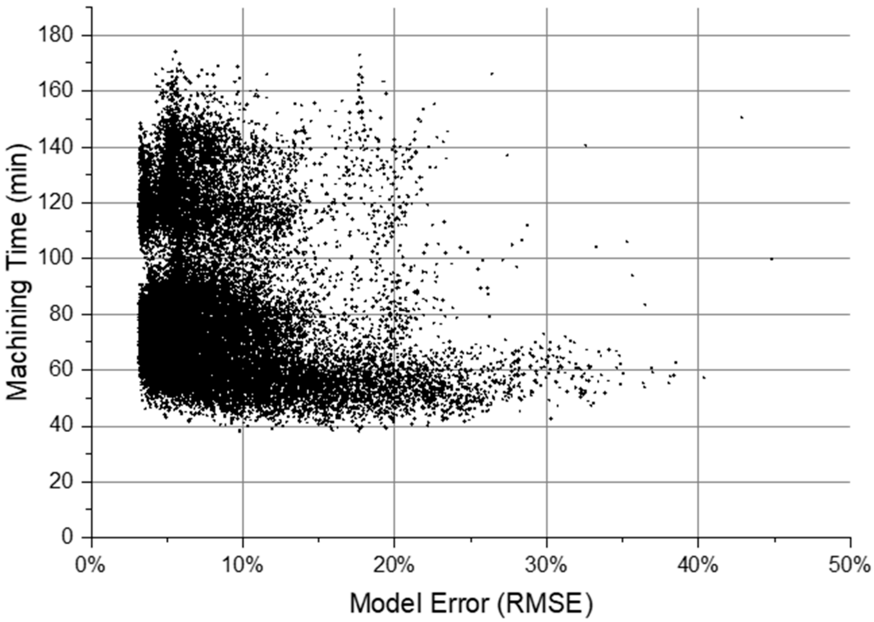


Figure 4.27: 26,334 Colding models plotted (●) where the macining time during testing is plotted on the Y-axis and the model error (RMSE) is plotted on the X-axis.

A significant parameter when selecting input data in creating a model is how well the input data represents the outer max and min parameters, in this specific case, max and min v_c, h_e and T. By maximizing the range of v_c, h_e and T any extrapolative errors can be avoided as suggested in section 4.6.1. Figure 4.28 visualizes the weighted ratio of min/max for v_c h_e T on the Y-axis and model error on the X-axis. It can be noted, as expected, that a larger ratio of the input parameters will increase the probability of a smaller model error. By maximizing this ratio no tool performance data point errors are from extrapolated cutting data, given that the presented errors from the models inside the blue box are only approximated and interpolated errors.

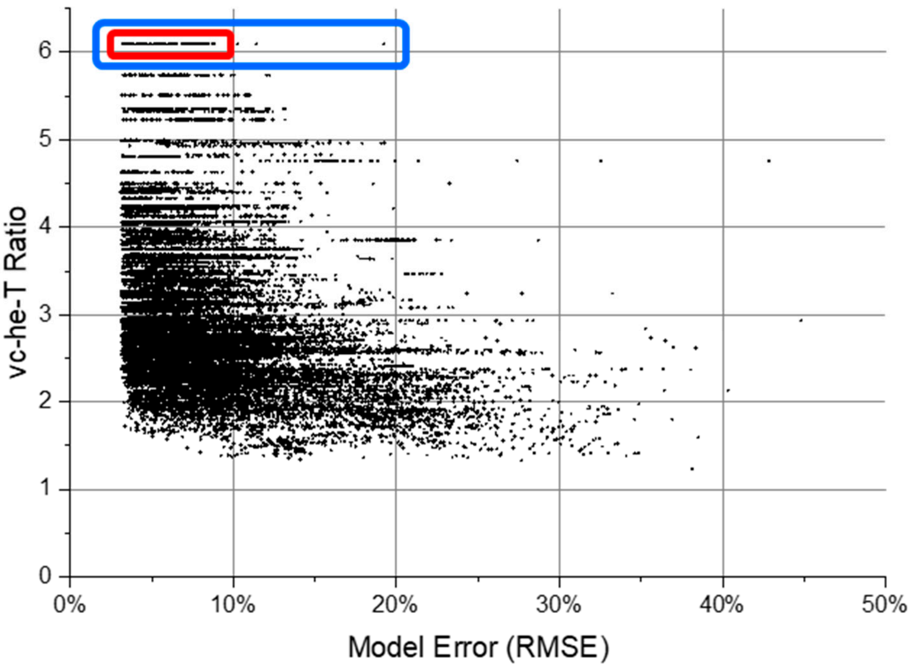


Figure 4.28: 26,334 Colding models plotted (●) where the wheighted ratio of v_c h_e T is plotted on the Y-axis and the model error (RMSE) is plotted on the X-axis.

