VETENSKAP OCH KONST

KTH

Capability in Machining Systems

A licentiate thesis
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Abstract

The vehicle industry has derived a vision of simulating machining systems and their cutting processes with accuracy and capability indices as a result. The accuracy of machined parts is the result of properties and characteristics of the total machining system and its environment. Natural deviation results in deviations between each machined part which in turn effect the functionality of an assembled product.

A machining system is defined as consisting of the five modules: machine tool, tool, cutting process, workpiece and fixture.

The thoughts and discussions about the vision of simulating a machining systems and its environment have resulted in a research question: "*What is required to give a reliable simulated value of capability and accuracy?"*

Being able to predict the accuracy of machined parts in a specific machining system and its environment gives the possibility of optimising the cutting process and detect errors in the machining systems. It also gives the possibility to design more robust machining systems and avoid mistakes during the designing of the machining systems.

This study has shown that to be able to predict capability indices for both existing and future machining system it is necessary to have thorough knowledge in four areas; *capability as a statistical tool*, *accuracy in machining system*, *measurement tools and methods,* and *modelling and simulation*.

To achieve a reliable capability index, the capability study has to be properly planned, performed and evaluated. The statistical method of capability indices needs to be well-known when choosing index, comparing different indices and when making comparisons between indices from several machining systems.

The machining accuracy of a machining system is dependent on four groups of characteristics: temperature influence, geometry and kinematics, static stiffness and, finally, dynamic stiffness.

There are a great number of models available for cutting processes, process state variables and different modules of a machining system. Usually, these models can only be used discretely since there is almost no relationship between the structures, required data and assumptions of the models. It is therefore not yet possible to model and simulate a machining system to achieve a reliable accuracy value.

*"Livet – det är inte de
dagar som gått utan
de dagar man minns"*

Pjotr Andrejevitj Pavlenko

Acknowledgement

The research work for this thesis has been carried out at The Royal Institute of Technology, KTH, at the former Department of Manufacturing Systems, which is now the Department of Production Engineering. It has been done in collaboration with SCANIA CV AB in Södertälje.

The number of people who has contributed in one way or the other to make this thesis possible is very long, but I would like to point out a few. First of all I would like to acknowledge three people, both my academic supervisors Professor Gunnar Sohlenius and Professor Bengt Lindberg at KTH and Mats Lundin, IVF, for their support and for chairing their point of views on the subject of production. Professor Bengt Lindberg is the successor of Professor Gunnar Sohlenius. Further I would like to thank SCANIA CV AB for making this work possible by financial as well as technical support. I would also like to thank Tekn lic Ulf Bjarre, SCANIA, for the contribution with helping me getting started with the writing of this thesis.

A special thank you is to all friends at IVF – KTH – Woxéncentrum for making a fun and stimulating working environment. Thank you Tekn lic Jan Ackalin, it was fun to co-operate with the DBB measurements.

Finally, but most importantly, I would like to thank my family and Anders for everlasting support and love throughout the work with this thesis. You've made all the difference!

Tullinge, November 2002

Annika Larsson

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1 Introduction

1.1 Background of the Research Project

The industry is today working intensively and on a goal-oriented way towards introducing regular studies in manufacturing. The present study is part of a large overall spanning project aiming towards an increase in productivity, i.e. more products produced per year with available manufacturing equipment and a minimum of investments.

Manufacturing companies are today increasingly facing new customer demands as well as a tougher market window. The time interval between new models is constantly decreasing. In addition to this development, products are more individually produced to fit each customer's demands. Tough competition creates a demand to improve effectiveness in production.

1.2 Why Capability?

One way for SCANIA CV AB to work towards achieving an improved effectiveness has been to financing six Ph.D. students at The Royal Institute of Technology, KTH, Stockholm, Sweden. The first students in this Ph.D.-program started working at the end of 1995. Each student was given one topic to work with out of five different fields: manufacturing systems, cutting processes, casting, forging and grinding.

One out of the topics is *capability* and the vision is to enable the development of a reliable model of a specific existing, or an imaginary, machining system with the possibility of simulating the model to achieve a capability index. The author of this thesis was employed in the spring of 1996 in order to contribute to this vision.

1.3 General Problem

An overall aim for companies producing some sort of physical product is to increase productivity and profitability. By productivity is meant producing more parts per hour, or producing parts cheaper. One way of achieving this is by a more optimised way of manufacturing products. If all parts are machined with properties close to target value and within defined tolerances, the outcome will be 100% useful parts and this saves time and money. If the machining process is done with a sufficiently reliable process, there will be no need for controlling whether dimensions on the resulting parts are within tolerance or not. A capability study is one way of visualising the ability of a process to produce products according to defined properties of the product.

1.4 Introduction

In industry today there is a need to produce products more accurately and environmentally more friendly, at the same time as reducing the lead time. One way of facing the requirement on more accurate parts is to perform capability studies. It is the aim of this study to structure and describe a way of taking a step closer toward producing more accurate parts in manufacturing. The optimum would be a process machining products with all defined geometric values within given tolerance limits, every single time it is performed. Consequently there would be no waste and no re-machining of parts. If the machining processes does not produce any waste, both time and energy is saved.

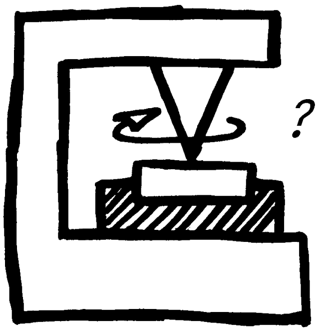
Even a stable process produces products with small deviations from a defined target value; this phenomenon is called natural deviation. In the future, preferably every machining process will give desired output values i.e. a process distribution with a mean value equal to target value and a small standard deviation, well within defined tolerance limits. If this becomes a reality, products will be produced faster due to a reduced need of control by repeated measurements as well as a reduction of waste. By not producing incorrect parts, the environment will be less damaged due to less use of energy and less waste.

A possible way of working towards more accurate machining is by optimising a process with the help of capability indices. In this thesis a schematic picture of what is required to achieve a useful value by simulation of a machining system is presented. Although this thesis is not emphasised on the model or the simulation of the same, it can be looked upon as a way of structuring the requirements of such a working procedure. The basic idea is to use a capability index showing the relationship between the result from machining and the defined target value and tolerance limits.

Simulation of a modelled machining system is proposed as a tool to calculate one or several chosen capability indices. Input data consist of values both from the machining system, as well as from its environment. The virtual machining system can either be a model of an existing system with known properties, or an imagined system with data obtained from experience or experiments. A model of a machining system consists of five different modules: *machine tool, tool, cutting process, workpiece* and *fixture*. All of these modules co-operate when machining and the final result of the machined part is dependent on the properties of each module as well as the interfaces between them.

1.5 The Mission

The mission for this research work given by Scania CV AB is to make a reliable model of an existing or an imaginary machining system including a workpiece. This in order to be able to simulate a machining system and thereby achieve one or more capability indices for a specific part machined in a specific machining system.



The usefulness of such a tool is connected with its level of generality as well as a possibility to recognise each machining system as an individual. It is desirable to have a model with a general structure where machining systems can be put together of modules. Input values from each particular module are then added to the model.

What kind of research question does this vision give? The question guiding this work is:

"What is required to give a reliable simulated value of capability and accuracy?"

This is not a hypothesis; it is a research question used in the search of knowledge about the subject of capability and accuracy of machined parts.

1.6 Research Objective

To be able to model and simulate a machining system in order to get a capability index for machined parts or the machining process is considered as a valuable tool. The usefulness of such a tool is connected to its level of universal applicability. Desirable is a model with a universal structure where machining systems can be put together by modules to which input values of each module and the interfaces are added. Running a simulation process with the model would be a useful tool giving as a result a capability index for a specific part machined in a specific machining system in a specific environment. This can be illustrated as in figure 1.1.

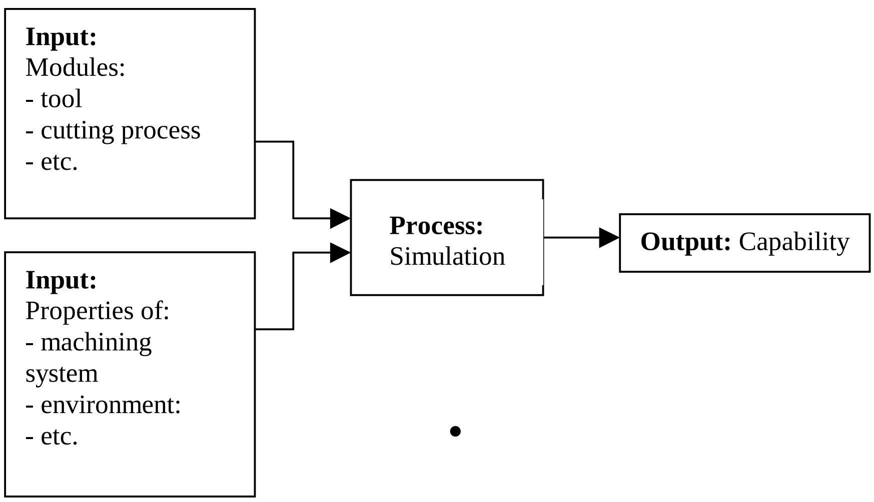


Figure 1.1. This is an illustration of the process of simulating a machining system with capability as output.

1.7 Scope of the Work

The studies described in this thesis address capability and accuracy of parts machined in a machining system. A production system include several different functions e.g. processes, machines and human aspects. However, the machining systems considered in this thesis are machine tools making chips and they are looked upon from a clear technical aspect.

Capability indices are a statistical way of describing how well a product is machined compared to defined target values and tolerances. This thesis describes how capability indices are calculated and presents a brief historical view of their development.

1.8 Delimitations

This research work is limited to cover capability, as a parameter desirable as an output from simulations of a model describing ~~of~~ a machining system. A cutting process can be of various types. This thesis however, focuses on machining in lathes and machining centres. Furthermore, these machining systems are only studied from a technical point of view.

A natural continue of studying capability and machining systems would be to simulate a machining system with capability indices as output, however this is not done in this thesis.

Capability can be divided into **machining** and **process** capability. In general and if not anything else is mentioned, the use of *capability* in this thesis refers to *process capability*.

1.9 Definition of Important Words

Capability
Capability is the ability of a process to produce products according to specified requirements [Deleryd, 1995].

C_p is a measurement of the allowable tolerance spread divided by the actual 6σ data spread. C_{pk} has a similar ratio to that of C_p except that this ratio considers the shift of the mean relative to the central specification target [Breyfogle, 1991].

For further details about capability, see chapter 3.

Manufacture

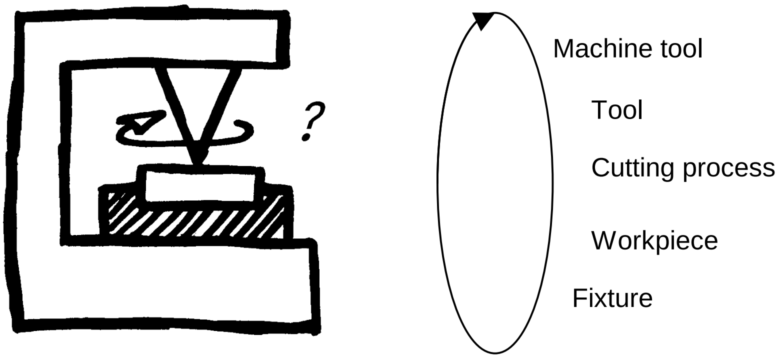
n. [Fr.; ML. *manufactura*, a making by hand; L. *manu*, abl. of *manus*, hand, and LL. *factura*, a making, from L. *factus*, pp. of *facere*, to make.]
1. the making of goods and articles by hand of, especially, by machinery, often on a large scale and with division of labor.
2. anything so made; manufactured product.

3. the making of something in any way, especially when regarded as merely mechanical.

Syn.–production, fabrication, composition, construction, manipulation, molding. [Webster's New Universal Unabridged Dictionary, deluxe second edition, ISBN 0-671-41819-X]

Machining system

A machining system is defined as a system consisting of several physical **modules** connected to each other: workpiece, fixture, machine tool, tool and cutting process. A module may consist of several systems or parts; for example the control system is included in the machine tool module and tool holders in the tool module. Each of these modules has an interface towards other modules through which they interact.



Maintenance

Any activity intended to eliminate faults or to keep hardware or programs in a satisfactory working condition, including tests, measurements, replacements, adjustment and repairs [CIRP, 1990].

Model

A model is an abstract way of describing a physical system and it's connections, properties and behaviour.

Process

Deleryd (1996) refers to a suitable definitions in SS-EN-ISO 8402:1994:

A process is a set of interrelated resources and activities which transforms inputs into outputs.

This is a very wide definition covering all kinds of processes, but a process capability study only monitors a certain characteristic produced by a single machine carrying a process of its own [Deleryd, 1996].

Product realisation system

This is the superior system serving the manufacturing system with functions like distribution, purchasing or procurement, inventory control, production planning, design engineering, customer sales and forecast, financing and inspection.

Production

n. [L. *productio* (-*onis*), from *producere*, to produce.]
1. the act or process of producing.
2. the rate of producing.
3. (a) something produced; product; (b) a work of art, literature, the theatre, etc.
4. in economics, the creation of economic value, the producing of goods and services: opposed to consumption.
Syn.–evolution, formation, genesis, product, work.

[Webster's New Universal Unabridged Dictionary, deluxe second edition, ISBN 0-671-41819-X]

Robust Design

The fundamental principle of Robust Design is according to Phadke [1998] "… is to improve the quality of a product by minimising the effect of the causes of variation without eliminating the causes". For further information, see appendix A.

Simulate

To represent certain features of the behaviour of a physical or abstract system by the behaviour of another system [CIRP, 1990].

Simulation

The representation of certain features of the behaviour of a physical or abstract system by the behaviour of another system [CIRP, 1990].

Stable process

A process is generally considered to be “in control” whenever the process is sampled periodically in time and the measurement from the samples are within the upper and lower control limits (UCL and LCL respectively), which are positioned around a centre line (CL). These control limits are independent of any specification limits [Breyfogle, 1992], see appendix B.

1.10 Variables

σ	Standard deviation calculated from an infinite number of samples. True standard deviation.	Chapter 3.3.2
s	Standard deviation calculated from a finite number of samples. Estimated standard deviation.	Chapter 3.3.2
SD	Standard deviation	Chapter 3.1
μ	Mean value of a population, average.	Chapter 3.6.5
ξ	An estimation of μ in a random sample of a population.	Chapter 3.6.5
τ	Standard deviation from target value.	Chapter 3.11
T	Target value.	Chapter 3.11
C_m	Machine capability index.	Chapter 3.5
C_p	Process capability index.	Chapter 3.5
C_{pm}	Machine capability index, used when a defined target is of the essence.	Chapter 3.1
C_{mk}	Machine capability index, used when USL and LSL are relevant.	Chapter 3.1, and 3.6.3
C_{pk}	Process capability index, used when USL and LSL are relevant.	Chapter 3.1, and 3.6.3
C_{pmk}	Capability index used when the target value is not centred between the USL and LSL.	Chapter 3.1

T_u	Upper tolerance limits.	Chapter 3.3
T_l	Lower tolerance limits.	Chapter 3.3
m	Target value centred between tolerance limits.	Chapter 3.6.3
n	Sample size.	Chapter 3.6.5
C_{pk}*	Estimated Process Capability	Chapter 3.6.5
C_{mk}*	Estimated Machine Capability	Chapter 3.6.5
SPC	Statistical Process Control	Appendix B
USL	Upper Specification Limit.	Chapter 1.9, 3.1 and appendix B
LSL	Lower Specification Limit.	Chapter 1.9, 3.1 and appendix B
TC	Target Value Centring.	Chapter 3.6.4
TV	Target Value.	Chapter 3.6.4
L(x)	Loss function.	Chapter 3.11
x	Measured value of characteristic X.	Chapter 3.11
	Central Limit Theorem	Chapter 3.3.2, appendix B
	Short-term capability	Chapter 3.5
	Long-term capability	Chapter 3.5

2 Research Method

When investigating a problem, both research method and research material interacts with each other as well as with the problem. Ejvegård [1993] states in his publication about research methods, that this interaction forms the final research result, as illustrated in figure 2.1.

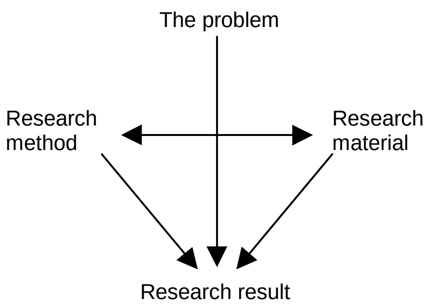


Figure 2.1. The problem, method and material interacts and influences the final research result [Ejvegård, 1993].

The arrows in the picture show the influence between the three co-operating parts necessary to achieve a research result. The given problem, the used research method and material all affects the obtained research result. In addition to this the selected, or given, research method and material affects each other. The given problem which needs an answer, is more important than the research method and material and should be treated accordingly [Ejvegård, 1993].

The research method, used in this thesis, is based on a scientific methodology by Sohlenius [Sohlenius, 1990]. During a presidential address at a CIRP conference, he defines engineering science and states that it always combines knowledge with problem solving. He states in his publication that an *engineering scientist* should work by the following steps.

1. Analyse what is.
2. Imagine what should be.
3. Create what has never been.
4. Analyse the results of the creation.

According to Sohlenius this statement is a development of a definition by Theodore von Karman at MIT, University of Massachusetts, USA, of the two professional categories, i.e. the scientist and the engineer. von Karman made the following definition of the two professions; *the scientist explores what is* and *the engineer creates what has never been*. Sohlenius has in a later publication [Kjellberg, Rundqvist, Sohlenius, 1996] extended the methodology by one more step:

1. Analyse what is.
2. Imagine what should be.
3. Create what has never been.
4. Analyse the results of the creation.
5. Conclude facts, theories and methods.

These five steps describe the steps of research and development in engineering science. This science is based on a number of basic fields of knowledge from science and from practical experience. The dual dependence between engineering design and engineering science is described by Sohlenius by figure 2.2.

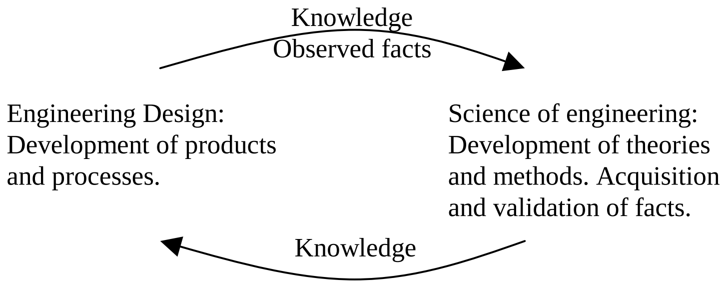


Figure 2.2. The dual dependence between engineering design and engineering science according to Sohlenius [Kjellberg, Rundqvist, Sohlenius, 1996].

The research question of the present thesis, i.e. what is required to enable to reliably simulate the capability of a machining system, is derived from industry and therefore goal-oriented and well suited for the five steps in the described methodology. The third step would correspond to a simulation method where any product in any specific machining system may be evaluated concerning capability. Preferably, this would be done even before the modules of the machining system are manufactured and assembled.

The present study represents the first two steps in the scientific methodology developed by Sohlenius. Step one, *analyse what is*, has been performed by use of literature study, courses and by practical studies. This part of the study has been done with the aim of achieving an understanding of the subject and by getting an overall picture of important factors, properties and their relations with capability in machining systems.

The first analytic step has been followed by a second and more creative step, i.e. *imagine what should be*. In accordance with the increased understanding of the subject, ideas on possible applications and the usefulness of the possibility of simulating capability took shape.

Furthermore, the second step has also lead to the conclusion that thorough knowledge in four areas is necessary to fulfil the desired goal of simulating a machining system with high reliability. The four areas are:

- capability as a statistical tool
- machining system and their properties
- measurement methods on both products and machining systems
- methods and tools for making models and running simulation.

The conclusion of combining knowledge within these four areas with the purpose of simulation is the input to step three, create what has never been. This step would be to describe and realise a model of a machining system and its environment with the purpose of simulating machining with capability as output. However, this is not done in this thesis. Step four is the evaluation of the outcome from step three, and is consequently neither included in the present thesis.

The present research question can in itself be evaluated according to the described method. If today's need of improving the efficiency of manufacturing is analysed, i.e. the first step of Sohlenius methodology, a demand of a value dealing with how well a process in a machining system performs, is quite possibly the answer. The second step, imagines what should be, will result in an idea of simulating the capability of products machined in a machining system.

The knowledge about capability as a tool to evaluate machining systems is based mainly on a literature study, an experiment at KTH and by an example from industry. Literature for present studies comprises books, publications and academic theses.

Measurement proved to be an important part of this thesis, and has thereby partly been studied in a course in Industrial measurement technique. The understanding of the importance of the two subjects *machine tools* and *machining systems* was clarified after discussions with personnel at SCANIA, Södertälje, Modig Machine Tool, Virserum, and SMT Machine Tools, Västerås.