When studying the models with the highest available v_c h_e T ratio in figure 4.28 (marked with a blue box), only 3 combinations of tool performance data points render a model with a model error larger than 10 %. An in-depth analysis of the models with the highest v_c h_e T ratio and a model error under 10 % (marked with a red box) provide the following conclusions on how to avoid model error over 10 % for this data:

- Maximize the range of cutting speed.
- Maximize the range of equivalent chip thickness.
- Maximize the range of tool life.
- Include two cutting data points using the same equivalent chip thickness.

To fulfil these criteria, but preferably avoiding issues like plastic deformation and build up edges, a suggestion of placing the five test points is presented in figure 4.29 and selected with the following criteria:

1. Smallest possible h_e within working range and high v_c.
2. Aiming for economical T and h_e.
3. Minimum T and relatively large h_e.
4. Maximum h_e within working range and economical tool life T.
5. Maximum h_e, within working range, low v_c and a high T.

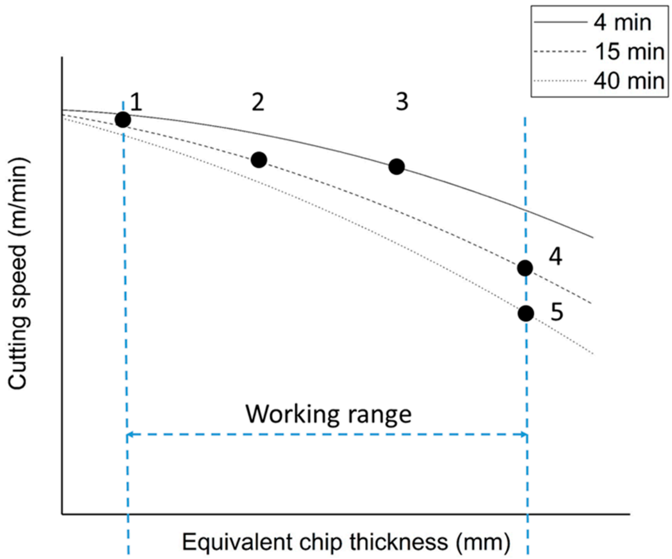


Figure 4.29: Suggestion on placement of the cutting data points in a test series of five tool perfomance tests.

4.7 Cost Optimization

Previous sections in this thesis have manly focused on modelling tool life for varying cutting data. This section focuses on how these established tool life models can be used as decision support for optimising cutting data and selecting cutting tools.

When optimizing cutting data, there are two major goals after securing a stable machining process that are meeting set criteria connected to the desired geometries and tolerances of the produced part as well as avoiding unpredictable tool deterioration. These two goals will either optimize with regard to minimizing machine time or minimizing part cost. If the part produced is dependent on several machining systems or several machining operations a bottle neck might arise. This will be a typical case of aiming to reduce machine time for one or several operations.

If a machining centre or an operation has a utilization less than 100 %, cutting data can be optimized with regard to lowering part cost. A combination of the Ståhl cost model and the Colding model is presented in section 4.7.1, and in section 4.7.2 there are some examples given on how to use the model as decision support. The Cost Performance Ratio (CPR) is introduced in section 4.7.3.

4.7.1 Ståhl cost model for varying cutting data

When optimizing cutting data with regard to machine time, the highest possible MRR is the aim. This case will be based on the balancing of MRR, tool life and tool change time, discussed by Hägglund [32]. When optimizing cutting data with regard to part cost, a system approach is needed to connect cutting data to part cost. This model should include parameters such as quality rejections and downtime losses as well as setup times, tool transportation times, time for tool changes, batch sizes and all corresponding costs in a manufacturing system with detailed information on the machinability of the selected tool setup and work material.

The Colding model can be used as an input model to a micro economic model such as the Ståhl cost model [35, 90]. This model was further developed by Windmark et al. as a Cost Performance Ratio (CPR) model to use as decision making support for e.g. new machine investments [34].