3 Research on Capability

3.1 A Brief History of Capability

Deleryd [1995] states in his report of capability studies performed in Swedish industry, that no one really knows why variation exists, but it is a part of reality. Though this variation is a nuisance for industry struggling to manufacture identical products, it might be a requirement for the evolution of living species.

According to Deleryd [1995] the first real attempts to master variation in a scientific way was done by Walter A. Shewhart in the early 1920's. In his book Economical Control of Quality of Manufactured Product[1], Shewhart presented both a strategy for how to deal with variations, as well as a tool to use in the improvement process. Shewhart looked at variability as being either within limits set by chance (normal deviation), or outside those limits. This gave the strategy of first identify all assignable causes of variation and then eliminating them. This gives the possibility to predict the behaviour of the process within the near future. The tool introduced by Shewhart is a control chart (often referred to as a Shewhart control chart). These charts are based on a combination of probability and practical experience.

J. M. Juran presented the first capability index in 1974. He had identified a need in industry to be able to compare the actual process deviation to defined specification limits on products. This gave the definition of the first process capability index, C_p, as follows.

$$C_p = \frac{USL - LSL}{6\sigma}$$

[1] Shewhart W. A., (1931), Economical Control of Quality of Manufactured Product, D. Van Nostrand Company, New York. Republished in 1980 as a 50th Anniversary Commemorative Reissue by American Society for Quality Control, Milwaukee, Wisconsin. BookCrafters, Inc. Chelsea, Michigan.

USL is the upper specification limit, LSL is the lower specification limit and σ denotes the standard deviation (SD) of the studied characteristic. The multiplier "6" in the denominator is chosen after notification that three sigma-limits work well in practice [Deleryd, 1995].

The use of capability indices has resulted in improvements of them to fit different demands and situations. Kane introduced the capability index, C_{pk}, in 1986 [Deleryd, 1995]. This index takes into consideration the cases where USL as well as LSL are relevant.

The index C_{pm} was introduced independently by Hsiang & Taguchi in 1985 and by Chan, Sheng & Spiring in 1988 [Deleryd, 1995]. This index is used when a defined target value is of the essence.

Pearn, Kotz & Johnson introduced the index C_{pmk} in 1992. This index can be used when the target value is not centred between the USL and LSL. Vännman presented in 1995 a general capability index, $C_p(u,v)$. This index summarises the most widely used capability index today. Over all, the development has given indices with better statistical properties. Concomitantly, they have become more sensible to changes in deviation and in relation to target value [Deleryd, 1995].

	First introduced in	**Introduced by**
C_p	1974	Juran
C_{pm}	1985	Hsiang & Taguchi
	1988	Chang, Sheng & Spiring
C_{pk}	1986	Kane

Figure 3.1. This is an illustration of a part of the history of capability.

3.2 Definition of Capability

According to Deleryd [1996] it is difficult to find definitions of the concept of capability. He has established a definition of the concept of capability and it reads as follows:

Capability is the ability of a process to produce products according to specified requirements.

This is a very wide definition covering all kinds of processes, but a process capability study only monitors a certain characteristic produced by a single machine carrying a process of its own. This applies unless a multivariate process capability index is used [Deleryd, 1996].

3.3 Capability

Capability is a statistical method describing the outcome of a process compared to given tolerance interval, which means “the ability of a process to produce products according to specified requirements”. A capability study is performed in four steps:

- planning the study
- measurement of important properties
- calculation of capability indices
- analysis of the received capability values

If a process shows a good capability value it can be assumed to produce most of the products within defined tolerances.

As a result of introducing the expression “good capability value”, it becomes necessary to evaluate what is meant by “good” in this context. There is no simple answer to what a good value is. The higher capability value, the better result from the process is achieved. But, in addition, as can be seen in equation (3.1) it becomes clear that the resulted value is dependent on given tolerances.

$$C_p = \frac{T_u - T_l}{6\sigma} \tag{3.1}$$

T_u = upper tolerance limit, T_l = lower tolerance limit.

Consequently, the resulted value has to be judged individually. A value that is often given as a minimum level for an acceptable capability value is 1.33. Increasing demands on effectiveness in machining, causes requirements of higher value, typically 1.67 or 2. On the contrary, it is very easy to get a large capability value if the tolerances are large which is observed in the capability equations.

Fluctuation of the result from machining will always be present, partly due to natural deviation and partly due to deviation caused by other reasons. The natural deviation can, on the contrary, not be controlled. But the result from machining is also influenced by many other factors concerning for example wear of tools, heat produced in the machine tool or in the environment. These factors can be controlled, and furthermore need to be controlled to achieve the best machining result.

3.3.1 Capability Values

A smaller deviation compared to given tolerance interval, results in a larger capability index. A commonly used required value on a capability index is 4/3 (=1.33), or a larger number. Any capability index below 1.00 is not acceptable, it means that the process is not capable of consistently producing parts within the tolerance interval. A capability index of above 1.00 is desirable [Doty, 1996].

A capability index of 1.33 is equivalent to a tolerance limits of ± 3.99 standard deviations (3.99σ) from the average value of the process, see figure 3.2. A standard deviation of 3.99σ is equal to a probability value of 0.999967 [Doty, 1996].

$$C_p = \frac{T_u - T_l}{6\sigma} = 1.33$$

$$T_u - T_l = \frac{1}{1.33 \cdot 6\sigma} = \frac{1}{7.98\sigma}$$

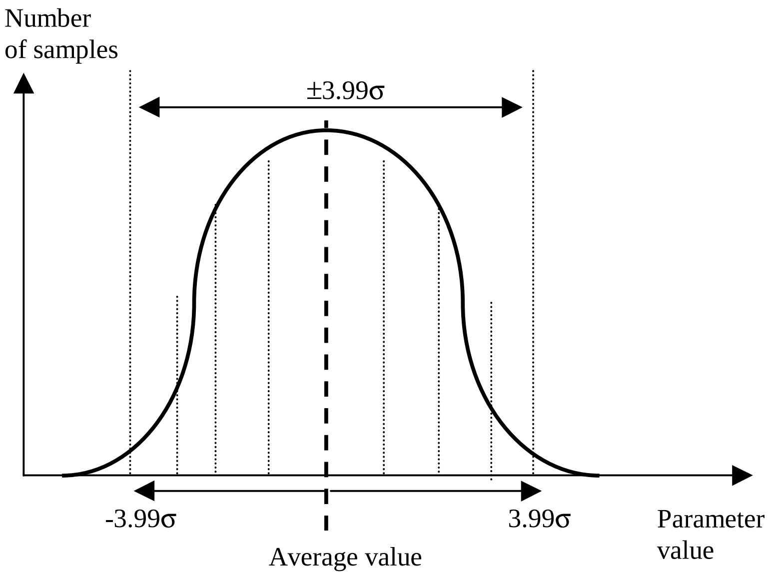


Figure 3.2. A capability index of 1.33 is equivalent to a tolerance limits of ±3.99 standard deviations.

Assuming a tolerance interval of ±4σ the capability index will be 8σ/6σ = 4/3 = 1.33. The same kind of reasoning but with an assumed tolerance interval of ±5σ, will give an index of 10σ/6σ = 5/3 = 1.67, see figure 3.3. In these assumed situation very few outcomes of the process will be outside the tolerance levels. But the process average and the middle of the tolerance interval do not always coincide. This gives a need for a process outcome with a 6σ-value small enough to make the process able to drift within the tolerance interval without the result of values outside the tolerance limits. The value of the standard deviation is the key to secure a possibility of process drift. The standard deviation of a process is dependent of improvements and to control affecting properties to remain as an optimised process.

$$C = \frac{8\sigma}{6\sigma} = \frac{4\sigma}{3\sigma} = \frac{4}{3} = 1.33$$

$$C = \frac{10\sigma}{6\sigma} = \frac{5\sigma}{3\sigma} = \frac{5}{3} = 1.67$$

Figure 3.3. Capability index with a tolerance interval of $\pm 4\sigma$ and $\pm 5\sigma$.

If the SD is used as tolerance limits, the statistically percentage of correct manufactured products can be seen in table (3.1). Figure 3.4 describes a normal curve with its characteristic bell-shape and limits of standard deviations, σ. All normal curves are symmetrical, and therefore are the percent area under the curve from the average to 1, 2 and 3 standard deviations always the same. This means that the area from the average value to plus 1 standard deviation is always 34.1 % for all normal curves. The area under the curve also refers to a probability value, i.e. the probability that a measurement will be below or above a certain value, or between two values [Doty, 1996].

Tolerance limits	% of machined parts within tolerance limits
±1σ	68.26%
±2σ	95,46 %
±3σ	99.72 %

Table 3.1. The area under the curve with the tolerances of 1, 2 and 3 standard deviations is equal to the percentage of the total number of measured values.

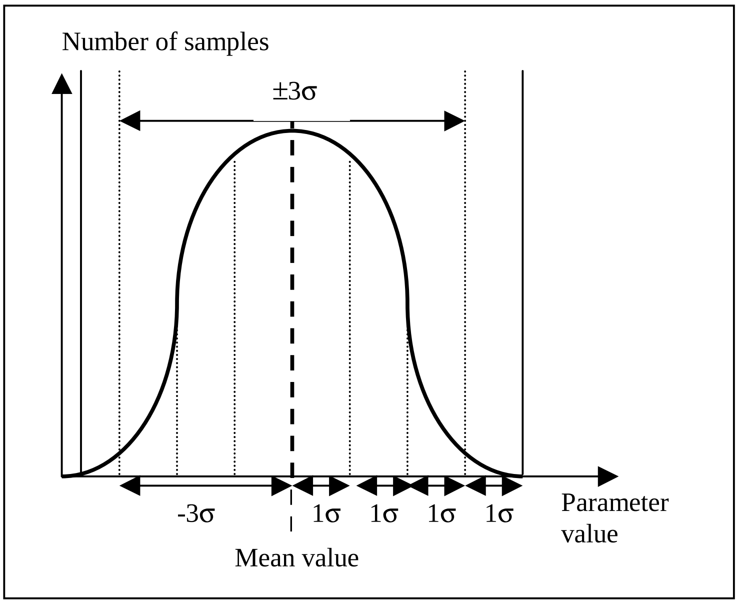


Figure 3.4. A normal distribution and its standard deviation limits.

3.3.2 Normal distribution and Standard Deviation

The calculation of capability indices is based on the assumption that the process is stable and that the result of the process is normally distributed. One way of analysing whether or not a process is normally distributed is to present data in a form that illustrates the frequency of measured values. A histogram is one type of plot useful in making the process result more visual. A normally distributed curve is distinctive in its shape, it is symmetrical, unimodal and bell-shaped, see figure 3.5. Unimodal means that there is only one high spot in the curve.

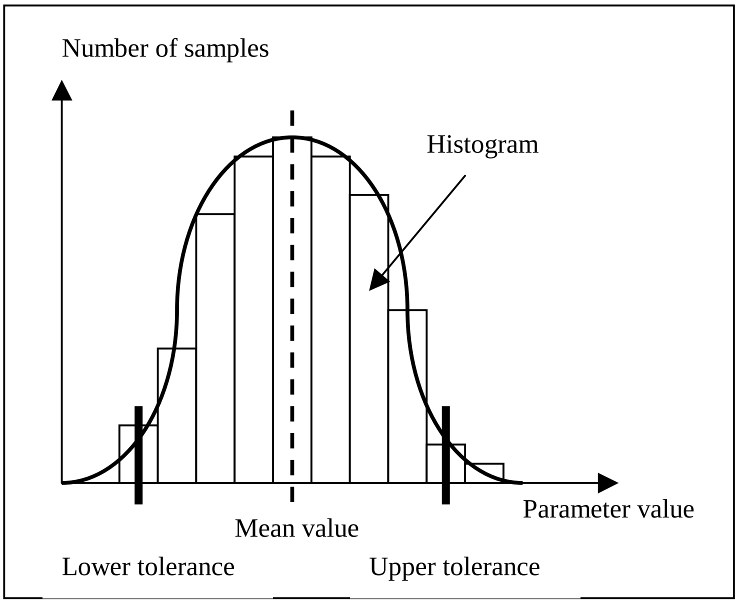


Figure 3.5. Normally distributed values have a characteristic bell-shape. The process result is in this case plotted as a histogram with a curve to show the normal distribution and the mean value.

W. A. Shewhart introduced statistical process control, SPC, and while developing the mathematical proof for his procedure, Shewhart used the Central Limit Theorem [Doty, 1996]. This theorem states that a plot of sampled average values from a population tend to be normally distributed, even if the population in itself is not normally distributed. A population is a number of items that have similar characteristic and a sample is a number of values from a population. The reason for the Central Limit Theorem is the mathematical relationship between the standard deviations, see equation (3.2). s_x is the standard deviation of the sample averages, σ is the standard deviation of the individual values and finally, n is the number of the samples (should be 4 or greater).

$$s_x = \frac{\sigma}{\sqrt{n}} \tag{3.2}$$

The standard deviation is calculated by two similar equations dependent on the number of values. A *population* is all possible values, while a *sample* is a small number of these values collected at random. The standard deviation (s) of normally distributed values from a sample is calculated by equation (3.3).

$$s = \left[\frac{\sum_{i=1}^{n} (x_i - \overline{x})^2}{n-1} \right]^{1/2} \tag{3.3}$$

The standard deviation (σ) of a *population* is calculated by equation (3.4).

$$\sigma = \left[\frac{\sum_{i=1}^{n} (x_i - \mu)^2}{n} \right]^{1/2} \tag{3.4}$$

The *n*-1 term in the denominator is commonly called “degrees of freedom”, which is a function of the sample size, n. The mean of a sample, ξ, or from a population, μ, is the sum of all the responses (measured values) divided by the sample number. The mean of a population (μ) is the sum of all responses of the population divided by the population size. In a random sample of a population, ξ is an estimate of μ of the population [Breyfogle, 1991].

3.4 Capability Family Tree

The capability index has been developed through time, resulting in different capability indices, represented in figure 3.6. Capability indices are, as given in the figure, divided into two different branches, one for machine, C_m, and one for process capability, C_p, see section 3.6.1 for definitions. These two branches provide results on how well a machine and a process performs in relation to defined tolerance limits. C_{pk} and C_{pm} gives information about the result in relations with given upper and lower tolerance limits, see section 3.6.2. The capability indexes C_{pm} takes in consideration the relationship between both mean and target value in comparison with upper and lower tolerances, see section 3.6.5.

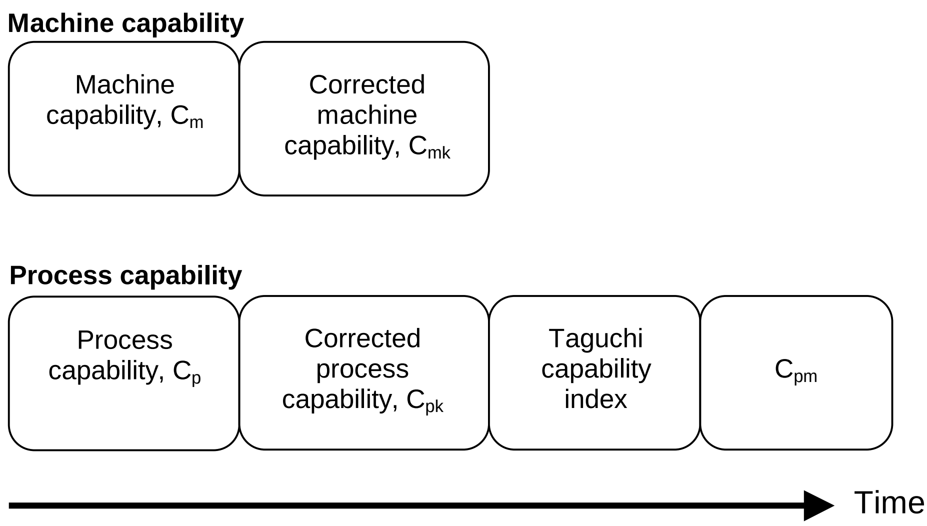


Figure 3.6. The different capability indices have developed through time as a result of efforts on improving and increasing the usability of the indices.

3.5 Machine and Process Capability

Even when all affecting parameters have been minimised or eliminated the average value of a process may still vary with time. The variations which varies with time might, according to Bergman and Klefsjö [1991], depend on for example different shifts (i.e. different operators) and variations in workpiece material. This gives a possibility to assume the variation of the average value of the process as a random variable, which deviation is possible to estimate. This deviation consists of two components, one variation from unit to unit, and one that is due to the slower variation of the average value. Machine capability is commonly only the first mentioned variation, the one from unit to unit. Process capability, on the other hand, takes in consideration both components of variation see figure 3.7.

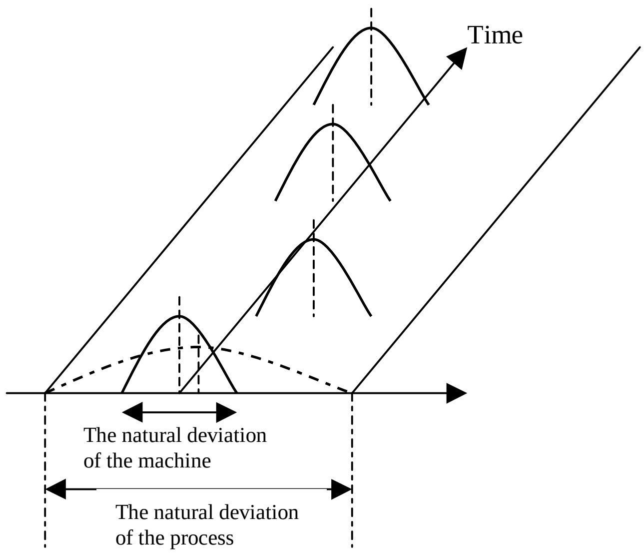


Figure 3.7. A schematic picture of natural deviation of the machine and the process [Bergman and Klefsjö, 1991].

A machine capability index is usually indicated by an *m*, e.g. C_m and C_{mk}, and in a similar way with a *p* for process capability, e.g. C_p and C_{pk}, see section 3.6.1.

Machine capability explicitly refers to the ability of a machine tool to machine parts. Process capability, on the other hand, gives a value on the ability of a machine tool to perform with the influence of anything that affects the machining result, including the environment.

Process capability focuses on the ability of a process to meet specified requirements, although it is possible that one or several previous processes influence the characteristic of a machined part.

A machine capability value gives information of a machine tool's ability to produce certain product characteristics with no effect from the environment and changes in time; e.g. temperature changes and tool wear. In order to minimise and hopefully even eliminate all affecting parameters the machine capability study is performed during a short period of time. Deleryd [1996] notes that machine capability only focuses on the short-term variability of the process as opposed to process capability, which focuses on the long-term variability of the same process. He also notes that in literature the term machine capability is today more often replaced by *short-term capability,* and similarly for process capability, which is replaced by *long-term capability*.

3.6 Calculation of Capability

The calculation of capability indices is based on the assumption that the process is stable and that the result of the process is normally distributed. A great number of processes give a result that is normally distributed, but not all as seen later in this chapter.

3.6.1 Machine and Process Capability Index

Even when every known factor of disturbance to a process are eliminated or maximally reduced, the result will still fluctuate during an interval of time. The fluctuation occurring during normal machining consists of two different components of deviation, i.e. deviations originating from variations between workpieces and deviations from the slower changing average value, see section 3.5. The first component of deviation is the machine capability and the second is the process capability. To be able to estimate a machine capability the machining process needs to be performed with as few variations as possible; e.g. as little differences in workpiece and tool geometry as possible.

Process capability is, on the other hand, the contrast to machine capability. When performing a process capability study it is important to make sure that all normal deviations are included in the test. Therefore the process needs to be studied during a longer period of time [Bergman and Klefsjö, 1991].

Machine capability index, C_m, is the ability of a machine tool to produce details according to given requirements, see equation (3.5).

$$C_m = \frac{T_u - T_l}{6\sigma} \tag{3.5}$$

The standard deviation times six, 6σ, in the equation is referred to as the normal distribution of a process [Karlebo Handbok, 1992].

Process capability index, C_p, is how well the process performs under the influence of changes in environment and machine settings. The capability index, C_p, is given by equation (3.6).

$$C_p = \frac{T_u - T_l}{6\sigma} \tag{3.6}$$

These indices take notice on tolerances, with other words how well the process performs in comparison to defined tolerance interval.

3.6.2 The Capability Indices C_{pk} and C_{pm}

In order to get a more accurately result on how well the machine or process performs, the standard deviation is calculated in comparison with each tolerance level instead of a tolerance interval. A 'corrected' capability index is indicated C_{pk} or C_{mk} depending on if it is a machine or a process capability. Mathematically C_{pk} or C_{mk} can be represented as equation (3.7), (3.8) and figure 3.8, where μ is the mean value of the process distribution.

$$C_{pk} = \min\left|\frac{T_u - \mu}{3\sigma}, \frac{\mu - T_l}{3\sigma}\right| \tag{3.7}$$

$$C_{mk} = \min\left|\frac{T_u - \mu}{3\sigma}, \frac{\mu - T_l}{3\sigma}\right| \tag{3.8}$$

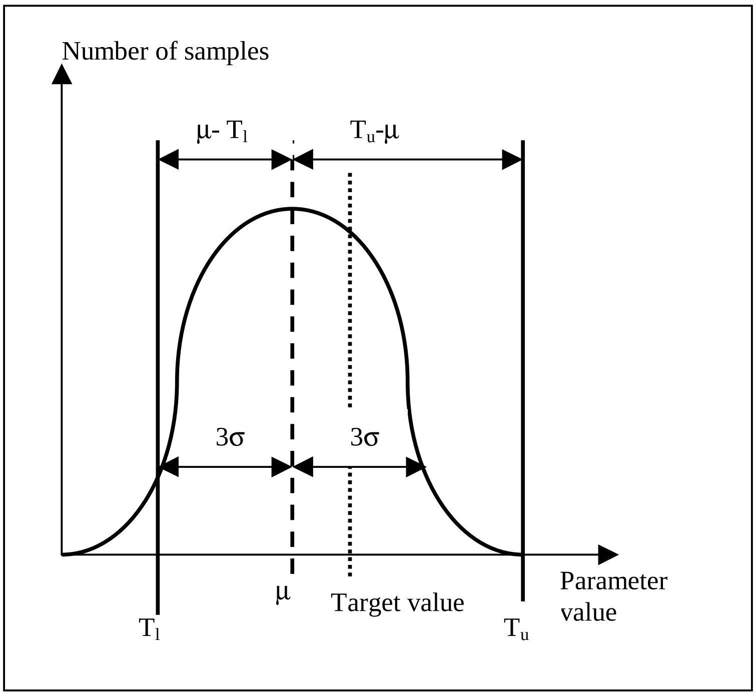


Figure 3.8. This figure is an illustration of equation 3.7 and 3.8.

Equation (3.9) relates C_{pk} to C_p. It applies for C_{mk} and C_m as well.

$$C_{pk} = C_p(1-k) \tag{3.9}$$

The *k* factor quantifies the level by which the process is off target value and is calculated according to equation (3.10), $0 \le k \le 1$. The parameter

m is the midpoint between upper and lower tolerance limits,
$m = (T_u - T_l)/2$ [Breyfogle, 1991].

$$k = \frac{|m - \mu|}{(T_u - T_l)/2} \tag{3.10}$$

3.6.3 Target Value Centring, TC

TC gives a value on how well a machine or process meets the requirements on the target value, see equation (3.11). Johnson and Tisell [1989] see target value centring as a goal for manufacturing based on the assumption that the less deviation from the target value, the better total outcome of an assembled product consisting of several parts. The value, TC, is the difference between target value, TV, and the mean value of the process distribution, μ, divided by the tolerance interval. TV is the midpoint between upper and lower tolerance limits. As opposed to capability indices, this measure has a unit. The calculated value reflects how far, in percentage, the mean value is from the target value [Johnson and Tisell, 1989].

$$TC = \frac{\mu - TV}{T_u - T_l} \cdot 100\% \tag{3.11}$$

The equation can be illustrated as in figure 3.9.

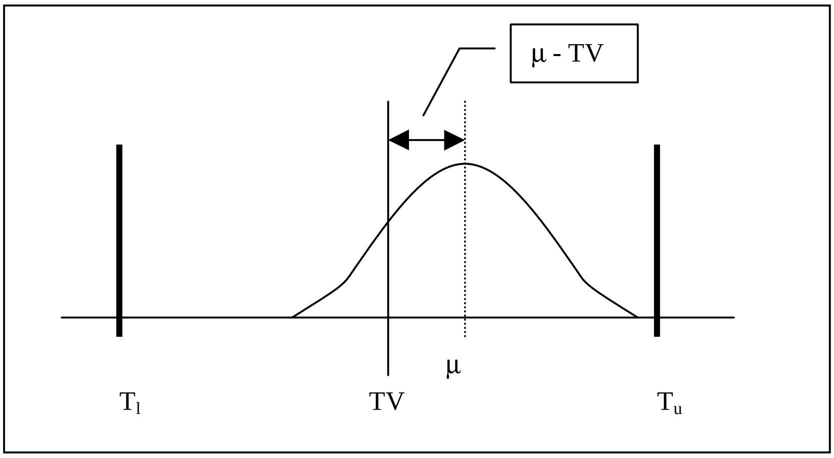


Figure 3.9. Illustration of TC, which is a value on how well a process or machine reaches target value [Johnson T, Tisell J, 1989].

3.6.4 Estimated Capability Indices

If the mean value, μ, and the standard deviation, σ, is unknown for a process, these values have to be estimated with data from the studied process. The parameters μ and σ are calculated from an infinite number of samples. Normally an infinite number of samples are not possible to achieve. When the calculations are done with a certain number of samples, μ and σ are replaced by ξ and *s*, these parameters are an estimate of the true values. Capability indices based on estimated values should according to Hallendorff [1979] be marked, for example with the symbol * as in equation (3.12).

$$C^*_{pk} = \min\left|\frac{T_u - \bar{x}}{3s}, \frac{\bar{x} - T_l}{3s}\right| \tag{3.12}$$

3.6.5 Capability Index with Respect to Target Value

Taguchi first introduced the Taguchi capability value in 1985. His alternative definition C_{pm}, of C_p fits with his loss function approach, and is confirmed by the following argument.

In cases where it is important to achieve a result when machining as close to target value as possible, then a Taguchi capability index or C_{pm} can be used. The definitions of these two concepts and the context of the following piece of text are gathered from the publication *The Taguchi Capability Index* by R. A. Boyles [1991]. According to Boyles, Taguchi introduced a capability index, which by later authors was named C_{pm} and is based on the assumption that the process average coincides with the target value. Boyles stresses that the assumption is wrong and uses C_{pm} without such a restriction as seen in this section.

Any measured value *x* of a product characteristic *X* gives a monetary loss *L*(*x*) to the customer as well as society. The loss function *L* is usually assumed to have the equation (3.13).

$$L(x) = k(x - T^2) \qquad (3.13)$$

For a positive constant, *k*, so that *L(T) = 0* and any deviation from the ideal value *T* (target value) gives some loss (cost) to the customer or to society. The capability of the process is represented by the expected loss *E*(*L*), which is a measure of process variation in terms of deviation of the characteristic *X* from target, see equation (3.14). This equation expresses the loss in monetary units, which has its advantages for decision-making. The difficult part is to come to consensus on an appropriate definition on the monetary loss for a customer or society. The use of a unitless capability index eliminates this problem.

$$E(L) = kE\left\{(X - T)^2\right\} \qquad (3.14)$$

Boyles uses an alternative definition of the capability index C_p (defined by Taguchi in 1985) which fits with the loss function approach, see equation (3.15) and (3.16). This expression of C_p was later given the name of C_{pm}.

$$C_p = \frac{USL - LSL}{6\tau} \qquad (3.15)$$

τ is the standard deviation from target given by equation (3.16). By comparing equation (3.21) and (3.19) it is evident that τ^2 is the expected loss if *k*=1.

$$\tau^2 = E\left[(X - T)^2\right] \tag{3.16}$$

τ^2 may also be written in an alternative form, see equation (3.17).

$$\tau^2 = \sigma^2 + (\mu - T)^2 \tag{3.17}$$

This expression describes variation from target in terms of its two components, process variability (σ) and process centring (μ - T), see figure 3.10. The expression of τ in (3.17) in combination with (3.15) gives a C_p as in equation (3.18), which is illustrated in figure 3.10.

$$C_p = \frac{USL - LSL}{6(\sigma^2 + (\mu - T)^2)} \tag{3.18}$$

This capability index coincides with the usual definition of C_p when μ = T, i.e. when the process average is equal to the target value.

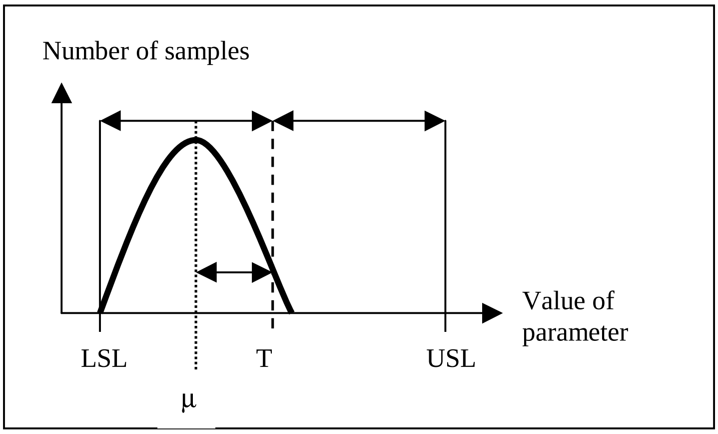


Figure 3.10. Variation from target value T. μ is the process average.

3.6.6 C_{pm} in the Case of Unilateral Tolerances

A unilateral case is when a characteristic has a possible minimum value, for example zero, and the minimum value is the optimum. Consequently, the smaller parameter values the better. Examples of unilateral characteristics are circularity and surface roughness. Unilateral cases normally do not have a normal distribution. Even in unilateral cases, C_{pk} is defined by establish the ratio between distance D1 and half the deviation (i.e. 3σ). But as can be seen in figure 3.11 illustrating a situation where target value is 0, the calculation of C_{pk} sometimes leads to curious results. C_{pk} is in both illustrated situations equal to 1.33, i.e. an acceptable capability index [Pillet, Rochon and Duclos, 1997]. However, obviously population 1 will give a better level of quality in terms of probability of reaching the target value of 0.

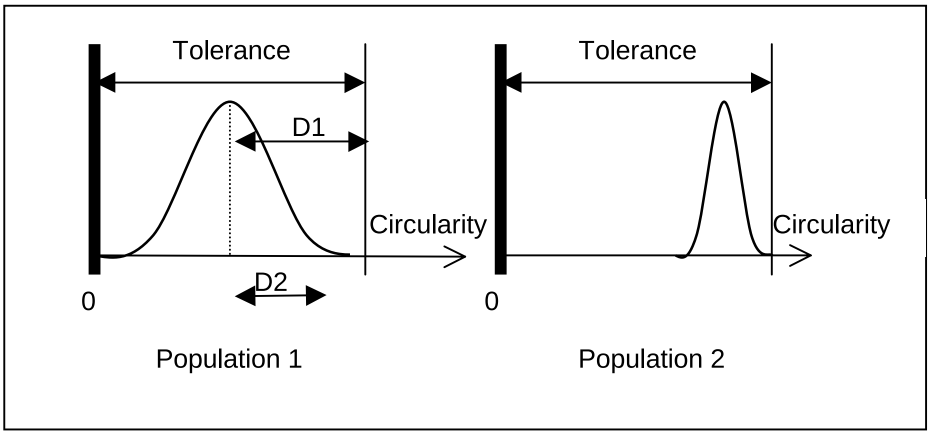


Figure 3.11. Two different unilateral cases (circularity) with C_{pk} equal to 1.33 [Pillet, Rochon and Duclos, 1997].

Generally a machined part is not considered to generate any monetary loss if measured characteristics is within its tolerance interval, but Taguchi defines the loss seen from the perspective that any deviation from target value results in an economical loss to the customer. The loss function is defined as a second-degree function and it is equal to zero on the target value and increases with the square of the difference between the target and the measured value.

In the case of unilateral tolerances, Taguchi defines the general loss function by $L=KX^2$, see appendix A. In a bilateral case the loss function is defined by $L=K(X-X_0)^2$, see figure 3.12. K is a constant dependent on the problem, X is the measured value, X_0 is the target value and $X_{AVERAGE}$ is the average of the process.

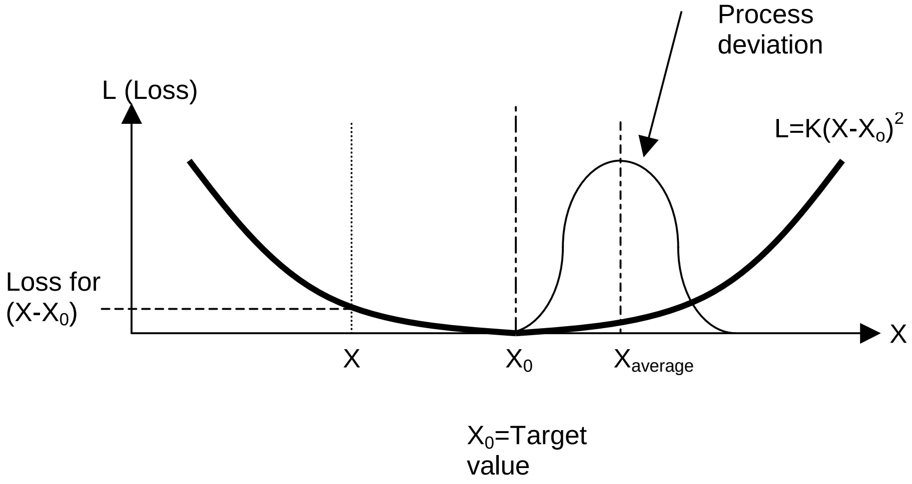


Figure 3.12. Loss function in a bilateral case. X is the measured value (quality characteristic), X_0 is the target value and L is the quality loss [Pillet, et. al., 1997].

Circularity is a case of unilateral tolerance since the target value is one of the tolerance levels. Usually a process with a unilateral tolerance is non-normal. The authors Pillet et. al. [1997] states that C_{pm} can be calculated with equation (3.24) independently of the distribution type. The reference situation as the authors define is illustrated in figure 3.13. The quality characteristic, X, is in this situation circularity (defined in appendix C) and the most desirable value of circularity is zero, i.e. the target value m is 0. The loss function, L, defined by Taguchi describes the assumed quality loss as the value of circularity increases.

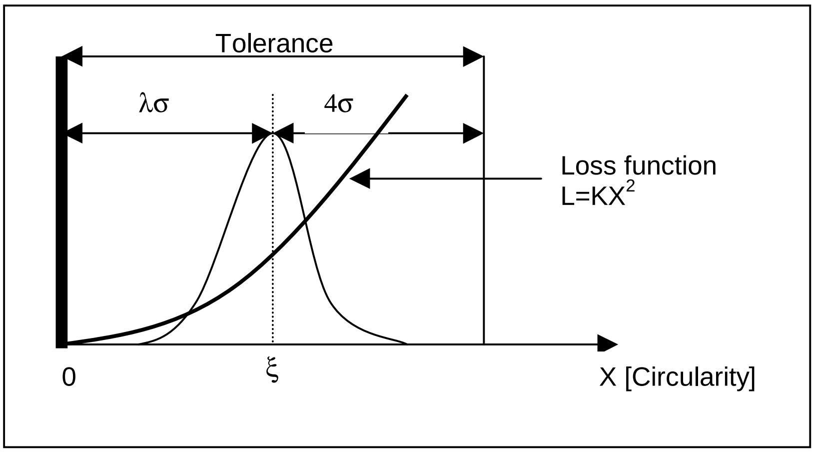


Figure 3.13. The reference situation for unilateral tolerance where 0 is the optimum value of circularity [Pillet, Rochon and Duclos, 1997].

The authors define the mean as located at λσ from the target value 0 and at 4σ from the upper limit. The interval of tolerance is (4+λ)σ wide. Pillet et. al. [1997] then achieve the average loss per part manufactured in a manufacturing process having a standard deviation of σ (not necessarily normally distributed) by equation (3.19). This expression is derived from the loss function $L=KX^2$.

$$\overline{L} = \frac{1}{n}\sum K(X_i)^2 = \frac{K}{n}\sum (X_i - \overline{X} + \overline{X})^2$$

$$\overline{L} = \frac{K}{n}\sum [(X_i - \overline{X})^2 + (\overline{X})^2 + 2(X_i - \overline{X})\overline{X}]$$

$$\overline{L} = K[\sum \frac{(X_i - \overline{X})^2}{n} + (\overline{X})^2]$$

One part of the expression, $[2(X_i - \overline{X})\ \overline{X}]$, is assumed to be 0. $\overline{L}$ is the average loss per part, σ is the standard deviation, $\overline{X}$ is the average of the process and X_0 is the target value and by this can the equation be written as in (3.19).

$$\overline{L} = K\left[\sigma^2 + \left(\overline{x}^2\right)\right] \tag{3.19}$$

C_{pm} is defined as inversely proportional to the average loss per part ($\sigma^2 + \overline{X}^2$) by equation 3.14.

$$C_{pm} = \frac{Tolerance}{A\sqrt{\sigma^2 + \overline{x}^2}} \tag{3.20}$$

σ is the standard deviation of the population, ξ is the mean of the population and A is a constant depending on the desired quality; 1.33, 1.46 or 1.66, see equation (3.21). The factor λ is defined in figure 3.13. The dependence of A on λ can be seen in table (3.3).

$$C_{pm} = \frac{Tolerance}{A\sqrt{\sigma^2 + \overline{x}^2}} = \frac{(4+\lambda)\sigma}{A(\sigma^2 + (\lambda\sigma)^2} = 1.33 \tag{3.21}$$

λ	3	4	5
A	1,66	1,46	1,33

Table 3.3. The dependence of A on λ [Pillet, Rochon and Duclos, 1997].

The average loss generated by the reference situation is:

$$\overline{L} = K\left[\sigma^2 + (\lambda\sigma)^2\right] \tag{3.22}$$

Thus the value of A can be calculated as in equation (3.23).

$$A = \frac{4+\lambda}{1.33\sqrt{1+\lambda^2}} \tag{3.23}$$

If λ for example is chosen to be equal to 4, the mean value is located at 4σ from 0 in the reference situation and A has a value of 1,46. C_{pm} is then defined as in equation (3.24).

$$C_{pm} = \frac{Tolerance}{1.46\sqrt{\sigma^2 + \overline{X}^2}} \tag{3.24}$$

C_{pm} can according to Pillet, Rochon and Duclos [1997] be calculated by this formula independently of the distribution type, i.e. valid for both normal and non-normal distributions.

3.6.6.1 Circularity Test on A Machine Tool

The capability index C_{pm} is used on the machine tool test described in section 7.5.1 and appendix C. Circularity is measured for nine different situations in a machine tool, i.e. the radius, the feed rate and the position on the working table has been altered. Parameter design has been used to reduce the number of combinations (see 7.5.1 and appendix A). Figure 3.14 clarifies that the circularity values are measured under different conditions, and that they seem to be divided into three groups. The number of measurements is too small to make a reliable test, but the measured results can be used as an example to visualise capability indices. The resulted circularity values are written in table (3.4). Circularity is defined as the difference in radius between two concentric circles encircling a measured circle, see appendix C.

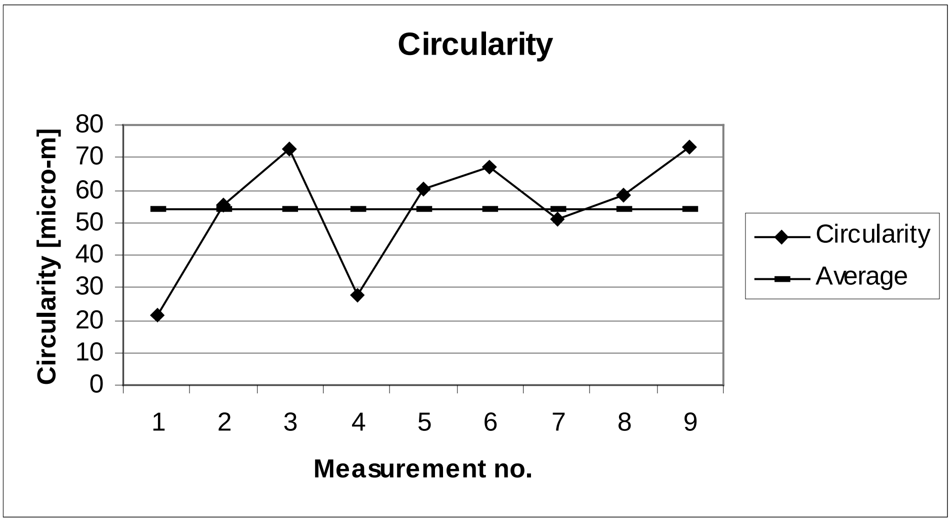


Figure 3.14. This is a diagram with the measured circularity values.

Circularity [µm]	21.5	55.5	72.8	27.5
60.6	66.9	51.2	58.2	73.4

Table 3.4. The result of circularity measurements in a machine tool.

The first capability index to calculate is the C_{pm}. The factor A is assumed to be 1.33 and by this assumption $\lambda = 5$. The standard deviation (σ) is equal to 18.46 and the process average is 54.178 µm.

$$C_{pm} = \frac{Tolerance}{1.46\sqrt{18.46^2 + 54.178^2}}$$

Assuming a tolerance of 70 µm gives a C_{pm} of 0.84 and if the tolerance is set to 80 µm, the C_{pm} equals 0.96. With other words, this is not a capable process with given tolerances and the very small number of measurement values.