When connecting a tool life model, such as the Colding model, engagement time t_e, will be the governing parameter. The tool engagement time is calculated using equation 4.16, using the volume of workpiece material to be removed V, the cutting depth a_p, the feed f, and the cutting speed v_c modelled using a Colding model.

$$t_e = \frac{V}{a_p \cdot f \cdot v_C} \tag{4.16}$$

The ideal cycle time t_0 for one or several machining operations is defined to include engagement time per part t_e, tool transportation and work material handling per part t_{rem}, and tool changing time per part t_{tct} [10]. Equation 4.17 presents the relationship between the times where T is the tool life and T_{tct} is the tool change time.

$$t_0 = t_e + t_{rem} + t_{tct} = t_e + t_{rem} + \frac{t_e}{T} \cdot T_{tct} \tag{4.17}$$

The total time to produce one part t_{pb} including quality losses and setup time, is defined as the time to finish a full batch divided by the number of parts, presented in figure 4.30. This can also be written as presented in equation 4.18. Production time per part is calculated based on setup time T_{su}, batch size N_0 and the quality parameters q_Q and q_S.

$$t_{pb} = \frac{T_{su}}{N_0} + \frac{t_0}{(1 - q_Q)(1 - q_S)} \tag{4.18}$$

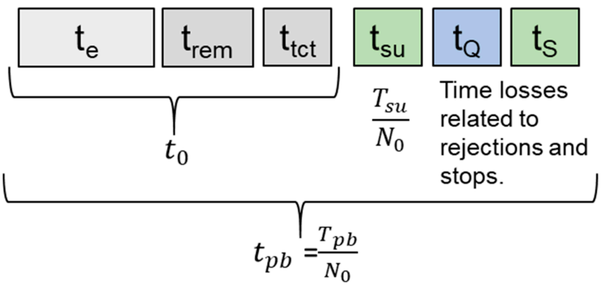


Figure 4.30: The individual times that lead to the total manufacturing time per part t_{pb} [10].

The loss parameter for the remaining time q_{rem} (time for changing work material and tool transportation) is related to the engagement time t_e and presented in equation 4.19. In the same way, the loss parameter for tool changing time q_{tct} is related to the engagement time t_e and the remaining time t_{rem} in equation 4.20.

$$q_{rem} = \frac{t_{rem}}{t_e + t_{rem}} \tag{4.19}$$

$$q_{tct} = \frac{t_{tct}}{t_e + t_{rem} + t_{tct}} \tag{4.20}$$

The total cost of producing a part, based on selected cutting data, is calculated using equation 4.21. Here the tool cost k_A is divided per part using the number of cutting edges z and the ratio between tool life T and tool engagement time t_e. The cost of work material is affected by the rate of quality rejections q_Q and the rate of material scrap q_B. The cost of the work material is removed so as to only provide the cost of the operation. The hourly cost of running the equipment k_{CP}, for idling equipment k_{CS} and salary costs are dependent on engagement time. For idling equipment and salary cost, the equipment set-up time and the rate of time losses will contribute to the total cost volume. When determining the salary cost, the number of operator's n_{op} is used. If an operator is running several machines, the parameter will be a fraction.

$$\begin{aligned} k = {} & \frac{k_A}{z} \cdot \frac{t_e}{T} + \frac{k_B}{(1-q_Q)(1-q_B)} - k_B + \frac{k_{CP}}{60} \cdot \frac{t_e}{(1-q_{rem}) \cdot (1-q_{tct}) \cdot (1-q_Q)} + \frac{k_{CS}}{60} \\ & \cdot \left(\frac{t_e \cdot q_S}{(1-q_{rem}) \cdot (1-q_{tct}) \cdot \left(1-q_Q\right) \cdot (1-q_S)} + \frac{T_{su}}{N_0} \right) + \frac{k_D \cdot n_{op}}{60} \\ & \cdot \left(\frac{t_e}{(1-q_{rem}) \cdot (1-q_{tct}) \cdot (1-q_Q) \cdot (1-q_S)} + \frac{T_{su}}{N_0} \right) \end{aligned} \tag{4.21}$$

The model to determine the cost per part can be used for several types of investigation. Not only can optimal cutting data with regard to part cost be calculated but any of the included parameters can be related and investigated with regard to part cost. Production capacity utilization U_{RP} is not included in the model presented and is therefore equal to 100 %. Production where $U_{RP} < 100\ \%$ can be included in the model and has been discussed by several authors [16, 34, 90]. Optimization of cutting data towards highest possible MRR becomes obsolete when the production system is not fully utilized.