The C_{pm} index can be compared to C_{pk} index, both indices taking in consideration the difference between target and process average value.

$$C_{pk} = \frac{USL - \bar{x}}{3\sigma} = \frac{USL - 54.18}{3 \cdot 18.46}$$

The C_{pk} index has a value of 0.29 with a tolerance of 70 µm, and a value of 0.47 with a tolerance of 80 µm. Theses values indicates an even less capable process compared to the C_{pm} index.

The number of samples is too small to make it a reliable capability test, , but the result can be used as a survey of the process. C_{pm} is claimed to be valid for both cases, but C_{pk} is valid only for normally distributed processes. C_{pk} is based on tolerances while C_{pm} takes in consideration a more overall quality consideration.

3.7 A Limitation of Capability Indices

Capability indices are used to evaluate the adequacy between a machining system and quality target. However, in some cases a high C_{pk} can give less satisfaction than a lower C_{pk} in the terms of probability on achieving the target value [Pillet, Rochon and Duclos, 1997].

To evaluate the ratio between the interval of tolerance and the observed deviation, a capability index is established as the ratio between these two values. C_p establishes the relationship between the tolerance interval and 6σ as in equation (3.25).

$$C_p = \frac{USL - LSL}{6\sigma} \qquad (3.25)$$

C_{pk} takes in consideration the target value, see equation (3.26).

$$C_{pk} = \frac{D1}{3\sigma} \qquad (3.26)$$

USL and LSL are the upper and lower specification limits, respectively, and D1 is the distance between upper limit and mean value. As can be seen in figure 3.15 the production situation described by the left figure is well adjusted since the maximum density of probability coincide with the target value. The result of a production described by the plot at the right hand side in the figure is not centred at the target and indicates that the process mean is far away from target [Pillet, Rochon and Duclos, 1997].

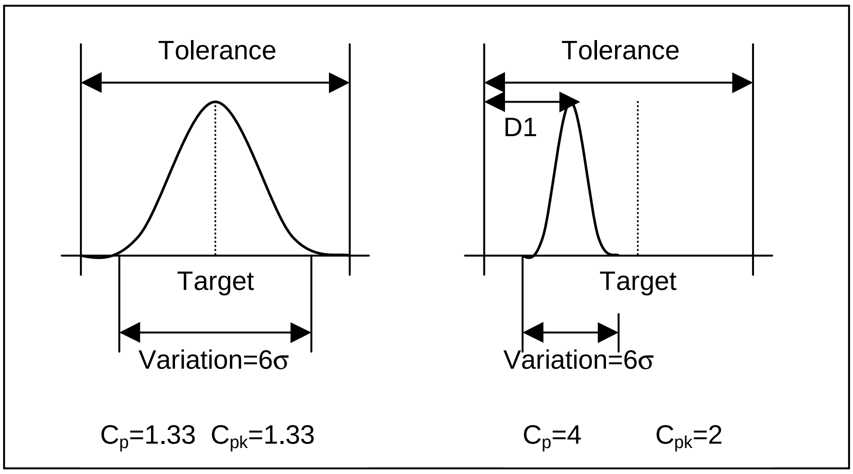


Figure 3.15. Two bilateral cases where, according to Pillet, Rochon and Duclos [1997], the C_{pk} proves to be a non-sufficient tool for quality.

The importance of the target value is emphasised in the case of assemblies. If all achieved values are concentrated near a tolerance limit, it might lead to impossible assemblies [Pillet, Rochon and Duclos, 1997].

3.8 Capability with a Non-Uniform Normal Distribution

An example of parameters that gives a non-uniform distribution is surface roughness and flatness of a surface. Deleryd [1995] states that there are a few methods to handle capability studies for these cases. Some methods transform the data material with a non-uniform distribution into a normal distribution (or close to a normal distribution), see for example the Central Limit Theorem in section 3.3.2. This reworked data is then used in a capability study [Deleryd, 1995].

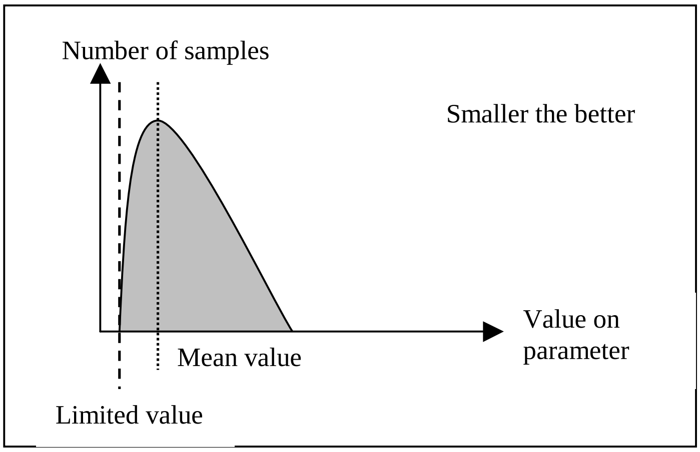


Figure 3.16 illustrates the result of a non-uniform process deviation, the limiting value is the most desirable value (the smaller the better).

An example of a non-uniform process is circularity, which is the difference in radius between two concentric circles encircling the measured circle (see appendix C). From the definition is the conclusion drawn that the smaller value, the better. A machine tool test by measuring the circularity is presented in chapter 7.5.1 and appendix C.

Non-uniform is made uniform
By using the Central Limit Theorem a non-uniform deviation is changed into a uniform deviation. The 200 measured values from the capability study presented in chapter 3.10 are assumed to be the result from measuring the diameter on 200 gear wheels. The diagram in figure 3.17 shows the number of values within the same interval, and the deviation of the process is non-uniform.

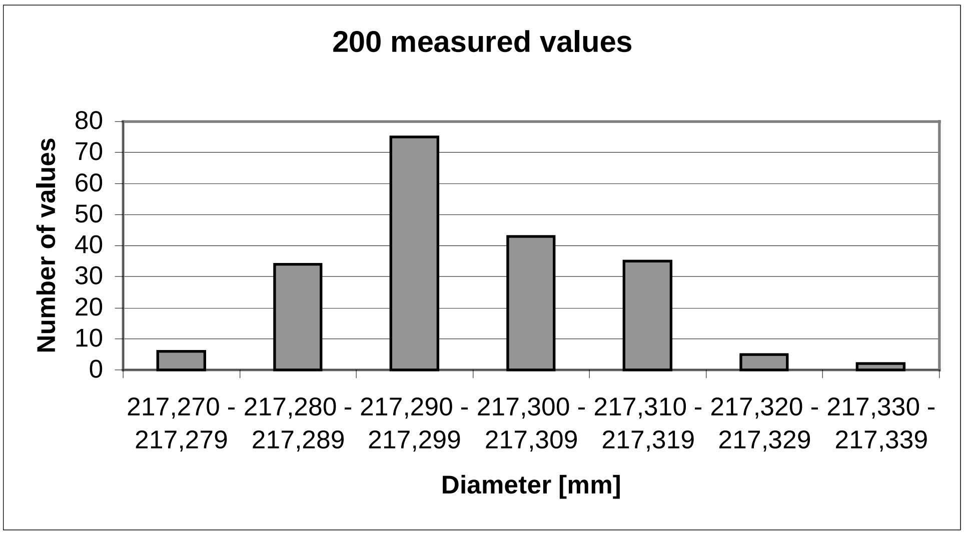


Figure 3.17. A chart of the distribution of 200 measured gear wheels.

When the measured values are grouped in four and the average of each group is calculated, the process shows a somewhat more uniform deviation as seen in figure 3.18. The groups are composed by four measured values in succession. This phenomenon of the Central Limit Theorem becomes clearer the larger the number of measured values.

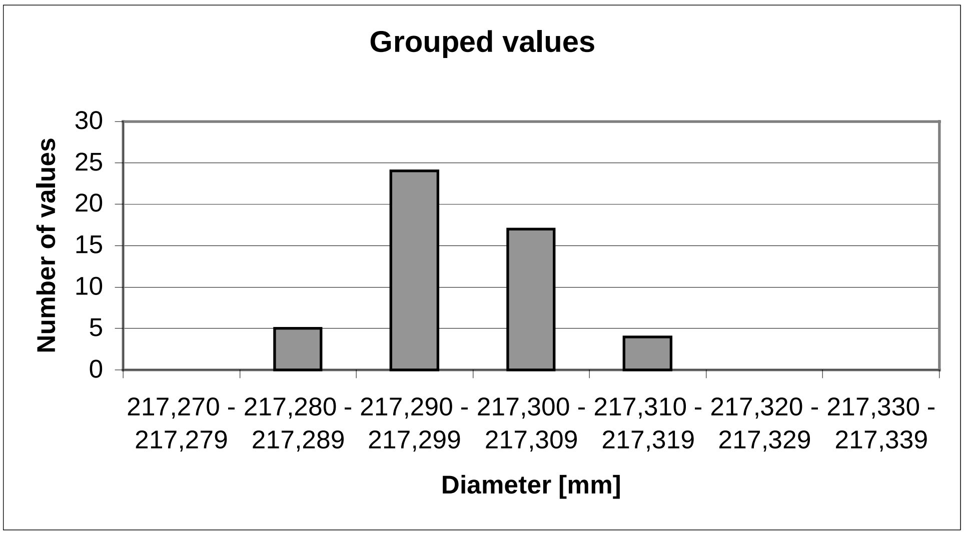


Figure 3.18. A chart showing the distribution of 50 average values calculated from 200 measured values, grouped four by four.

3.9 Reliable Capability Values

There are some requirements that have to be fulfilled in order to calculate a capability value with sufficient reliability. A capability study is a statistical method that will give a reliable answer under the conditions that the outcome of the process is normally distributed, the sample size is sufficient and the process is stable. Another important demand concerns the number of values in the study. They must to be measured in a reliable and standardised way.

To be able to decide if a capability index is reliable and comparable or not, it is necessary to complete with information about sample size, tolerances, measurement tool and environment. Summarised, the information has be as complete as possible.

3.9.1 Specification of a Good Capability Value

When comparing two capability values, one of which is greater than the other, the largest one is the most desirable. But by taking a closer look at the performed measurements and tolerance interval, the largest index might not be the best one. A comparison between capability index requires a close study of the test before any conclusions can be drawn.

The calculation of capability indices is based on the assumption of a normally distributed process outcome, but this is not always the case. If the sample size is large enough, it is preferable to use the Central Limit Theorem.

Lundin [1993] reports on capability studies in machine tools and includes experience from Swedish companies. He points out three important matters to consider when performing, analysing and comparing capability values.

1. Due to lack of standardised methods for performing capability studies, each user has a tendency of developing a method of their own.
2. A capability value has to be validated with respect to the used method and the matters during sampling and measurement.
3. When a capability value has a decisive influence, it is important that all involved agree on the method to be used.

By 'method' is here meant how the measurement is performed, how tolerances are defined and how the capability indices are chosen.

Deleryd listed in 1995 a number of issues to be considered when preparing and performing a capability study. Regarding the issues, all seem in most cases obvious in achieving a reliable capability value. However, Deleryd, who interviewed a number of Swedish companies found that it is rarely ever the case.

The defined issues are as follows:

- Measuring tool must be calibrated and its deviation should not exceed 10% of the tolerance interval of the studied parameter.
- Sample size, the larger the better i.e. the more reliable result.
- Make sure the investigated process is statistically stable before making a capability study.
- Collect data from machined parts in a well-defined way. For a process capability study samples are taken during a long period of time and for a machining capability study samples are taken during a short period of time.
- Decide if one or several capability indices are to be used. One index may give one result and another index an opposite result. The indices have different properties and therefore different applications.
- To be able to compare capability values from different processes they must have a similar process distribution. Capability values from one process can always be compered to another.

The reliability of a capability value depends on statistic and measurement correctness. Hence, well-designed and carefully planned methods are essential in order to achieve a useful result when performing capability studies.

3.9.2 Designing an Effective Process Capability Study

To perform a successful, reliable and useful capability study, it requires a conscious strategy. McLaughlin [1988] stresses that ”The most successful Process Capability Studies utilise a wide variety of effective statistical and quality engineering principles”. He suggests a step-by-step guide with details on how to design an effective process capability study. The first step is process identification. Both process and product characteristics must be measurable and quantifiable. To be able to justify the selection of a process there are according to McLaughlin [1988] several excellent tools, among them Taguchi’s Loss Function (see appendix A) and Pareto analysis. A Pareto analysis is a graphical technique used to quantify problems to find the most economically profitable problems, as opposed to work with just any or all problems at random.

The second step, according to McLaughlin, is identification of process characteristics. This is the step where, for the process and processed part, important characteristics are identified. As with any statistical test some assumptions have to be considered, e.g. the chosen characteristics should be both measurable and quantifiable and the number of samples large.

Developing causal relationships concerning the process is the third step. McLaughlin states that ”The key to a successful capability study is the ability to measure (and quantify) such variables that truly affect process performance”. Process flow diagram and Ishikawa Fishbone diagram (figure 3.19) are two examples of helpful tools in this respect.

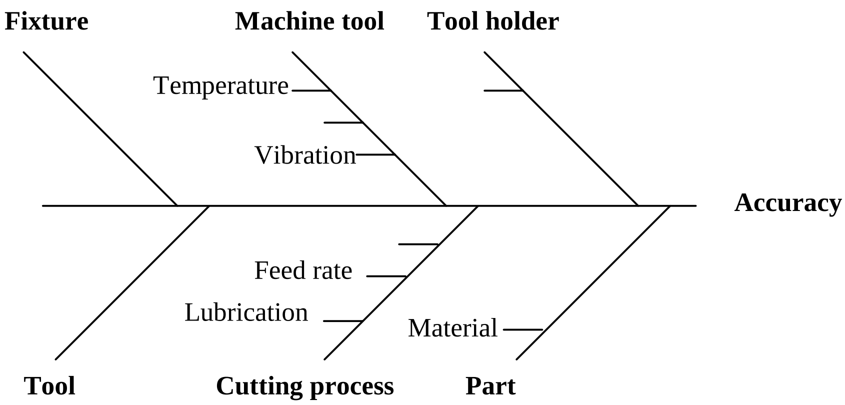


Figure 3.19. A cause-and-effect diagram, also known as an Ishikawa diagram or a fishbone chart, is an effective tool as part of a problem solving process.

The fourth step is to develop a plan. This is to assign activities into measurable tasks and offer the opportunity to document what is done and clarify failure points. After this the next step is to analyse the achieved data. Control charts (see appendix B) and accompanying capability analysis will for example give information about process variability. Statistical methods will give further information concerning overall process capability.

The last step is an investigative and/or corrective action. To make sure only relevant information is considered in the process capability study, all unusual out of control points and trends are eliminated. Long-term trends may for instance not be addressed in the study, or out of control points may indicate several problems of no concern to the study [McLaughlin, 1988].

3.10 A Capability Study at Scania

This is an example of a capability study perfomed at Scania CV AB in January 2000. A gear wheel is machined by gear shaving, see figure 3.20.

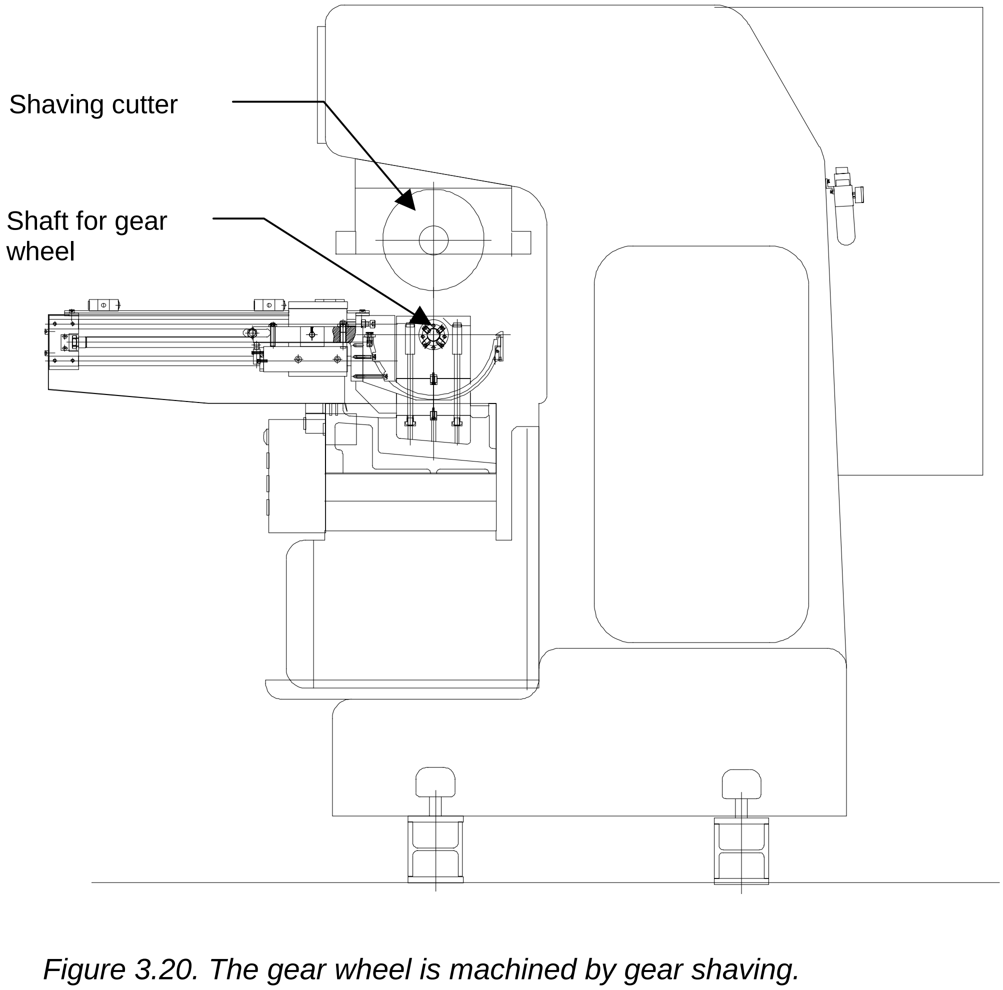


Figure 3.20. The gear wheel is machined by gear shaving.

The diameter of the gear wheel is measured as the distance between two cylinders. The number of samples is 50, and each sampel is measured four times as given in figure 3.21.

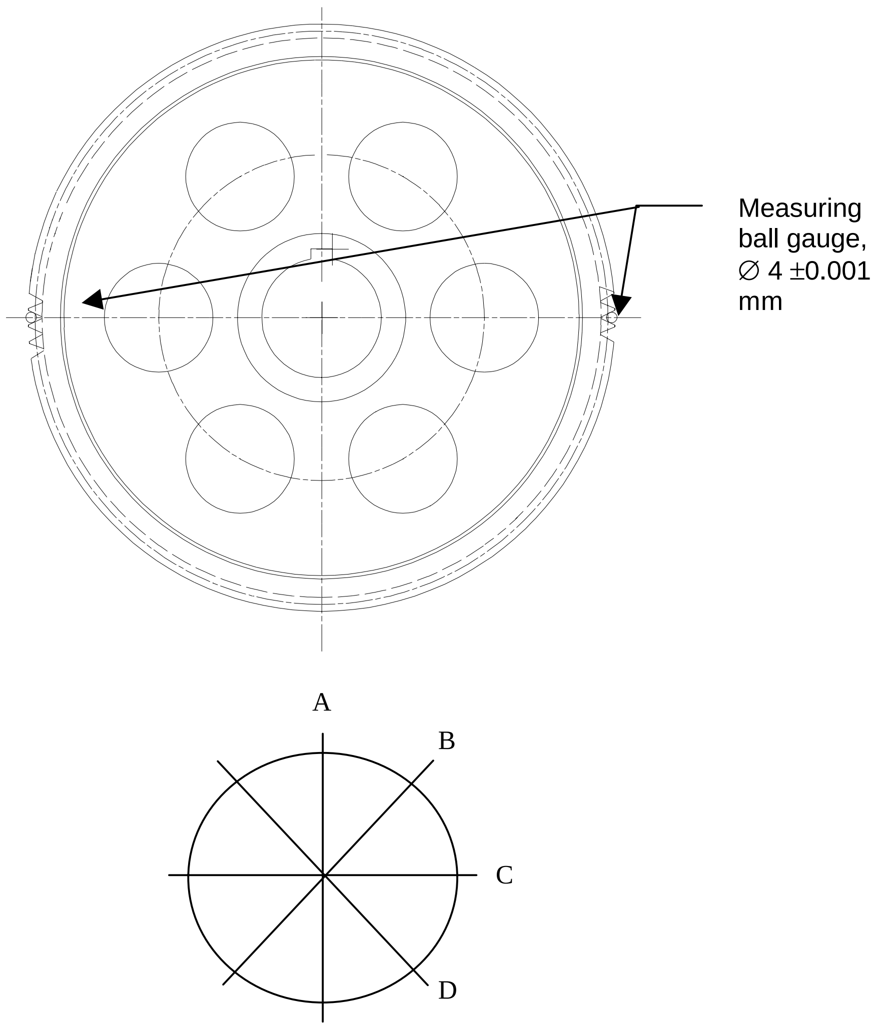


Figure 3.21. The gear wheel with a diameter of 217.41 mm is measured by a measuring ball gauge in four different places, A, B, C and D.