4.7.2 Ståhl cost model adapted for metal cutting

Data presented in this section is based on a Colding model for the 22 experimental tool performance points presented in **paper VII**. A steel bar of C45 E is to be machined from a diameter of 200 mm to 194 mm using indexable cemented carbide inserts. No limitations are set on surface requirements, spindle speed or machine power, models to handle such limitations have been presented by Hägglund [32]. A total volume of 1000 cm^3 of workpiece material is to be removed. Nominal input parameters are presented in table 4.6.

Four parameters are investigated bellow with regard to production time per part and production cost per part. Please note that the Y-axis is not held constant so as to more clearly display the output data from the cost model. Figure 4.31 presents the influence of selected feed. At a tool life of approximately 31 min the curves of feed 0.3 and 0.4 are crossing. This is not a Colding singularity effect or an effect of data from the Colding model from the left side of the H-line, presented in section 4.2.3. In this case, the cutting data presented is well to the right of the singularity and H-line and the effect is based on a decrease of MRR due to low speeds.

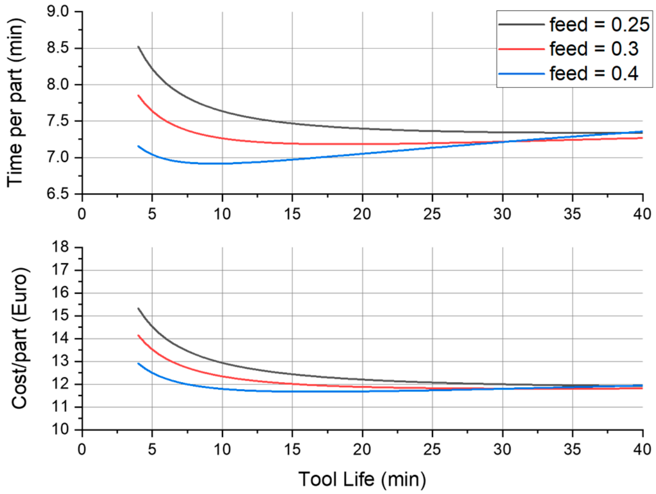


Figure 4.31: The effect of selecting *f* = 0.25, 0.3 and 0.4 mm/rev on the production time and part cost when removing 1000 cm^3 of workpiece material.

Table 4.6: Nominal input data.

Parameter	Descipition	Unit	Value
a_p	Depth of cut	mm	3
f	Feed	mm/rev.	0.4
H	Colding constant	-	-1.330771
K	Colding constant	-	6.136025
k_A	Cost of tool	€	10
k_B	Cost of material	€	70
k_{CP}	Machin cost (running)	€/h	40
k_{CS}	Machin cost (idle)	€/h	35
k_D	Salary cost for operators	€/h	45
L	Colding constant	-	-0.288728
M	Colding constant	-	0.609649
N_0	Batch size	units	200
N0	Colding constant	-	0.498538
n_{op}	Number of operators	units	1
q_Q	Rate of quality losses	-	0.02
q_S	Rate of time losses	-	0.1
q_{rem}	Rate of remaining time	-	calc.
q_{tct}	Rate of tool changes	-	calc.
r_ε	Tool nose radius	mm	0.8
T	Tool life	min	4 to 40
t_0	Cycle time	min/part	calc.
t_e	Tool engagement time	min/part	calc.
t_{pb}	Production time per part	min/part	calc
t_{rem}	Remaining time incl. workpiece change and tool transportation	min/part	2
T_{su}	Set-up time per batch	min	180
T_{tct}	Tool change time	min	2
t_{tct}	Tool change time	min	calc.
V	Volume of work material to remove	cm^3	1000
v_c	Cutting speed	m/min	calc.
z	Nr. of cutting edges	units	4
κ	Major cutting angle	degrees	95

The effect of selecting different a_p is presented in figure 4.32. The diameter of the workpiece is machined down from 200 mm to 194 mm with one tool passage of a_p = 3 mm, two tool passages with a_p = 1.5 mm and three tool passages with a_p = 1 mm. For this presented case, tool transportation between passages is neglected but it could easily be added in the t_{rem} parameter. If adding tool transportation, limiting the number of tool passages would be even further beneficial with regard to both production time and part cost. This result agrees with previous work by Hägglund [32] on optimizing cutting data where Hägglund suggest to:

1. Maximize the depth of cut considering the applicable physical constraints.
2. Maximize the feed considering the applicable physical constraints.
3. Optimize the cutting speed considering the applicable physical constraints.

For a given operation using this approach, a higher MRR can possibly be achieved without decreasing tool life.

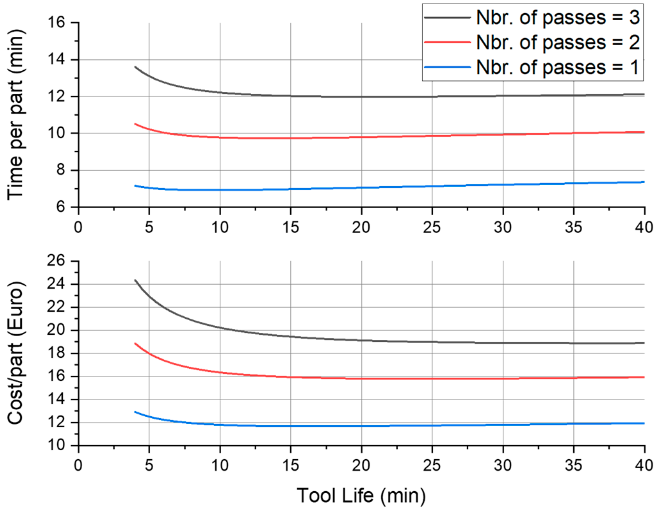


Figure 4.32: The effect of selecting a_p = 1, 1.5 and 3 mm on the production time and part cost when removing 1000 cm^3 of workpiece material.

The effect of the batch size N_0 is investigated in figure 4.33. It should be noted from the figure that batch size and cutting data are not linked together, hence batch size is irrelevant when selecting cutting data but can have a large impact on both production time and production cost. The driving parameter is the setup time T_{su} and costs associated with setup such as k_{CS} and k_D. This work does not intend to investigate batch size optimization nor warehouse management. Still, it is quite obvious that the batch size has a large impact on both production time and part cost. The product turnaround must be low, and costs associated with storage, including the cost of tied-up capital must be relatively high, not to mention producing extra stock as in this example case. The Ståhl cost model can be expanded to include costs related to batch size optimization, warehouse costs and other relevant parameters according to Windmark et al. [17].

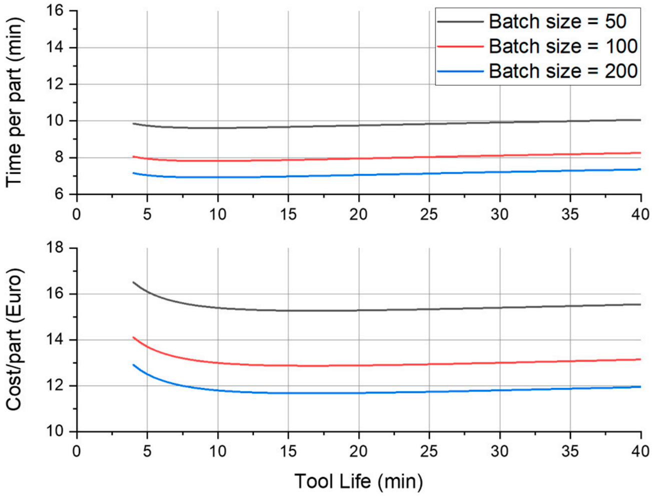


Figure 4.33: The effect of selecting N_0 = 50, 100 and 200 parts on the production time and part cost when removing 1000 cm^3 of workpiece material.

The fourth and last parameter investigated is the tool change time, presented in figure 4.34. Two setups are modelled, one where it is estimated that each tool change requires 2 min of production stop, when the operator manually changes the tool or rotates the indexable inserts, T_{tct} = 2 min.