Capability at Scania

The Scania TFP [2] describes basic requirements for purchasing of equipment for production. The required value of the capability index in relation to number of samples differs between process and machine capability. For process capability the required value is 1.33, independent of the number of samples. For machine capability is the value dependent on the number of test samples, the greater number the smaller index is required, see table (3.5). According to the TFP less than 25 samples should normally not be used.

Sample size	**C_m or C_{mk}**	**C_{pk}**
25	> 1.5	1.33
50	> 1.4	
500	> 1.35	

Table 3.5. Requirements on capability index according to the Scania TFP.

Machine capability, C_m or C_{mk}, is calculated by use of values measured on parts machined in succession.

3.10.1 The Result of the Capability Study

The 50 gear wheels are measured at four positions and the result shows if the machine tool is capable of producing gears according to given tolerances and target value or not. The gear wheels are machined twice without altering the clamping. This reduces the number of affecting properties, which is important in a machine capability study. Since the gear wheels are machined twice the target value will not be achieved. The gear wheels are measured at four different positions, A, B, C and D, see figure 3.21 and table (3.6) for the measured values.

[2] Scania TFP, Tekniska Föreskrifter för Produktionsutrustning, TFP 2000-07-01, edition 2/2000.

	Position on gear wheel			
Measurement nr.	A	B	C	D
1	217,31	217,303	217,291	217,298
2	217,332	217,318	217,311	217,312
3	217,312	217,307	217,301	217,292
4	217,315	217,301	217,301	217,31
5	217,296	217,306	217,284	217,297
6	217,311	217,304	217,317	217,306
7	217,315	217,304	217,311	217,319
8	217,301	217,316	217,3	217,316
9	217,285	217,299	217,299	217,319
10	217,306	217,309	217,298	217,299
11	217,291	217,291	217,3	217,295
12	217,305	217,302	217,304	217,3
13	217,284	217,296	217,296	217,301
14	217,298	217,3	217,298	217,296
15	217,286	217,286	217,291	217,288
16	217,29	217,294	217,294	217,298
17	217,293	217,289	217,296	217,294
18	217,311	217,302	217,297	217,313
19	217,302	217,294	217,288	217,291
20	217,312	217,296	217,293	217,291
21	217,298	217,293	217,294	217,31
22	217,285	217,313	217,284	217,296
23	217,286	217,305	217,299	217,287
24	217,312	217,295	217,293	217,293
25	217,297	217,314	217,29	217,286
26	217,308	217,295	217,296	217,299
27	217,32	217,302	217,294	217,298
28	217,319	217,299	217,293	217,291
29	217,299	217,295	217,293	217,29
30	217,285	217,307	217,284	217,299
31	217,304	217,28	217,3	217,294
32	217,32	217,304	217,302	217,298
33	217,32	217,322	217,292	217,316
34	217,318	217,305	217,299	217,298
35	217,3	217,296	217,287	217,29
36	217,307	217,333	217,308	217,319
37	217,317	217,29	217,302	217,308
38	217,312	217,301	217,304	217,314
39	217,29	217,319	217,294	217,312

40	217,299	217,314	217,3	217,298
41	217,316	217,3	217,288	217,283
42	217,3	217,293	217,299	217,295
43	217,288	217,282	217,286	217,289
44	217,286	217,285	217,282	217,277
45	217,31	217,289	217,285	217,289
46	217,283	217,29	217,294	217,304
47	217,29	217,277	217,283	217,277
48	217,284	217,279	217,29	217,29
49	217,273	217,294	217,308	217,286
50	217,32	217,317	217,279	217,282

Table 3.6. Measured values from the four positions A, B, C and D on the 50 gear wheels.

From these measured values, average (x) and standard deviation (s) are calculated for each measuring position. These values are used for calculating capability indices, se table (3.7).

Target value	T	217,340 mm
Upper tolerance limit	T_u	217,365 mm
Lower tolerance limit	T_l	217,315 mm
Number of gear wheels	n	50 peices
A		
Average	x	217,302 mm
Standard deviation	s	0,013336
The deviation	6*s	0,080018
C_m	$(T_u - T_l)/6*s$	0,624861
C_{mk}	$(T_u - x)/3*s$	1,57415
C_{mk}	$(x - T_l)/3*s$	-0,0324428

B		
Average	x	217,3001 mm
Standard deviation	s	0,011666
The deviation	6*s	0,069995
C_m	$(T_u - T_l)/6*s$	0,714336
C_{mk}	$(T_u - x)/3*s$	1,854417
C_{mk}	$(x - T_l)/3*s$	-0,425744
C		
Average	x	217,2954 mm
Standard deviation	s	0,008122
The deviation	6*s	0,048732
C_m	$(T_u - T_l)/6*s$	1,026029
C_{mk}	$(T_u - x)/3*s$	2,854823
C_{mk}	$(x - T_l)/3*s$	-0,802765
D		
Average	x	217,2981 mm
Standard deviation	s	0,010918
The deviation	6*s	0,065507
C_m	$(T_u - T_l)/6*s$	0,763273
C_{mk}	$(T_u - x)/3*s$	2,04374
C_{mk}	$(x - T_l)/3*s$	-0,517194

Table 3.7. The result from measuring 50 gear wheels at four positions, A, B, C and D.

The result can be evaluated by the aid of a graphical view of the result, see figure 3.22. A diagram like this makes it easy to compare the actual result with the desired result. In this case, almost all the values of the diameter are outside the lower tolerance limit; this is the result when machining the gear wheels twice (due to performing a machine and not a process capability study). Had this been the result after only one machining, it would have proved the process to be out of control.

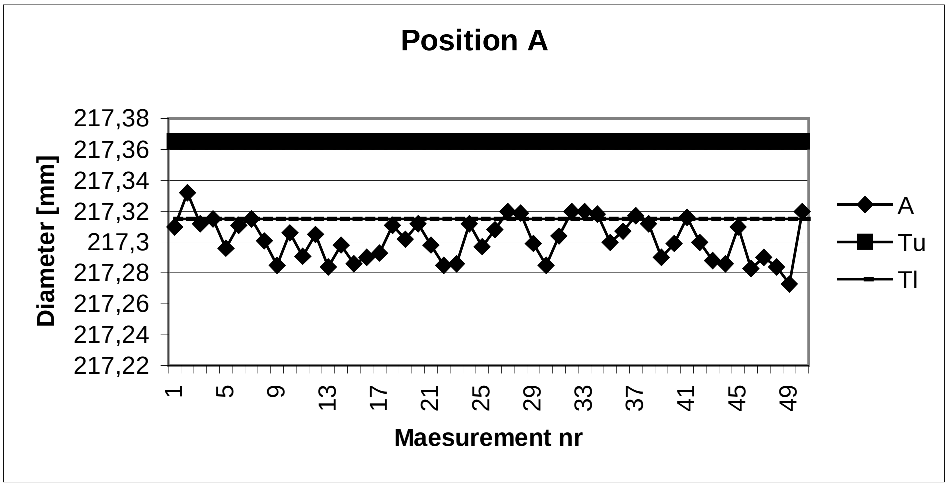


Figure 3.22. The result from measuring 50 gear wheels in position A (A) and the upper and lower tolerance levels (T_u and T_l).

Consequently, the measured result needs to be adjusted to compare the measured value with the target value and the tolerance limits. The target value and the average are assumed to be equal, and that adjusts the measured values so as to be compared with the tolerance interval, see figure 3.23. The measured values are adjusted by the expression (A-x)+T= A'. Most of the measured values of the diameter are within the tolerance interval but the deviation of the process needs to be reduced.

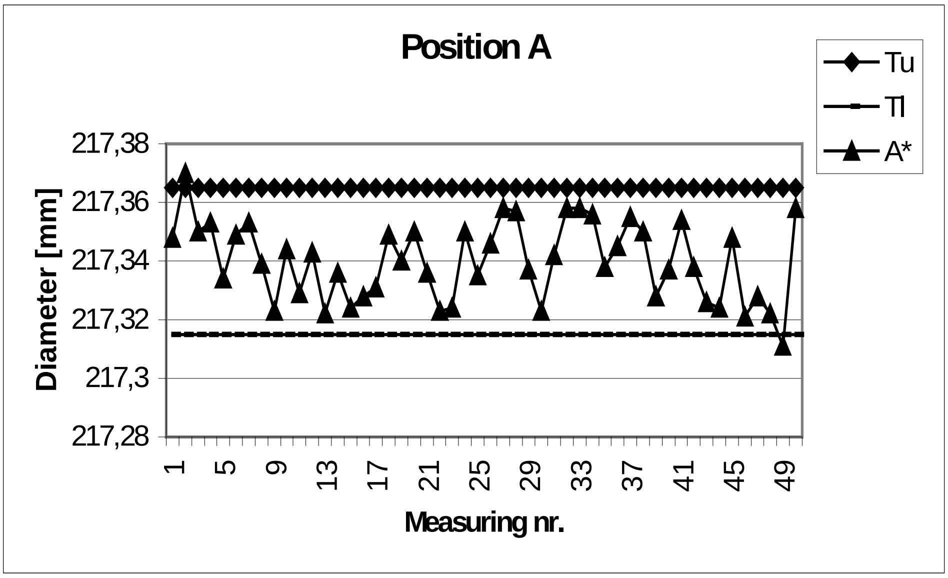


Figure 3.23. The figure illustrates adjusted measured values of the diameter and the tolerance levels (upper level T_u, lower level T_l) for position A. The average of the measured values is here assumed to be equal to the target value.

The capability index C_m is low (C_m = 0.62), which indicates a possibility to achieve gear wheels with a diameter outside tolerance limits. A value that is often given as a minimum level for an acceptable capability index is 1.33. Increasing demands on effectiveness in machining causes requirements of even higher index value. In order to achieve an acceptable capability value in this example, the standard deviation needs to be reduced. In addition, the average diameter of the gear wheels needs to be close to target value, and properties causing the process deviation needs to be reduced or eliminated.

By calculating the capability index C_{mk} the accordance between target value and average value is determined. Since these gear wheels are machined twice it is not of interest to compare the average of the process to the target value by this kind of capability index, se figure 3.24.

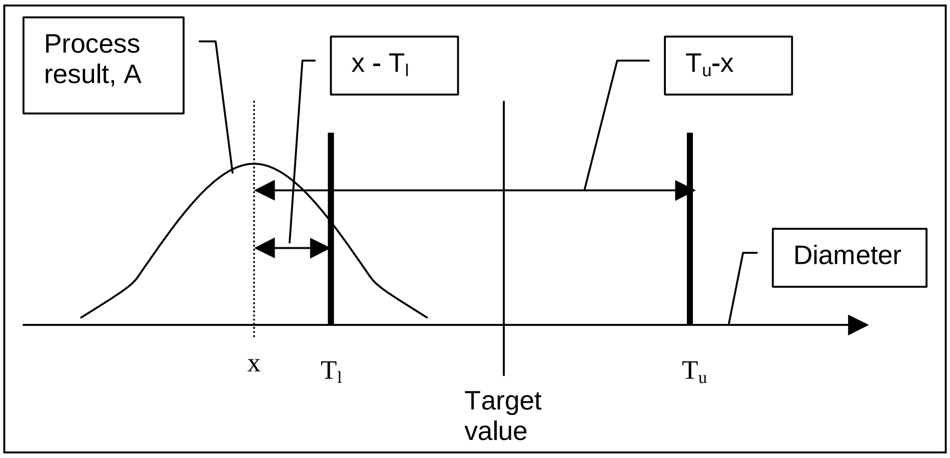


Figure 3.24. An illustration of measured values (A), tolerance limits (T_u and T_l), average of measured values (x), adjusted tolerance level (T_u -x and x- T_l) and the target value. This result is due to the gear wheels being machined twice.

Although the process outcome is outside the tolerance interval, see figure 3.24, a TC-value (Target value Centring, see section 3.6.3) can be calculated as an example.

$$TC = \frac{x - T}{T_u - T_l} \cdot 100\%$$

A TC-value describes how well a process accord with the requirements on reaching the target value. The TC-value is the difference between target value (T) and the average value (x) of the process distribution, divided by the tolerance interval. As opposed to capability indices, this measure has a unit (%). The calculated value reflects how far, in percentage, the average value is from the target value. In this case the average value is outside the lower tolerance level due to the double machining. What is noticeable is the big difference between the smallest and largest value, 76 and 89 %, between the four groups (A, B, C and D) of measurements. The TC-values are seen in table (3.8).

Target value	T	217,34 mm
Upper tolerance limit	T_u	217,365 mm
Lower tolerance limit	T_l	217,315 mm
Number of gear wheels	n	50 peices
A		
Average	x	217,302 mm
TC	$[(x - T)/(T_u-T_l)]*100$	-76 %
B		
Average	x	217,3001 mm
TC	$[(x - T)/(T_u-T_l)]*100$	-79,8 %
C		
Average	x	217,2954 mm
TC	$[(x - T)/(T_u-T_l)]*100$	-89,2 %
D		
Average	x	217,2981 mm
TC	$[(x - T)/(T_u-T_l)]*100$	-83,8 %

Table 3.8. Calculated TC-values from the four positions A, B, C and D.

4 Introduction to Accuracy in Machining Systems

The accuracy of a machined part is determined by the deviation of the cutting point between the tool and the workpiece. Weck [1984] states in his publication dealing with machine tools that machining accuracy is dependent on four characteristics, shown in figure 4.1. Basically, all machine characteristics are influenced by a large number of variables, which causes variability since they change randomly both periodically and systematically.

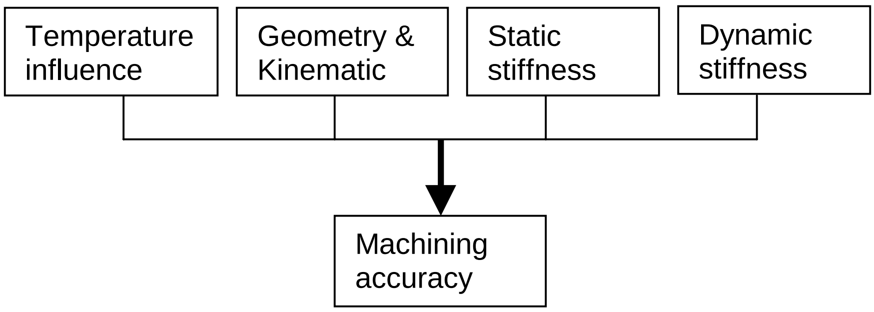


Figure 4.1. Machining accuracy depends on the characteristics of the machine tool.

S. Larsson [1993] presents in his publication four characteristics dealing with equipment for measuring accuracy in machine tools.

- Thermal influence comes from geometrical deviations due to temperature changes during time.
- Geometrical factors is geometrical deviations on and between each mechanical component e.g. straightness and squareness. Kinematics determines how accurate the axes in a machine tool co-ordinate moving together positioning the tool in the work area.

- Static stiffness is a value on the load a machine tool can endure before accuracy is altered. Load in this case can be cutting forces and dead weight of a workpiece.
- Dynamic stiffness is a factor referring to how well the system can damp vibrations.

The causes of machining accuracy, or deviation from optimal values, can be divided into three different groups, i.e. systematic errors, random effects and a mix of the two. By measurement of a number of products machined in a machine tool followed by statistical evaluation techniques, it is possible to separate systematic errors from random effects. Generally, it is not possible to identify the causes of machining inaccuracy, since all four groups of characteristics of a machine tool affects each other and consequently, the result showed on machined part is a summary of them all.

Temperature influence
The geometric dimensions of a machine tool changes when it is exposed to sources of heat. These sources can be of both internal, e.g. a motor and a gearbox, and of external nature, e.g. temperature changes in the air. Apart from influencing the machine tool, every module in a machining system is affected by heat deviations and together this give an unknown influence on the relative distance between tool tip and workpiece. [Larsson S, 1993]. The total effect on the accuracy of a machine tool due to thermal influence on modules in the machining system, may be determined by measurement of the geometric and kinematic behaviour [Weck, 1984].

Geometric and kinematic behaviour of machine tools
The causes of deviations from the defined relative motions between the tool and the workpiece may be divided in one of the two categories geometric and kinematic. The first category, geometric, includes positional inaccuracies and errors in the shape of the machine components, e.g. tables and tool holders. Deviations due to kinematic behaviour, the second category, occur in co-ordinate movements, i.e. functional movements. Both types of deviations are the result from production and assembly of the components in the machine design, as well as their elastic deformations due to static, dynamic and thermal loading conditions [Weck, 1984].

Machine tool motions can cause positioning errors, i.e. a deviation from expected distance between tool and workpiece (geometric deviations). Every axis in a machine tool has six possible geometrical errors in every single point along the axis when the slide moves, three translatory and three rotary deflections. These errors are pitch, yaw, roll, vertical and horizontal straightness and finally, linear positioning. Between the three axes a deviation from complete squareness can occur. This kind of error also causes positioning error between the tool tip and the workpiece. In addition to these errors, also rotating axes, e.g. spindle and chuck, in a machine tool can cause errors. Examples are run out, radial and axial pitch [Larsson S, 1993].

The kinematic behaviour of a machine tool is the result of relative motion of several moving machine components. For machine tools the co-ordination of different rotary motions is of particular importance. Examples are rotary/translatory, i.e. feed rate in a lathe, and translatory/translatory movements between two axes in a machining centre [Weck, 1984].

Static stiffness

Gravity, acceleration and cutting forces affect the static stiffness of a machine tool. These parameters affects the geometry of a machine tool, which can cause changes in accuracy [Larsson S, 1993]. This kind of errors can alter the performance of a process in a machine tool during a period of time. Gravity can for example cause the weight of a machine tool to slowly deform its structure and thereby introduce errors when machining.

An overall static stiffness in a machining system is illustrated as the sum of a spring system consisting of all modules in a system. Some of the modules are put together by a stiff joint and others by a movable joint, e.g. guideways, see figure 4.2. It has been shown that most of the spring effect originates from these joints. Hallendorff [1979] states this in his publication about machine tools.

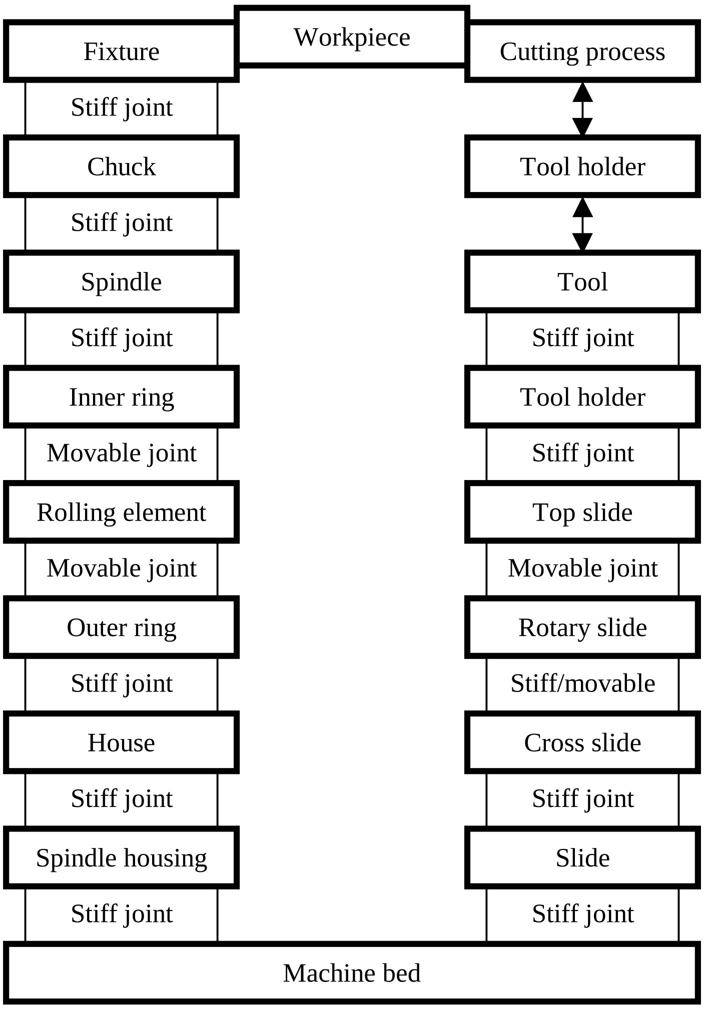


Figure 4.2. An overall static stiffness in a machining system is the sum of a spring system resulting from adding all modules [Hallendorff, 1979].

An inadequate static stiffness of a machine tool mainly causes errors on geometric dimensions on the produced part [Weck, 1984].

Dynamic stiffness
Uneven dynamic characteristics will generate vibrations, an effect which may lead to poor surface finish on the workpiece, increased machine and tool wear. Consequently, it may cause tool fractures and damage to both the machine and workpiece. A machine tool is a number of

mechanical components coupled together and therefore, with reference to their individual behaviour, may be considered as a system of vibrators [Weck, 1984].