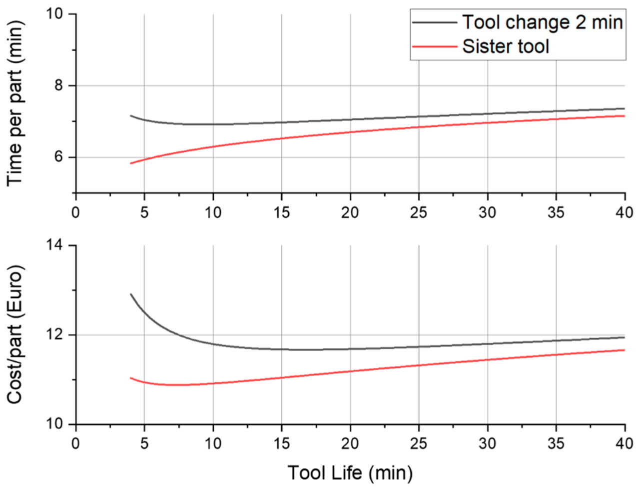


Figure 4.34: The effect of a 2 min tool change time and a sister tool with no internal tool change time.

In the second setup a sister tool is used, which allows the operator to manually change the tool outside of the machine, hence no production stop is required during tool change, T_{tct} = 0 min. The alternative of using a sister tool is not affected by tool change time resulting in shortest production time at tool life T = 4 min and with a maximized cutting speed. The alternative with an internal tool change needs to be balanced between production time and tool change time and the lowest production time is at a tool life of approximately 9 min. Part cost has a minima for both alternatives as it requires a balancing of costs; tool cost increasing for low tool life and hourly costs increasing for long tool life.

4.7.3 Cost Performance

The Ståhl cost model for varying cutting data can also be used to analyze cost performance for two or more different cutting tools as presented in **paper VIII**. The benefit of the presented approach is not to compare two different tool materials using fixed cutting data. A typical example would be when analyzing time and cost performance of a Cemented Carbide CC tool compared to a Poly Crystalline Diamond PCD tool. To maximize MRR the CC tool is often benefited by a high depth of cut and feed while reducing cutting speed, whereas a PCD tool is benefitted by a low depth of cut and feed while increasing cutting speed [91]. Figure 4.35 presents a case of machining 10 cm^3 Ti6Al4V with two grades of tool materials, uncoated cemented carbide CC and polycrystalline diamond PCD [91].

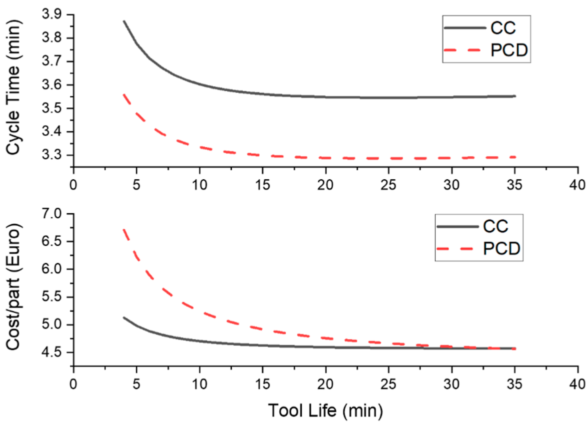


Figure 4.35: The perfomance in cost and time for a CC tool and a PCD tool machining 10 cm^3 Ti6Al4V [91].

The model presented can also be used to estimate the cost performance of a new tool selection:

- At what tool cost is tool B cost neutral to reference tool A for a given machining operation?
- For known tool costs, what performance is needed of tool B compared to tool A for a neutral part cost?

This model can also be used to investigate surface tolerance requirements directly connected to tool nose radius and feed selection or workpiece material with varying machinability.

5 Summary and conclusions

The appended papers are summarized in the following chapter. Eight papers are appended to this thesis. The main objective of this work is the development of tool life modelling and cutting data recommendations. The focus has been on empirically verifying existing models, suggesting improvements to data collection and finally connecting tool life and cutting data to part cost and production time. The conclusions of the results presented in the appended publications are also given. The last subsection covers suggestions for future research work.

5.1 Summary of appended publications

Different aspects of tool life and cutting data modelling have been investigated. Several different tool life models were investigated in **paper I**, the Woxén equivalent chip thickness was investigated in **paper II**, the Colding tool life model was investigated in **papers II-VII** and finally the Colding model was connected to production time and part cost in **paper VIII**.

5.1.1 Paper I

This paper investigates the most commonly used empirical tool life models on a large set of empirical data. A total of 11 sets of data and a total of 7 workpiece materials (steel, stainless steel and cast iron) were used in the investigation. It is concluded that the Colding tool life model is the most successful model in approximate tool performance for the investigated data. The work in this paper also concludes that h_e is the more superior than h_m or a combination of f and a_p in describing the uncut chip thickness when using the extended Taylor tool life model. Extrapolation on the left side of the Colding H-line is also investigated and it is concluded that the model error increases when the Colding curves are extrapolated as straight lines and particular high alloy steels and stainless steels are affected negatively.

5.1.2 Paper II

Empirical data is used to evaluate the equivalent chip thickness model by Woxén. Two cases are investigated. In each case h_e is held constant and f and a_p are varied. The ratio of a_p/f was varied with a factor of close to 10 times. It is concluded that in this specific study the tool life was not constant for a constant h_e, contradicting the hypothesis of the study. In the paper, a relatively large ratio of a_p/f was used, beyond the intended use of the tool geometry design. In an industrial application the range of recommended a_p and f is smaller and therefore the h_e model can still be expected to give relevant results.

5.1.3 Paper III

This paper investigates the effect of different wear criteria on the Colding model, its five constants and the model error. For wear criteria of VB = 0.10 - 0.20 mm the approximate error is higher than for VB = 0.25 - 0.60 mm. It can be noted that the constants are affected by a change in wear criteria and all constants but the M constant shows a linear relationship to a change of wear criteria for $VB > 0.25$ mm. The non-linear behaviour of $VB < 0.25$ mm is expected to be related to coating effects. It can be concluded that one set of Colding constants is only valid for one tool material and cannot model both coating and substrate material.

5.1.4 Paper IV

In this work two major limitations of the Colding model are investigated and a solution is suggested. Firstly, all data used to create a Colding model needs to have reached specific wear criteria. Secondly, when a Colding model is created, the wear criteria cannot be changed. These issues are solved by combining the Archad wear model with the Colding tool life model. It is shown that it is entirely possible to combine these two models and thereby, it is possible to include tool performance tests with varying wear criteria. Furthermore, this model can be reversed so that it is also possible to calculate the tool life for any selected wear criteria within the limitations of the model.

5.1.5 Paper V

In this investigation the extrapolative power of the K constant in the Colding model is investigated. Three tool grades, A, B and C, based on the same substrate material but with varying tool coatings are used in machining stainless steel ASI 304. A full set of tests is used to create a Colding model for tool grade A. Two additional tests were conducted for grades B and C respectively. The first test point was used to calculate ΔK and the second was used to verify the extrapolated tool life model for grades B and C. It is concluded that for this set of experimental data the *K* constant had some extrapolative power and the model error of the extrapolated test points was below 10 %.

5.1.6 Paper VI

In this work the approximative, interpolative and extrapolative power of the Colding model is investigated. A set of 22 tool performance data points in turning C 45 E steel is used for the purpose of the investigation. It is shown that for any number of included data points the Colding model has a low approximative error. It is also shown that the interpolative and extrapolative error decreases rapidly when including up to 13 data points. Over 13 data points the decrease of interpolative and extrapolative model error was limited for this set of experimental data.

5.1.7 Paper VII

This work focuses on the most optimal way of selecting cutting data points when experimentally collecting data to create a Colding model. A set of 22 tool performance data points in turning C 45 E steel is used for the purpose of the investigation. It is shown that by only using five tool performance data points a model can be derived with a mean model error less than 10 % when tested on the full dataset. It is concluded that extrapolation should be avoided and therefore the range of the included parameters (v_c, h_e and T) should be maximized. It is also shown that for the investigated set of data, two tool performance data points should have an equal h_e to minimize model error.

5.1.8 Paper VIII

This work presents a novel methodology combining the Colding tool life model and a previously presented model for a cost performance ratio. The developed methodology combines cutting performance and production performance to allow a comprehensive cost assessment for a production process. The assessment includes cutting data, tool life and cost of tool inserts, quality rejections, process availability, equipment investment, operators and facilities. A case study based on experimental data when machining Ti6Al4V with two grades of tool materials, uncoated cemented carbide and polycrystalline diamond, was presented, verifying the proposed methodology.

5.2 Conclusions

Modelling tool life and cutting data in metal cutting is, as shown in this work, complex. It would have been impossible to investigate all aspects, models, cutting methods and commonly used tools and workpiece materials, thus several limitations have been applied. However, some conclusions can be made from the work presented in this thesis. Four major types of modelling approaches exist for tool life and wear modelling; empirical models, analytical models, numerical models and soft computing models. This work focuses on empirical models, as they can be used as decision support for several areas, from design to production with modest tool performance testing and low computational requirements.