Dynamic behaviour is characterised by the three quantities i.e. stiffness, mass and damping, see figure 4.3. Stiffness and damping of a system are, among other things, dependent of temperature and deformations. Periodically changing forces, which generate vibrations in machine tools, have different sources divided into two groups, i.e. internal and external sources. An example of an external source is when vibrations from one machine tool are transferred through the floor affecting other machine tools. Examples of internal sources in a system are unbalanced rotating elements and cutting forces due to intermittent force load [Hallendorff, 1979, a].

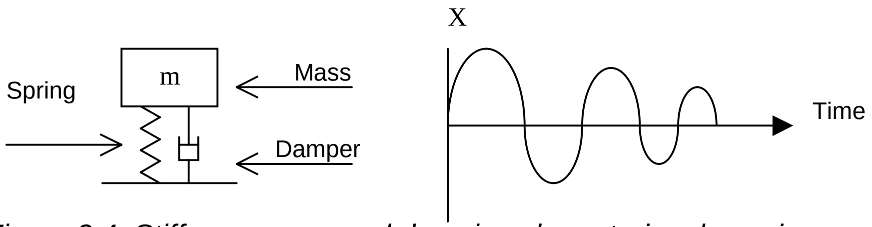


Figure 3.4. Stiffness, mass and damping characterise dynamic behaviour.

4.1 Improvement of Accuracy in Machining System

One way of improving the accuracy in a machining system, and thereby improve the result of machining, is to make changes in the *design* of the system. There are several different methods for improvements, e.g. Finite Element Methods (FEM) and several design methodologies. One of the latter is Robust Design, see appendix A, which is a method emphasising design of products insensitive to disturbing noise. By this is meant to design a machining system as insensitive as possible to affecting properties, e.g. vibrations, which would improve the outcome of the system.

4.1.1 Robust Design

The fundamental principle of Robust Design is according to Phadke [1989, p. 6] "… to improve the quality of a product by minimising the effect of the causes of variation without eliminating the causes". For achieving this, parameter design is used. This activity means that processes are designed to minimise the sensitivity of various causes of variation during performance. Naturally, an improved quality must justify the increased product cost, which might be a consequence of the quality improvement activities. For further details about Robust Design, see appendix A.

As the fundamental principle is to minimise the effect of the causes of variation, it is of vital importance to identify important noise factors. Noise factors, or causes of variations, can be divided into three different groups for both products and manufacturing processes [Phadke, 1989, p. 23].

- Products

1. *External sources*, two main sources are the environment in which a product works and the load to which it is subjected.
2. *Unit-to-unit variation* is the inevitable variation on products produced in a manufacturing process.
3. *Deterioration* causes changes in product performance as time passes.

- Manufacturing processes

1. *External to the process*, these noise factors related to the environment in which the process is carried out.
2. *Process non-uniformity,* this occurs when many products are processed at the same time.
3. *Process drift* occurs due to for example wear of tools.

4.1.2 Improving a Machining System

A manufacturing system can be described both as a product and a manufacturing process. It is a product for manufacturers of machine tools, tools and fixtures. But for those using a machining system to machine parts, it is a manufacturing process.

In the case when the machining system is considered as a product, Robust Design can be used to achieve better machining results. Minimising the influence of noise factors and thereby improving basic conditions for a machining process improves the machining result. However, to be able to do this, engineering experience and efficient experimentation to determine important noise factors is necessary.

Robust design is based on many ideas from statistical experimental design for obtaining reliable information about variables involved in making engineering decisions. Although "Robust Design adds a new dimension to statistical experimental design – it explicitly addresses the following concerns faced by all product and process designers:

- how to economically reduce the variation of a product's function in the customer's environment,
- how to ensure the decisions found to be optimum during laboratory experiments will prove to be so in manufacturing and in customer environments."

[Phadke, 1989, p.3]

5 Introduction to Measurement

The process of quantification of product and process characteristics is called measurement. By measurement is meant the use of tools (gauges) to quantify, or measure, the extent to which the part or process possesses the studied characteristic. The word *measurement* has several meanings, i.e. the process of quantification and the resulting number [Juran, 1988]

Competence in measurement techniques is necessary to enable to plan, perform and evaluate the result from measurement, whatever method or tool being used. Good knowledge and competence of all three activities is a requirement to avoid decisions made on inferior basic data. Generally, there are mainly two areas for measurements of machining systems, and they are measurements of parts (workpiece) as well as processes. Parts are measured either to ensure that they fulfil the requirements given by the customer, or to ensure that a process agrees with given requirements. A process on the other hand, is measured to ensure a proper processing, or to detect wear and damages on the machining system that includes the process.

5.1 The importance of Measurement

The idea of measurements in industry is to make sure that the result of a process meets with the desired tolerances. It is a way of expressing the result from a single performed process or the result from a manufacturing line, which consists of several processes. If a process and/or the results are measured and compared during a period of time, changes in the process can be detected.

Measurements on machine tools are performed because of different reasons. As a consequence of this, it is done at different stages during the lifetime of a machine tool. Examples on occasions when tests including measurements are performed, are given below [Larsson S, 1993].

- *Test before buying a machine*

These tests are carried out at the machine tool builder with the aim of achieving information about properties of the machine tool.

- *Delivery test*

Before a machine tool is delivered to the customer, tests are carried out at the machine tool workshop. Normally, both the machine tool (direct measurement) and the machined part (indirect measurement), are measured.

- *Installation of machine tool*

This test is done when the machine tool is delivered and installed in the workshop. Important factors to consider are for example, if the installation is properly done, if errors at the delivery test are corrected and that no damages during transportation have occurred.

- *Test before the warranty expires*

These measurements are done to detect errors that are covered by the warranty.

- *Error detection*

This is carried out when errors occur and the sources need to be detected. Tests are done to locate the problem and to give basic data for decision-making on how to solve the problem.

- *Periodical test*

The basic idea is to perform tests regularly to detect changes in performance and thereby be able to suggest maintenance to avoid errors and breakdowns.

- *Measurements before and after repair*

The purpose is to detect every error and deficiency in performance before the machining system is repaired. After the work is done, tests are used to make sure that the performance of the machining system is improved.

5.2 Description of a Measured Value

A measured value describes a characteristic of an object or an event, not the object or the event itself. The following example describes the basic definitions of a measured value according to Carlsson [1998]. In this example the measured object is a giant axis and its diameter is the dimension that has been measured. The result of the measurement consists of a measurement value multiplied by a unit, as well as indicated measurement uncertainty.

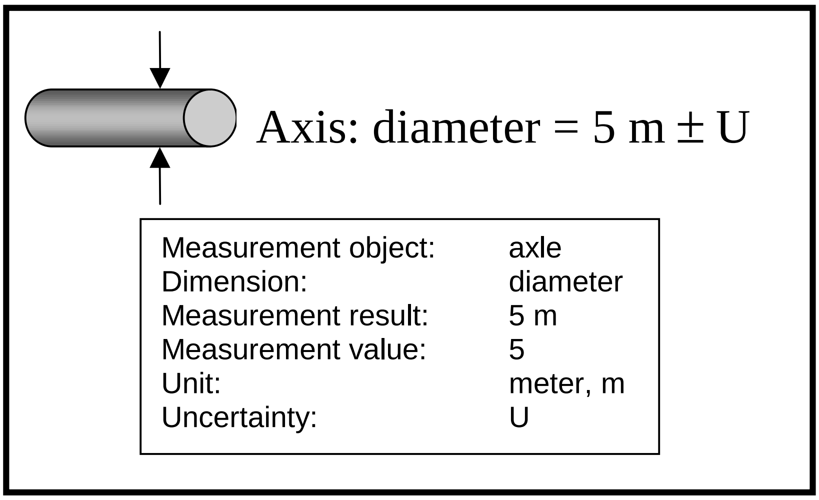


Figure 5.1. This is an example of a part and its measured value.

A *measurement uncertainty* is defined as the interval where the measurement result is “most likely” to belong to. This means that a measurement result is indicated with some sort of deviation value, which gives information of its reliability. A *measurement error,* on the contrary, is the difference between measured value and the true value. Since measurement errors are almost impossible to avoid, it follows that it is usually impossible to decide the true value, and thereby the measurement error [Carlsson, 1998].

Measurement uncertainty, u, for measurement of a variable x can be expressed as *absolute*, u_{abs}, or *relative*, u_{rel}.

u_{abs} = absolute measurement accuracy

$$u_{rel} = u_{abs}/x_{measured} = 100 \cdot u_{abs}/x_{measured}\% \qquad (5.1)$$

If a tool is specified to have a maximum absolute uncertainty, the relative uncertainty will increase for reduced values. This is important to consider when choosing *the measurement interval* of a measurement tool, the interval with the smallest uncertainty is the best [Carlsson, 1998].

5.3 Consequences of Uncertainty

A measured value of a parameter on a part includes a deviation from the true value. The measured value is the sum of deviations due to the machining process and a deviation from the measuring tool. The uncertainty of measured values can cause a situation when correct parts are rejected, i.e. the measured value is outside tolerance limits but this is not the correct value. Naturally the desirable situation is when all correct parts are accepted and every single defect part is rejected. The opposite situation is to be avoided since it might prove to be very expensive for the end-user and/or the producer of a part or product. The described situations can be visualised as in figure 5.2 [Carlsson, 1998].

In order to avoid a deviation on a measured value every precaution need to be taken as to reduce every cause of error from the measuring tool. Calibration of the measuring tool is one step towards reducing the uncertainty of a measured value. What is left if the preparations are done properly is a random deviation caused by natural deviation.

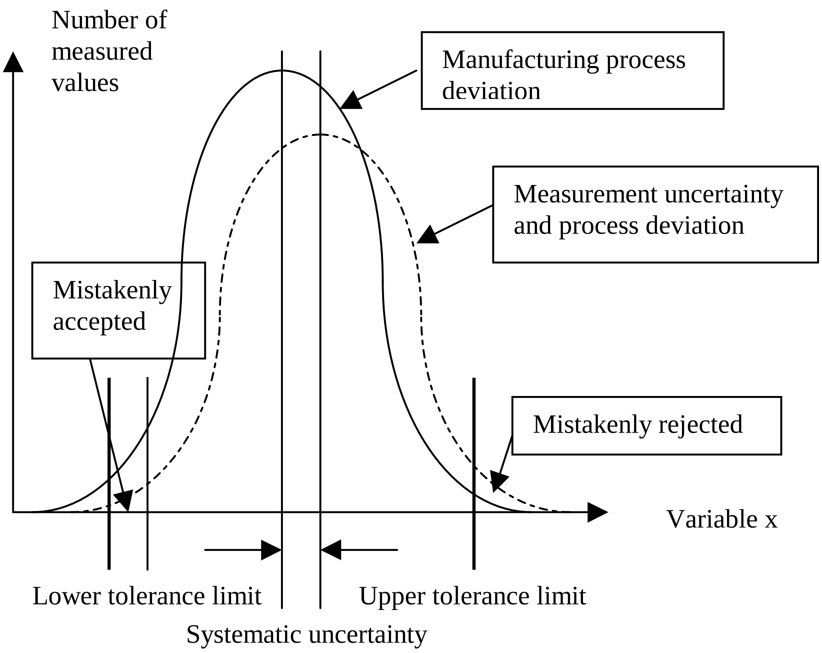


Figure 5.2. An illustration of systematic uncertainty [Carlsson, 1998].

5.4 Measurement Accuracy

Measurement is a process, which is affected by several factors according to Carlsson [1998]. A measurement is a combination of the performance of the measurement tool and the environment where it is used. To achieve a reliable measured value, measurement errors need to be minimised and the uncertainty has to be estimated. Measurement errors can be of two different kinds, *natural deviation* and *slowly increasing systematic errors*. Calibration of measurement tools is a necessary step to obtain a good measurement process, but it is not sufficient for dealing with the overall uncertainty. Calibration has three main purposes:

- To estimate the uncertainty of the measurement method.
- To compensate for systematic uncertainty.
- To secure the reliability of a measurement method.

Measurement accuracy is derived not only from the used measurement tool, it is also the result from the environment where the process of measurement is performed. According to Carlsson [1998] measurement accuracy is influenced by the performance of the measurement, the surrounding environment as well as the properties of the gauge and the measured part, see figure 5.3.

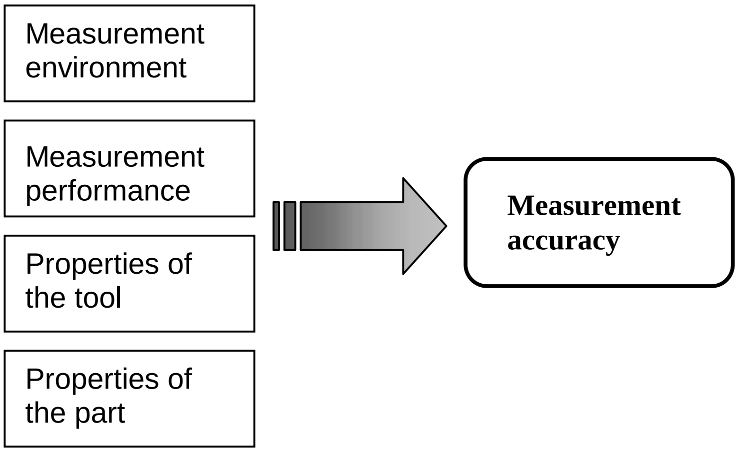


Figure 5.3. Measurement accuracy is influenced by the performance of the measurement, the surrounding environment and the properties of the gauge and the measured part [Carlsson, 1998].

Examples from the four groups of influences in figure 5.3 are given below.

- Measurement environment: e.g. temperature deviations, dust, stress on the operator and vibrations.
- Measurement performance: e.g. lack of skill and experience and the operator interface.
- Properties of the tool: e.g. design of the tool, maintenance and measurement forces.
- Properties of the part: e.g. surface roughness and clamping.

Measured values have to be evaluated in three ways, see figure 5.4. Firstly, is the *process of measurement* properly and reliably done, secondly, does the *performed measurement* give useful and desired information about the studied product or the process. Finally, the received data from the performed measurement is *statistically evaluated* in a proper way.

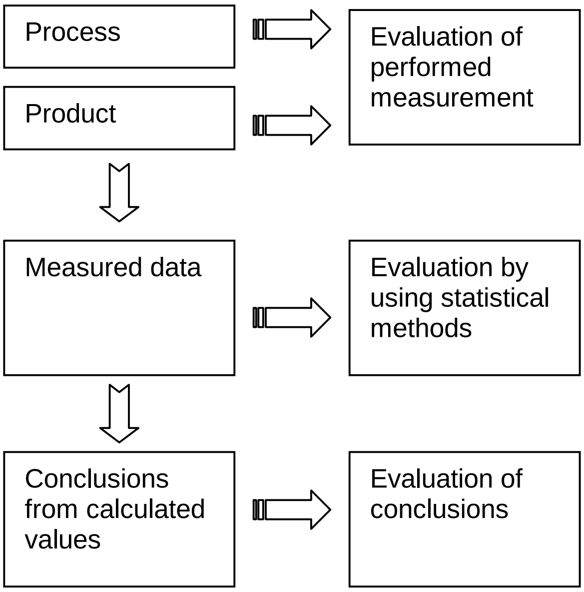


Figure 5.4. Measured data needs to be evaluated to ensure it is reliable. This also applies for the conclusions from measured data.

Examples of methods for evaluating whether the measurement process itself is reliable or not, are capability index and statistical process control, SPC. The reason for this evaluation is to achieve knowledge about a process, i.e. how well it works in relation to defined basic conditions [Carlsson, 1998]. For further details about SPC, see appendix B.

Measured data is evaluated through statistical methods in order to draw conclusions and to make the result more visual.

The evaluation of a performed measurement will give answers to several questions, e.g. whether or not it quantifies the defined characteristics, its reliability and if errors are influencing the measurement. Summarising what has been done, how it was done and what the original questions were, will give an overall view of reliability and usability of performed measurement and the gained information. It is then possible to translate the result to the process and or part as a base to improvements on their properties.

5.5 Measurement Environment

The accuracy of the process of measurement is dependent on the environmental conditions during performance. Physical conditions as temperature, pressure and humidity which affect the tools and thereby the result. If the demand on accuracy during measurement is very high, it is necessary to have a measurement room that is very clean and where the physical conditions can be controlled. Measurement tools are calibrated in a controlled environment. Another important physical condition is the force between the measurement tool and the object. The most important sources of errors during precision measurement is expansion due to temperature and forces between tool and object [Carlsson, 1998].

An example of another influencing factor is vibrations. Surrounding equipment can transmit vibrations and thereby affect the result. Another example is all kinds of dust, dirt and oil. Dirty tools or products make the result from measurement more uncertain.

5.6 Measurement Tool

The choice of tool (gauge) to get the desired value of either a process or a machined part depends on several factors. For example:

- The kind of property that is looked for, e.g. length or surface roughness.
- Existing gauges, available either on the shop floor or on the market.
- The needed accuracy of the measured value.
- The available time for the actual measurement.

Each evaluation of an equipment or part needs to be thoroughly planned to give reliable and useful results.

5.6.1 Direct and Indirect Measurement of Accuracy

Accuracy in a machining system can be measured either direct or indirect. An indirect measurement involves a machining test, i.e. a number of part are machined and measured and the achieved result is compared to predefined values. This gives an estimation on how well a specific machining system satisfies with defined demands on accuracy.

A restricted use of indirect measurements follows by a limited possibility to investigate individual errors in the machining system. This is due to the fact that it is hard, or impossible, to detect sources of errors in the machining system from results on a machined part [Larsson, S, 1993].

5.6.2 Errors in Measured Values

Measured values are of no use if they are incorrect. Errors occur for example if the used tools are defect or used in an incorrect way. To achieve a good and valid result from measurement the tool, for example, has to be carefully chosen. It has to have the right precision in comparison to the tolerance of the part and process. Precision is the ability of a tool to reproduce its own measurements, i.e. the deviation from the average of the measurements [Juran, 1988]. The tool also has to be suitable for the environment where it is going to be used.

A measurement done with a tool that is not calibrated and maintained according to given instructions is not reliable. There is always a difference between two measurements, even if the measurements are done exactly in the same way, due to normal deviation. To make sure that it is only natural deviations between each measurement it is vital that instructions on how to perform the measurement are carefully written and used [Juran, 1988].

Tools are subject to a number of sources of error, both within each individual tool and between the same kind of tool. Examples of sources are non-linearity, drift due to temperature changes and sensitivity to magnetic, thermal and electrical fields.

6 Introduction to Modelling and Simulation

The aim of evaluating a product as a model in a simulating environment, for example a machining system or a machined part, is to make the process of designing more efficient, considering time requirement and economically. The advantages with modelling and simulation are many, e.g. to avoid errors and mistakes and to improve properties of the product. It gives in addition an opportunity to evaluate the function of new solutions on a design. A model makes the design more visual and is a helpful test tool to pinpoint necessary changes and improvements on functionality and appearance of the product. Being able to visualise a product as a model in a virtual environment gives further opportunities and possibilities, even more so if the virtual environment is valid for simulation of the function and behaviour of the product.

6.1 The Advantage with Modelling

There are several reasons for modelling a cutting process. van Luttervelt et. al. [1998] discusses the present situation and future trends in modelling of machining processes in and they state that some of the most well known reasons for modelling are:

A. Design or planning of processes.
B. Optimisation of processes.
C. Control of processes.
D. Simulation of processes.
E. Design of equipment.

These advantages are briefly explained in the following sections.

A. Design or planning of processes

In principle, only quite simple models would be needed for selection of the proper type of operation (turning, face milling), type and main dimensions of the cutting tool and the class of tool material. The difficulty is of a different nature, e.g. if the intended operation can be performed without disturbances. To answer this an investigation of the boundary conditions for safe machining, which increases the demands of the model is necessary. The best available solution are certain rules, e.g. rules deciding the level of stiffness needed to prevent too large deflections and vibrations.

B. Optimisation of processes

Optimisation requires more complicated models. Some of these models are designed for technical or economical aspects. An example of a pure technical aspect would be a model for calculation of maximum feed for a specific cutting force. An economical aspect would be to calculate an economical cutting speed.

C. Control of processes

The application of models for control of metal cutting processes has so far not been shown much attention. This is remarkable since the use of appropriate models can prevent rejects due to scatter of results from metal cutting. The authors [van Luttervelt, 1998] states that "If the effects of the input variables could be predicted with better accuracy it should in principle be clear what tolerances on the input variables should be maintained if certain tolerances on the output variables are required".

D. Simulation of machining processes

This area is still in a basic state; in future it would be possible to simulate practical machining processes with an acceptable degree of reliability and accuracy. The authors also state that the finite element method recently has been used for simulation of the basic chip formation.

E. Design of equipment

There are today models that are convenient for use for design of equipment. An example is models used for estimations of expected values of cutting forces, torque, power and spindle speeds. These values are then used in order to specify machine tools for certain machining processes to be performed on a certain work material. Other examples are models used for studying elastic and thermal deformations as well as the dynamic behaviour of machine tools.

6.2 Several Models for a Machining System

According to van Luttervelt et. al. [1998] the field of prediction of workpiece precision is rather unexplored but of high practical importance. This field requires development of a suitable set of models for the whole machining system. They suggest that machining system models should be designed by using suitable models for each relevant module in the system. Machining systems as well as a production line can be divided into several modules, see figure 6.1.

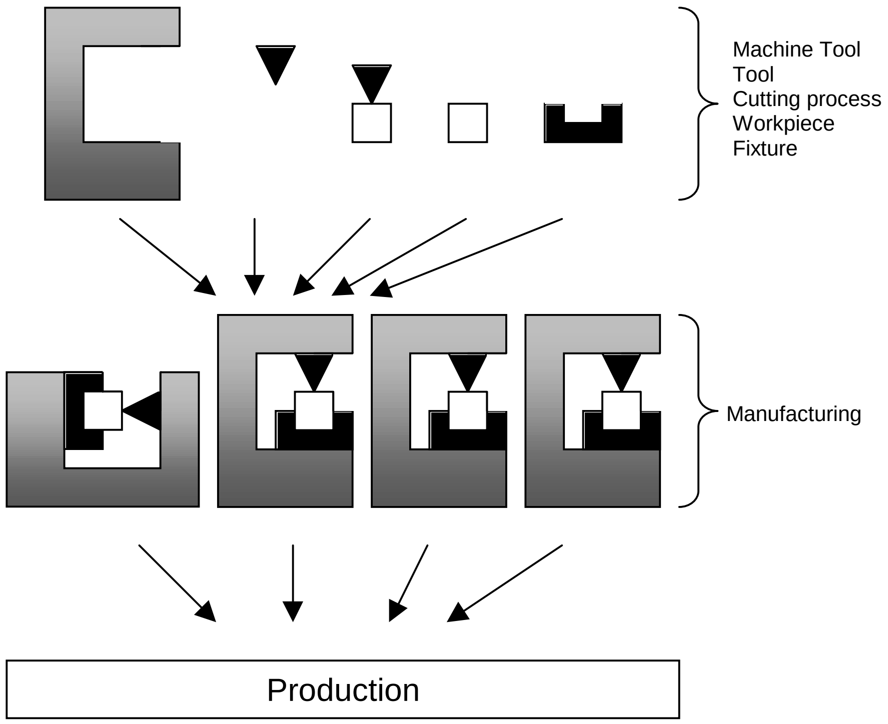


Figure 6.1. A machining system consists of several modules. Modelling and simulation can be performed on each single module and several co-operating modules.

Machining processes can be considered at different levels of abstraction as indicated in figure 6.2. Each level requires it's own set of input data and therefore also requires it's own model.

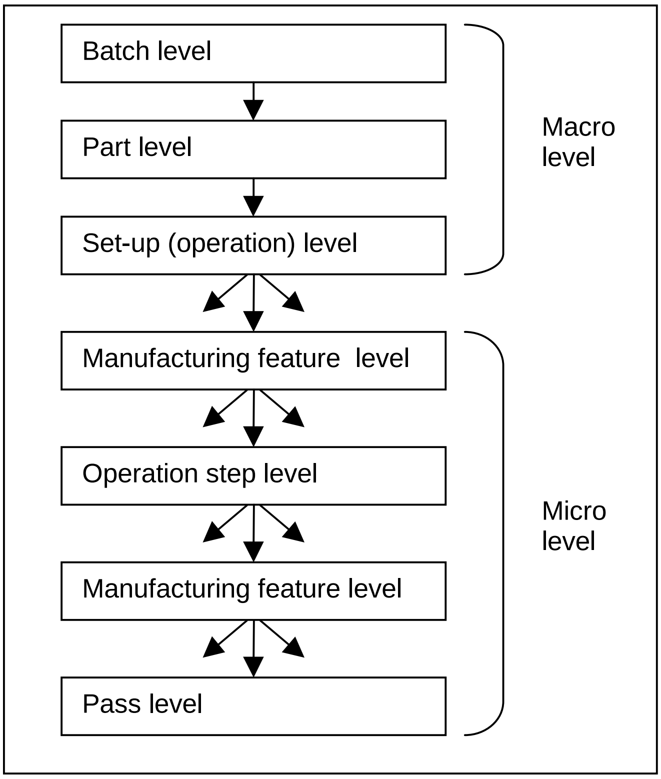


Figure 6.2. Levels of abstractions of machining processes (operations) [van Luttervelt, 1998].

Relevant information at the **batch level** includes number of parts to produced, required machining time, all processes (operations) to be performed, cutting tool etc. The **part level** deals with the information needed for the machining of a specific part, for example type of work material, shape of raw material and sequence of set-ups to be performed. At the **set-up level** the number of processes (operations) to be performed on one workpiece while it is retained in a fixture is considered. Examples of relevant information are sequence of processes to be performed and the number of tools.

At the **operation step level**, the details of each process (operation) are defined. Here process steps are unit process such as centring and drilling etc. and relevant information are for example specification of the cutting tool and the sequence of processes on each specific shape element of the workpiece. The **pass level** where the kinematical quantities, for example depth of cut, cutting speed and feed has to be selected follows this level. **Manufacturing feature level** is not commented on in the publication.

The authors conclude that when considering only the lower levels, models for these levels will form a good basis for modelling higher levels.

6.3 Modelling of Machining Processes

Accurate predictions of the result from manufacturing processes have today a great interest due to the interest of useful strategies for the control of processes. This interest is supposed to grow even further in the future due to a desire to be able to predict the accuracy of shape and dimensions, surface roughness, properties of the subsurface layer of produced parts, required machining time and cost of the operation.

van Luttervelt et.al. [1998] state that the primary objective of modelling of machining processes is to develop a predictive capability for machining performance. This aim is desirable in order to facilitate effective planning of machining processes to achieve optimum productivity, quality and cost.

6.4 Classification of Models of Machining Processes

The area of modelling of machining processes is very large due to the large number of different machining processes, models for different purposes, and many different techniques for modelling to be used.

Models can be classified into different groups depending on the type of model, as described by van Luttervelt [1997]:

1. *Descriptive models* describe certain effects in words or by similarities with other well-known effects; these models are mainly used to explain those effects, leading to a basic understanding.
2. *Qualitative models* show more clearly than descriptive models which variables are important and their effect, albeit not quantitatively.
3. *Quantitative models* describe the relations between variables by mathematical expressions.
    a. Empirical models are quantitative models in which the numerical values of the constants are derived from a series of cutting tests.

b. Scientific models in which fundamental physical properties are obtained from a fast simulation test.

Most models explain what happened during the machining process or what is happening while the process is going on, but very few models are able to predict what actually will take place.

6.4.1 Fundamental Aspects of Modelling

van Luttervelt et. al. [1998] states that “The primary objective of modelling of machining operation is to develop a predictive capability for machining performance in order to facilitate effective planning of machining operations to achieve optimum productivity, quality and cost”. The mentioned machining performance can be divided into two categories, i.e. technical and commercial aspects. Technical aspects are for example accuracy of shape and dimensions as well as surface roughness. Examples of commercial aspects are machining time and cost, fraction of rejects and handling time. These are useful for management.

6.5 Predictive Models for Machining

Figure 6.3 shows the phases of predictive modelling of machining processes for practical applications presented by van Luttervelt et. al. in 1998.

- Phase 1 is the development of models for machining variables.
- Phase 2 is the development of models of machining performance.
- Phase 3 may in the future become the phase used to determine optimal conditions.

Phase one consists of two steps, i.e. task definition and selection of a proper set of generic models according to the defined task. These models are then given appropriate input values for the case at hand. Typical input values include cutting conditions (e.g. tool geometry, tool and work material properties). It is suggested to produce the output in two steps. In the first step some basic phenomena in the chip formation process are predicted, e.g. strains, temperatures, friction and chip flow. The second step is prediction of one or more of the common machining performance measures, e.g. cutting force, torque, surface roughness/integrity and part accuracy.

The major challenge with this two step predictive modelling is the transformation of the output from step one, into inputs to the second step. Today a majority of research groups develop models for improving the outputs of task definition. The second step requires the development of predictive capability for machining performance measures. This brings in complexities since this needs to be done for several different cutting processes such as turning, milling, drilling etc.

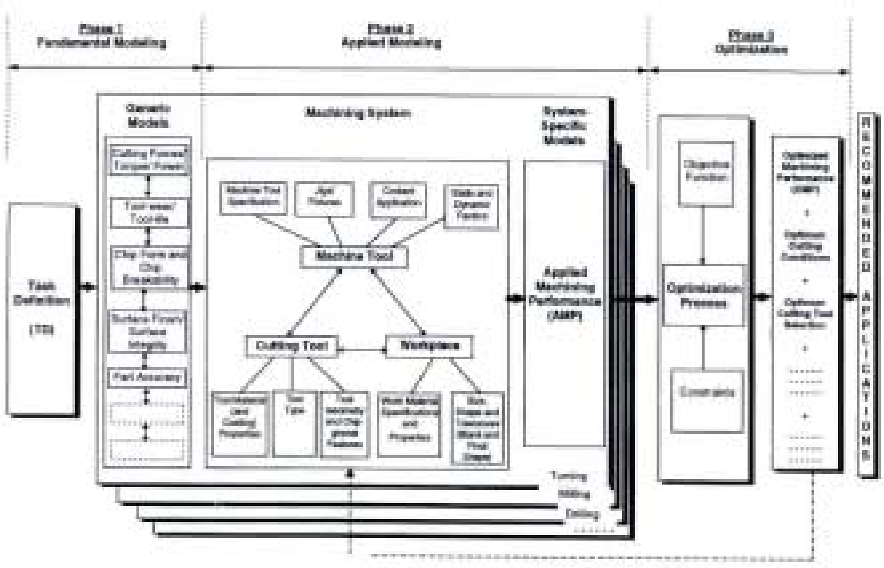


Figure 6.3. Predictive models for practical applications of machining [van Luttervelt, et. al.1998].

Fundamental modelling leads to generic predictive models for all kinds of machining processes. Applied modelling, on the other hand, involves the application of generic models to a certain process in a specific machining system, and thus needs to take into account the characteristics of all relevant components such as machine tool, cutting tool, workpiece etc. A model needs to be complemented with information in the form of data and knowledge to be used for its intended purposes of predicting the machining result and optimising parameters.

6.6 Difficulties with Models

A model of a system is an estimation of the system it is made to act like. The input values of properties are also estimates of the true values, therefore the generated results from a model are estimations of the modelled system.
It is not enough with a model, it needs to be "filled" with something, i.e. necessary data needs to be obtained and to make it useful for application in industry. van Luttervelt [1997] states that the development of new, reliable, and efficient methods to obtain required data is a major point of concern.

6.6.1 Models of machining processes

Difficulties with modelling machining processes are according to van Luttervelt et. al. [1998] mainly due to two factors:

1. Lack of fundamental understanding of the basic mechanisms and the interactions of cutting tool and work material.
2. The different purposes and the great variety and complexity of real machining processes, where the relations between input and output variables of each cutting process are only partially understood.

The authors conclude that scientific research work has during the last century produced an enormous amount of knowledge about metal cutting. Unfortunately, much of this knowledge is not documented in such a way that it might be analysed by use of computers. The reason for this is that the knowledge is not formalised, does not cover resent developments in metal cutting technology or is only known by some few experts. This makes it difficult or impossible to find out what knowledge is available for practical use in industry. Lack of reliable numerical data also makes it difficult to use models in industry.

The authors also states that two different schools in the field of modelling of machining processes can be distinguished.

1. Modelling as an engineering necessity.
2. Modelling as a scientific challenge.

Modelling as an engineering necessity is based on engineering practice and supported by systematic experimentation in a machine shop.

From the scientific point of view the work is based on trying to understand the basic mechanism of chip formation. This research work is mainly focused on how to understand and model a shear plane. A shear plane, or a shear zone, is "an abstraction of the zone of transition between workpiece and chip".

In conclusion none of these two schools are able to serve the needs of industry in a satisfactory manner. None of them has so far been able to model a machining process taking every parameter under every condition in consideration. A fast introduction of new material in both work material and tools along with new machining methods has made it even more difficult to achieve a model.

6.6.2 Modelling of a machine tool

Usually when cutting is modelled, the machine tool is considered to be ideal with infinite stiffness and no error motions. Models predicting chatter and part precision should, according to van Luttervelt et.al. [1998] contain a certain amount of information of machine tool, workpiece, fixture, cutting tool and tool holder. The difficulty with this is to decide what minimum information is required for each specific application, and how this information effectively can be obtained.

6.6.3 Modelling of a machining system

There are a large number of models available for several processes e.g. milling and turning, and process state variables e.g. cutting force and temperature. Still other models describe different elements of the machining system, such as the cutting tool, fixture and machine tool. Normally models can only be used discrete, i.e. there is almost no connection between models due to differences in structure, assumptions and required data. Therefore it is not possible to use different models as components in a larger system of models. This is necessary to achieve a large system as shown in figure 6.3 [van Luttervelt et.al., 1998].

6.6.4 Prediction of accuracy

To be able to predict the result with reference to accuracy and surface characteristics of a machined part is today the point of major concern [van Luttervelt et.al., 1998]. This is naturally most interesting for manufacturing of small batches. As a consequence of the small batch size, it is desirable to be able to select the machining method, cutting tools and cutting conditions in such a way that each machined part meets the accuracy requirements with a very high level of certainty. This is considered as a change in attention and causes two fundamental changes in the requirements of modelling; *the dynamic character of the chip formation process* as well as *the error motions* becomes important.

When surface characteristics are of importance, it is essential to be able to predict which mechanism of chip formation will occur. It would be desirable to be able to predict more details, such as the thickness of the chip and the frequency of the periodic variations, of the chip formation process. Another interesting topic is the magnitudes of the cyclic variations of the cutting force components caused by the dynamic chip formation processes.

When the accuracy and surface roughness of the workpiece are considered, the error motions are important. In other words, the machine tool and all other elements that determines the mechanical and thermal behaviour of the machining system should be included in the model of the cutting operation. A special problem domain is the prediction of chatter since this is caused by the mutual interaction of the dynamic properties of the mechanical system and the self-excitation by the cutting process.

The accuracy of models can not be properly tested due to the scatter of processes. Models are a simplification of the real system; this makes it most often impossible to test the accuracy of a model since the system it is made to behave like is more complicated than the model. van Luttervelt et.al., 1998, states that the reproducibility of machining process needs to be improved in order to be able to make proper test of models. Since models are a simplification of a real process, they are usually not fully comparable to an existing machining process but of very good assistance for various tasks.

6.6.5 Error motions

Error motions negatively affect workpiece precision and surface roughness. It is difficult to relate error motions exactly to the geometry of the machined part, and it is today not possible to accurately predict error motions by models. Consequently it is nearly impossible to predict the precision of a part. There are different sources of error motions:

1. Geometric errors of the machine tool, e.g. deviations due to reduction in straightness, parallelism, squarness etc.
2. Control error caused by the machine controller.
3. Load errors due to deformations caused by forces and temperatures, occurring during machining [van Luttervelt et.al., 1998].

6.6.6 Prediction of part precision

There are a number of groups of factors affecting the precision of parts produced by machining processes:

1. The geometrical product specification.
2. The geometry of the part before the machining takes place.
3. The work material.
4. The operational condition of the machine tool.
5. The position of the workpiece on the machine tool.
6. The clamping device of the workpiece.
7. The machining method.
8. The cutting tool and the cutting condition.
9. The cutting fluid.
10. The location of the tool-workpiece interaction.

If a model should be capable of predicting the precision of machined parts, it needs to include all factors that might influence the precision in one way or other. In each of these groups a large number of factors can be distinguished making the total number of variables in the model even larger. In addition, the precision of a part can be described in a large number of aspects, for example size and shape. These in turn should be studied for all geometric elements of the part. This makes a model of part precision very complex. For practical reasons the complexity needs to be reduced. There are according to van Luttervelt et.al. [1998] two ways of reducing the complexity of a model, both by *reducing the number of influencing factors included in the model* and by *reduction of the number of output variables*.

Reducing the number of factors can in itself be done in two ways, by leaving out influencing factors of minor significance and by combining several independent influencing factors into new combined influencing factors. The authors conclude that a model should include a maximum of ten factors. A reduction of the number of output values can easily be done since not every precision aspect is of importance for each geometric element. Many elements can be neglected since they are not critical, and some precision aspects of a number of related geometric elements may be grouped together. Reducing the complexity is an important step in modelling. The influencing factors and precision aspects, which should be included in each model, depend on the aim and the application of each specific model.

The available number of models for part precision is very limited and can be divided into six different groups.

1. Models for deflection of the machine, workpiece and tool due to the cutting force. Calculates the resulting displacement and its effect on the shape and dimensions of the part, by a nominal value of the cutting force component in the sensitive direction.
2. Models for error transmission take in consideration the finite stiffness of a machining system. Deflection of the system causes smaller variations of the shape and dimensions of the part.
3. Models for thermal deformations take in consideration the complex temperature fields in the machine tool, tool and workpiece, which cause thermal deflections. These deflections can be calculated and to a certain extent be compensated for once the actual temperatures are known.
4. Models for prediction of chatter takes in consideration the dynamic force component. Chatter affects the machined surface negatively and causes other nuisances in machining. In principle the theory to predict chatter is known. However, the main problem is to sufficient and accurate determining the data about the many important variables.
5. Models for fixturing errors take in consideration geometric deviations caused by fixturing of the work piece. These deviations are for example caused by uneven surfaces on the rough workpiece, and deformation of the workpiece and the fixture due to clamping forces.
6. Models for prediction of surface finish can not be based on engineering principles like those for elastic deformations. Most knowledge about surface roughness and modifications of the surface layer is empirical and a result of experiments performed in laboratories. This gives in turn very few mathematical relationships between surface parameters and cutting conditions.

7 Capability in Machining Systems

7.1 Introduction

To be able to model a machining system and achieve a capability index would be a valuable tool for optimising the machining of parts. The usefulness of such a tool is associated with its level of generality as well as its possibility to recognise each machining system as an individual. The individuality is facilitated by a model with a general structure where machining systems are put together of modules. This would result in a capability index for a specific product machined in a specific machining system, in a specific environment.

A machining system consists of several physical parts working together, e.g. workpiece, fixture, machine tool, control system, tool holder and tool. The mechanical modules in a machining system may be considered as an open loop, which by a cutting process is connected into a closed loop, see figure 7.1. Each module in a machining system has an interface towards one or several other modules through which they interact.

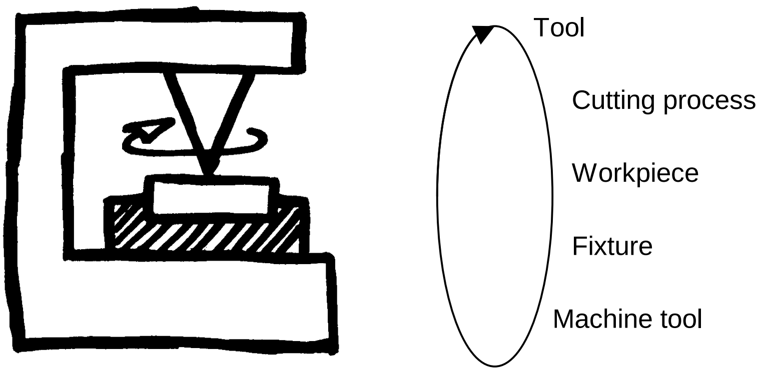


Figure 7.1. An illustration of a machining system and its interfering modules.

Capability index is used for showing how well a cutting process fulfils with given tolerances on machined parts. This result is derived from an existing machining system by measuring of one or more important characteristics of the machined parts, and the result is then used as basic data for calculating one or several capability indices, see figure 7.2.

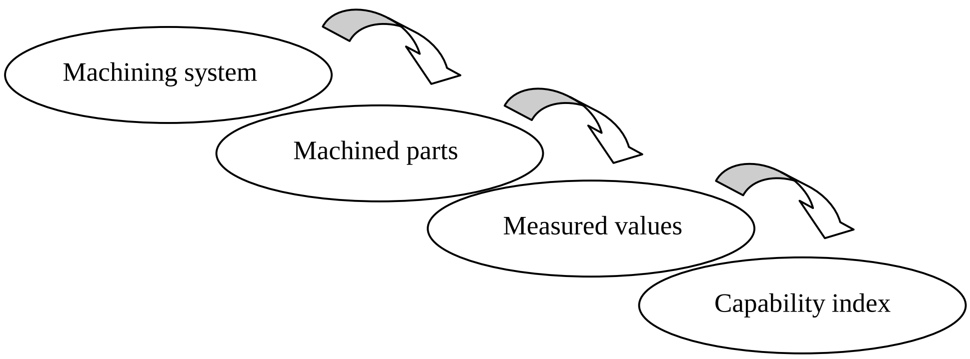


Figure 7.2. The arrows indicate the result transported between the course of events during the process of evaluating a machining system.