The title of this work is: **Modelling tool life and cutting data in metal cutting – testing, modelling and cost performance**. Different aspects of testing are investigated in **paper VI** and **paper VII**. The number of tool performance tests needed to secure a valid model is investigated as well as how these tests should be placed within the cutting speed range and the equivalent chip thickness range. Modelling has been investigated in **paper I-V.** It is concluded that the Colding model is a more valid model when compared to the more traditional extended Taylor model for the investigated data. Two different approaches to extend the Colding model for varying flank wear criteria have been presented, the concept of equivalent chip thickness has been investigated based on empirical tool performance data, and model modifications for varying performance have also been investigated. Finally, cost performance is introduced in **paper VIII**, a methodology whereby the Colding model is combined with a cost model for the calculation of part cost. This combination of models can be used as decision support for, among other things, cutting data selection and tool selection.

Summarizing the research presented in this thesis, the following answers can be given to the previously defined research questions:

RQ1. Is it possible to investigate the validity and further improve existing models for cutting data recommendation and optimisation using empirical data and today's computational power for multiple commonly used work materials?

A number of models have been investigated based on the empirical data in **paper I** and it is concluded that the Colding model is superior in modelling the investigated data. A number of improvements are suggested and some limitations have been noted relevant to tool life modelling. The Colding model can be combined with the Archard wear function to include varying wear criteria, **paper IV**. The K constant can be used with caution for adjusting the model for variation in performance, **paper V**. Caution should be taken when modelling low wear criteria, when the model is influenced by a tool coating, **paper III**. Also, caution should be taken for large ratio of a_p/f when using equivalent chip thicknesses, **paper II**.

RQ2. How should experimental testing be conducted to secure an accurate tool life model, while limiting the resources required to conduct such tests?

The variation of model errors based on the number of included test points is investigated in **paper VI** and the impact of how these test points are placed in the cutting speed and equivalent chip thickness range is investigated in **paper VII**. It is concluded that, for the investigated data, the Colding has a low interpolative error when based on only five tool performance tests. To minimize the amount of testing one should decide on a working range of cutting speed and equivalent chip thickness, where one intends to model tool life and cutting data and then include tests covering the full range of cutting speed and equivalent chip thickness. As the number of included test points are increased, model error decreases but over thirteen test points the model error improvements are limited for the investigated data. The author recommends, considering the cost and environmental impact of testing, that a reasonable number of tests to include for a Colding mode, based on five constants, would be six to ten tool performance tests covering the full working range of the tool.

RQ3. How can tool life models be used to assess selection of cutting tools and their performance based on part cost?

A methodology combining the Colding model and the Ståhl cost model has been developed and is presented in **paper VIII**. Based on this combined model, part cost and production time can be calculated for any selected cutting data or tool life. Additionally, any included parameter can be investigated as a parameter with regard to part cost or production time.

5.3 Future Research

During the last three decades, the amount of published research in the area of empirical tool life modelling in metal cutting is surprisingly limited, considering that these models are still highly relevant and the impact metal cutting has on our way of life. The research presented in this thesis is a step towards a better understanding of these models, what opportunities they offer as decision support and the limitations that exist. A considerable amount of research still remains to be done and this section reflects the author's own thoughts on potential fields of research related to the subject presented.

The Colding model, being an empirical model, has no clear connection to machinability. If the constants in the Colding model could be connected to physical parameters influencing machinability this would clearly help in limiting the testing required. By not having to establish a specific model for each tool material and workpiece material but rather one model for a set of related tool materials and workpiece materials and then adjusting the model constants for varying machinability both costs and resources could be saved.

Hybrid models have been touched upon but not mentioned in depth. The author sees two major approaches to introducing hybrid models. Firstly, combining the Colding model with analytical models describing tool deterioration to further allow for model adjustment whilst limiting testing. Secondly, using numerical models to perform tool performance testing and then feeding the results into a Colding model. With this approach, experimental testing can be limited and high computational times avoided when applying the model.

The work presented focuses on turning and continuous machining. Models for intermittent machining and other cutting methods, such as milling and drilling, have been presented in literature but verification of these models based on empirical data is lacking.

Cost performance and cost performance ratio is investigated in this thesis but, quite frankly, it only scratches the surface of a large research area. As machines become more interconnected, data becomes available for concepts like digital twins and digital manufacturing. To take full advantage of these concepts more advanced and precis models are needed.

6 References

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