A machining system can be modelled both as an existing machining system, or an imaginary one. In the first case the modules of the system are put together and the measured properties of the system and its environment are given as input values of the model. The output value of the model is a capability index, see figure 7.3.

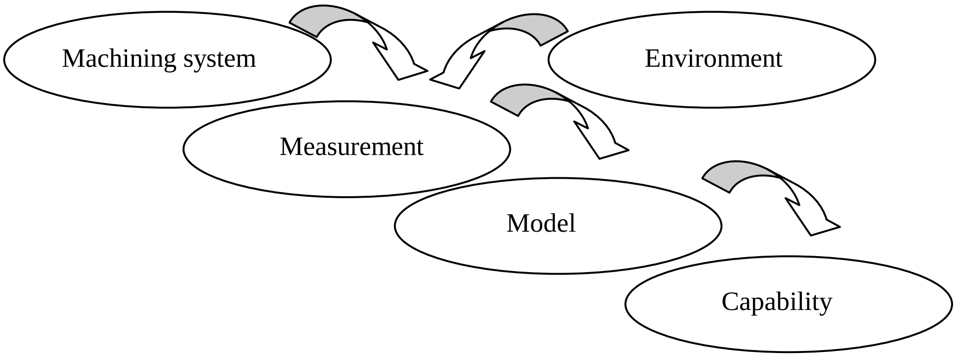


Figure 7.3. Properties from an existing machining system, affected by its environment, are measured and then used as input values for the model.

An imaginary system, on the other hand, is designed according to given requirements on the basis of experience. The design is modelled for evaluation. The necessary input values on properties are either achieved from previous experience or from similar modules.

The model is used for predicting the accuracy of machined parts. The result should illustrate properties of the part, e.g. dimensions, including the absolute value, the mean value and standard deviation. All processes are influenced by natural deviation. The resulting values of the property are compared with given tolerances whereby the capability indices can be calculated.

Working with capability index of a product naturally leads to several questions concerning how the process can be improved in order to achieve better parts. By “better” is here meant parts with properties as close as possible to target value. Modelling of machining systems would be a useful tool when optimising a machining process producing better parts.

Figure 1.1 in chapter one is valid as well to describe the process of simulating capability, see figure 7.4. The model consists of the five modules of a machining system and the values of their properties are added, and the resulting output of the model indicates one or several capability indices.

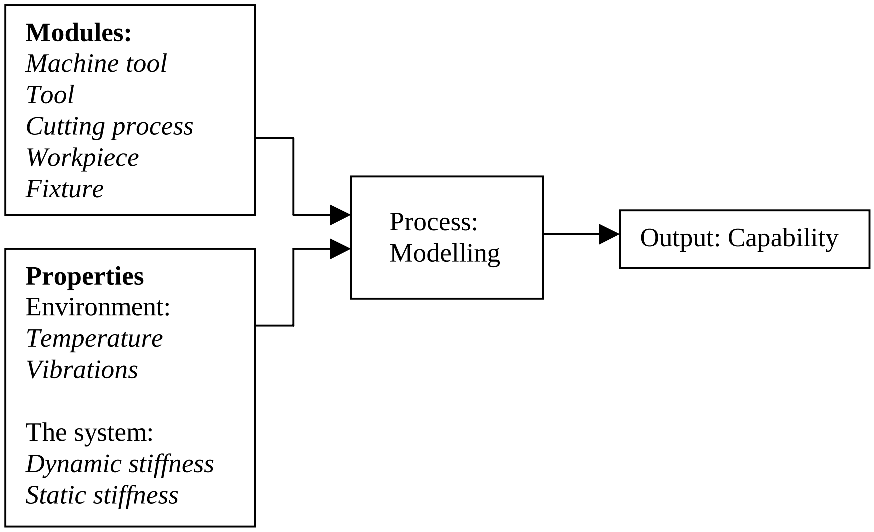


Figure 7.4. A way of visualising the process of simulation of a machining system.

Figure 7.3 shows four topics, which needs to be investigated and evaluated when working out a useful model of a machining system with capability as an output. The four topics are:

- Accuracy in a machining system
- Measurement
- Modelling and simulation
- Capability

The four areas illustrated in figure 7.5 The topics are illustrated in figure 7.5 and they are equally important to achieve a tool for modelling a cutting process in a machining system and with capability indices as an output.

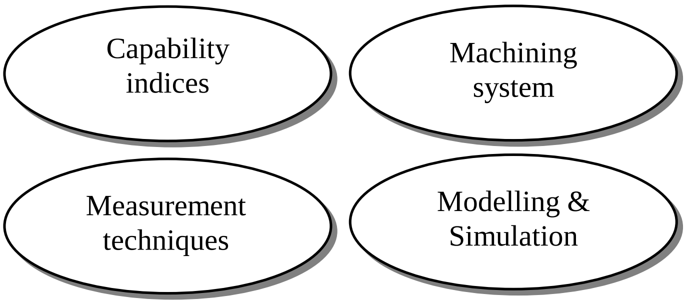


Figure 7.5. These are four topics necessary when predicting capability indices.

7.2 Predicting Machining Result Seen from a Value Adding Perspective

Predicting the result, i.e. the accuracy of parts of machining would give a possibility to optimise both the process and the machine tool affecting the result. Improvements are in close relation to products with properties close to target value, which thereby leads to a reduction of costs caused by quality losses. The following list includes examples of the use of process prediction.

- Evaluating changes of included modules in machining systems.

When one or several modules in a machining system is altered, the outcome of the cutting process will most likely not be the same as before. By evaluating these changes before they are installed, possible mistakes can be discovered early and necessary alterations can be made in advance. This makes sure that the intended improvements or changes in the system have the intended effect on the result.

- Optimising defined tolerances on parts.

The result from a machining process can be optimised with the aim of attaining target value and minimise the standard deviation and, thus, achieve a small tolerance interval. It is only meaningful to put effort in alterations of a machining process of this kind if the forthcoming result improves the functionality of the part or the assembled product. Realistically, efforts of this kind are demanding on resources and should therefore be thoroughly considered and deliberate activity.

- Optimisation of the use of machining systems.

If every machining system is evaluated and its capacity and level of accuracy is known, the manufacturing can be better planned, i.e. the most suitable system will perform the machining. In the case where several machine tools are capable of performing the necessary machining, the logistics of a workshop can be more optimal.

- Improve capability and increase quality on machined parts.

Quality of parts can be improved by manufacturing them with properties as close to target value as possible, and with a small standard deviation. High quality in this case stands for a product with no or small deviation from target value and a small standard deviation. A model of a machining system will give the opportunity to optimise the machining to reach the desired small deviations from the target value and the standard deviation.

- Evaluating a machining system during the design phase.

By evaluating a proposed design of a machining system, a number of changes can easily be done to guarantee a desired level o part properties. Alterations of a system during the design phase, are quicker performed and less expensive compared to alterations on the machining system. An early evaluation can also reduce the number of problems occurring during start up of a new machining system.

7.3 The Research Question

The question born from the given vision, which is guiding the present work is:

- *What is required to give a reliable simulated value of capability and accuracy?*

The question includes a constraint; the resulting capability value should be *reliable*. The vision gives a few more constraints. The tool for modelling and simulating need to be *general* since every machine tool, tool, fixture and workpiece is an individual, i.e. each and every individual has properties slightly different form each other. Furthermore, a tool used for predicting capability, which is meant to be used by many users, needs to be relatively *fast and easy to use*.

A method of structuring the research question is to make a schematic picture of the imagined system. The processes of interest are modelling and simulation of a machining system. Input data to the process is the machining system and its environment. The accuracy on a machined part is the output from the model and describes properties of the part. These values are then used to calculate capability indices.

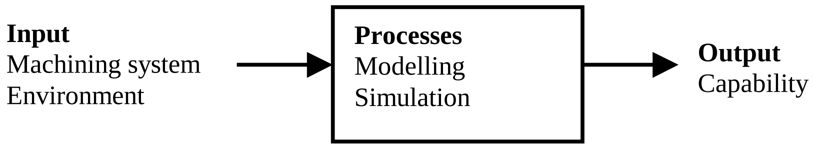


Figure 7.6. The process of modelling and simulation requires inputs to deliver the desired output.

To achieve a reliable and stable accuracy of machined parts, the robustness of the machining process needs to be improved. Robustness is the ability to withstand influences from different factors affecting a process [Phadke, 1989]. Reducing the sensitivity of processes to the most affecting noise factors will achieve two advantages; both an improvement of the accuracy of machined parts, and a more stable cutting process and thereby a more stable result of the machining.

The process in figure 7.6 can be expanded to illustrate important parts as in figure 7.7, which is an illustration of what in principle is required to achieve a solution to the research question. The outcome is one or several *capability indices*, and for this calculation some values are required, i.e. a mean value, standard deviation and the tolerance interval on the evaluated properties of the part. To achieve a statistical basis for the capability calculation, a sufficient number of *measured values* are necessary.

The *measured values* need to be simulated. The simulation in this case simulates a cutting process in a machining system, and the outcome is simulated measured values on a part. The simulation itself requires two things, *a model* and *input values*.

The *model* consists of six modules describing the machining system. Each module link together with two other modules when machining. The model will produce more accurate simulated values; the better and more detailed the model is. One of the modules is the machined part with the parameters, which is of interest to calculate capability indices from.

The model to be simulated needs *input values* describing the specific *parameters (characteristics)* of the modules included in the machining system and their interfaces. These input values are measured on the *machining system*, or on a similar system should the machining system of interest not exist (for example a during the design phase). Since a machining system is dependent on its *environment*, this is also measured (for example the room temperature) and used as input values for the simulation.

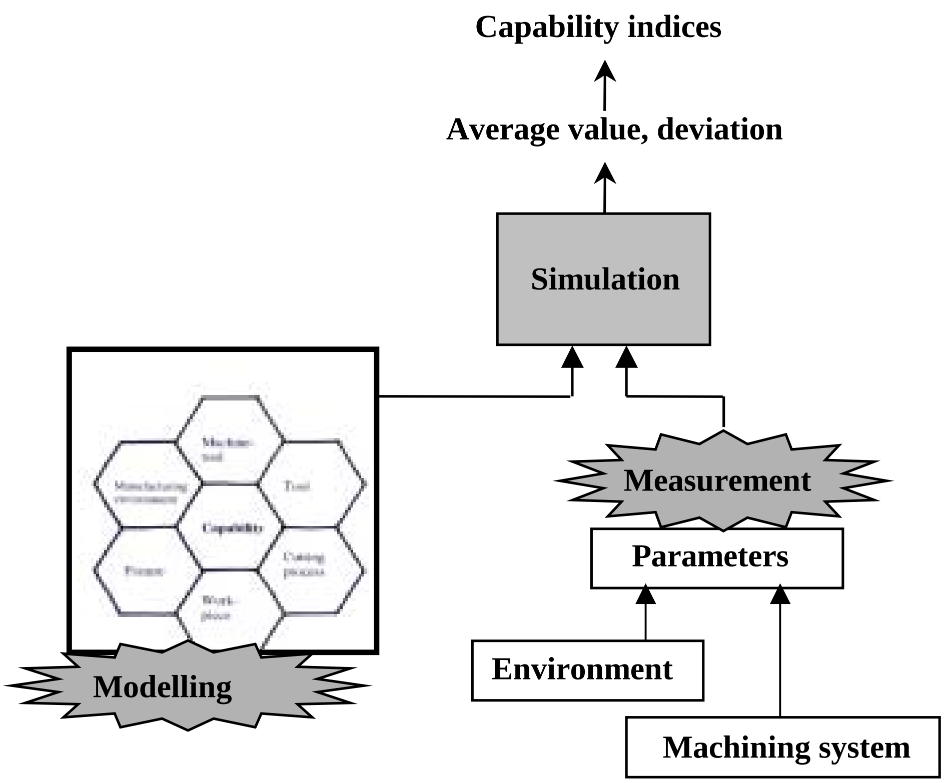


Figure 7.7. An illustration of the steps of estimating capability indices of a machining system.

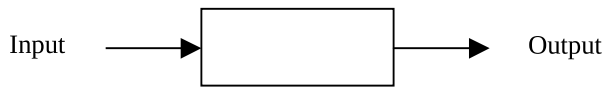
A tool estimating capability can be used for both evaluating the outcome of machining systems as well as predicting the result of potential changes in the system.

Simulations of a machining process can be used to improve the resulting output. Both the model and the input parameters can be alternated as to optimise the system to achieve a desired accuracy or capability index.

To make a tool useful, certain aspects has to be taken into consideration. It needs to be easy to use, reliable and the outcome must be easy to interpret.

7.3.1 Capability Indices as Output

The input values and its environment are specific for each individual machining system. As a result of this, the achieved capability indices are specific for the system.



The calculations of capability indices should fulfil requirements in a statistically reliable capability study; i.e. it should be calculated from a sufficient number of geometric dimensions on the part included in the model. The estimated capability index can not be more reliable than the input values.

The usefulness of a capability index is dependent on a thoroughly considered plan for how the index is going to be used. It can be used for evaluation, prediction and controlling of a machining system. The aim of the resulting capability index should be guiding the requirements on the input and output values as well as how the output result is to be presented.

To facilitate the understanding and the possibility to conclude from the resulting capability indices, illustrations on suitable diagrams are valuable, showing the result in relationship to target value, tolerances, standard deviation and mean value, see figure 7.8. An illustration of the result increases the possibility of drawing useful conclusions from the result.

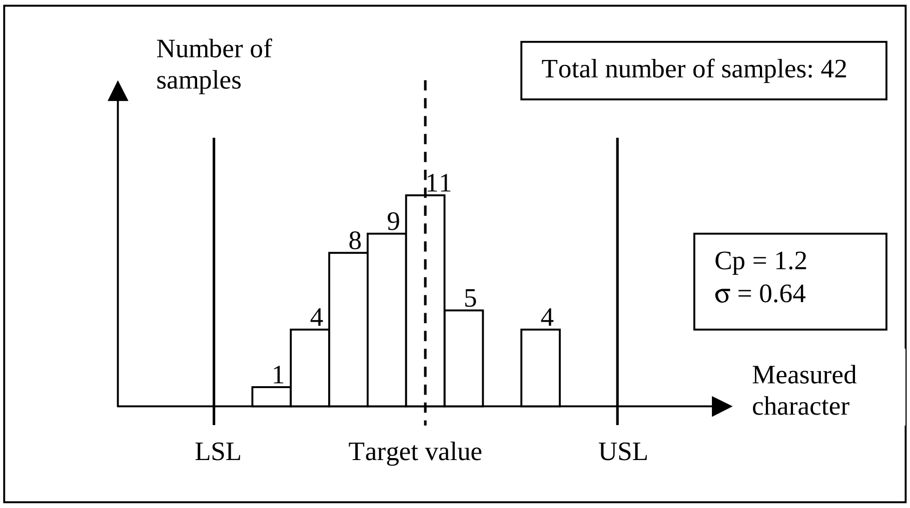


Figure 7.8. An example of an illustration of a process result.

7.3.2 A Model of a Machining system

The model of a machining system consisting of several modules: machine tool, tool holder, tool, cutting process, workpiece and fixture. Each of these modules has specific properties of their own and when put together they affect each other through their interfaces.

One property of a module can be reduced while another are increased due to interaction when co-operating as a system. Sensibility to temperature and vibrations are examples of properties affecting modules through interfaces.

7.3.3 Parameters

A model of a machining system requires input values (parameters) describing the system and its properties, as well as the environment. Estimations of capability indices require a model designed for predicting properties of machined parts.

Input values need to be sufficiently reliable to make sure the output is equally reliable, with the assumption of an equally reliable model.

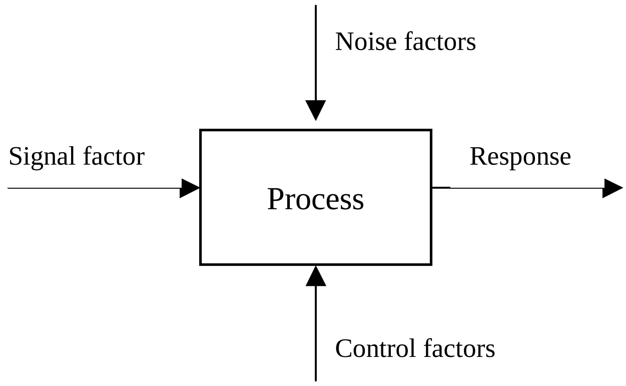


Figure 7.9. A P-diagram [Phadke, 1989].

A cutting process can be described in a P-diagram [Phadke, 1989] as follows: the *process* is cutting, *signal factor* is for example the used NC-code (Numerical Control code) and the *response* is the machined geometry of the part. *Control factors* might, for example, be feed rate and depth of cut. With these assumptions all other factors affecting the cutting process are thereby included in the *noise factor*. For further details about P-diagram, see figure 7.9 and section 1.1.7 in appendix A.

Some of the parameters affecting a machining system can be controlled and changed, others are very difficult to control or even unknown. Parameters that can be controlled and alternated can be defined as control factors and all other parameters are treated as noise factors.

- Characteristic data of a machining system

A model of a machining system needs both fixed and non-fixed variables. The cutting process has several non-fixed properties, e.g. cutting depth and feed rate. Every selection and combination of these two properties induce specific forces, vibrations and temperature affecting the machining system, and in turn the result of the machined part.

A machining system consists of several modules. The parameters of the machine tool are probably only to a certain extent affected by other modules in the system and by the environment. As a result it might be considered as a "black box" with very stable properties.

- Environment

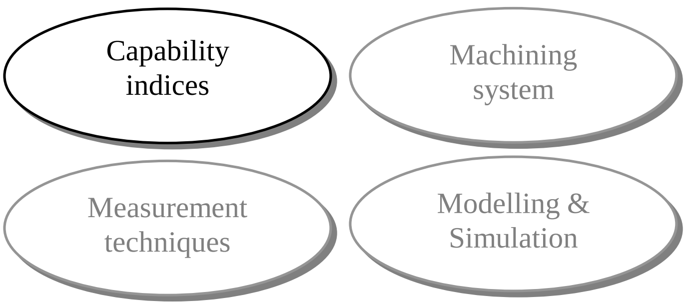
Temperature and vibrations affecting the machining system and thereby the resulting characteristics of the part, do not only origin from the machine itself. Heat and vibrations can be generated as well from other objects in the environment, e.g. sunshine and other machining systems.

- Measurement of Input Parameters

Input parameters from both the environment and the machining system must to be either estimated or measured. Parameter values used in a model need to be verified to make sure the final result will be as reliable and as close as possible to the real values. Performed experiments and tests can verify the parameter values.

7.4 The Use of Capability Studies

The first of the four groups in figure 7.5 is capability indices. In order to draw useful and reliable conclusions from different capability indices, it is important to understand the difference between each capability index.



Characteristics of machined parts are registered and evaluated by calculating one or several different capability indices, see chapter 3. It is a delicate question to decide which characteristic or characteristics of a part that are the most useful to evaluate. Performing a capability study takes time and must therefore be thoroughly planed as not to prolong the handling time more than necessary. The mechanical drawing of the part to be machined is an aid when deciding the characteristics (e.g. diameter) to use in the capability study. The machined part is the result of a machining process and therefore capability indices can be used for evaluating the process. Examples of the use of capability indices are:

- If a machining process produce parts according to given requirements, e.g. geometric tolerances, or not.
- An alteration of a cutting process, e.g. when a tool or a machine tool wears out, can be indicated by the change of a capability index. The change requires adjustment or maintenance of the machining system.
- Evaluating new machining systems with reference to how it fulfils given specifications.

Predicting capability indices with a model of a machining system can be used for evaluating a machining system. It can for example be used for:

- Evaluate alternations in a machining system to make sure they correspond to the expectations on improvements.
- Evaluating the result of adjustment or maintenance of a machining system.
- Evaluating a new machining system during the design phase to make sure it fulfils given specifications on machined parts.
- Evaluating new machining systems during the design phase to make sure they are robust against disturbing noise.

A capability study of either a model or an available machining system can be useful when working with improvements. In both situations, i.e. when capability indices are calculated from measured values and when it is predicted from a model, it is important to interpret the result correctly. This requires a thorough understanding of the limitations of capability indices and the assumptions made when designing the model, choosing input parameters and capability indices. It is equally important to have a clear idea of how the indices are going to be used; this in order to chose the best index for a specific situation. In other words, the aim of an evaluation of a process to be performed needs to be clearly defined.

7.4.1 Accuracy Defined as Standard Deviation and Mean Value

Capability indices give a value on how well the result of a studied process accord with a tolerance interval, a tolerance level or a target value. Since it is easy to achieve a good capability value with a large tolerance zone, it is easier to draw conclusions from a capability study if it is graphically presented as in see figure 7.10.

A product assembled of parts with geometric characteristics very close to target value and with a small standard deviation will function better than the same product assembled of parts with fluctuating values. Better functioning products generates more satisfied customers [Phadke, 1989]. This implies that the target value and standard deviation of the characteristics of a part are important for evaluating a process. An easy method of describing how well a process succeeds might be to calculate a standard deviation and a mean value and compare these with given target value and tolerances.

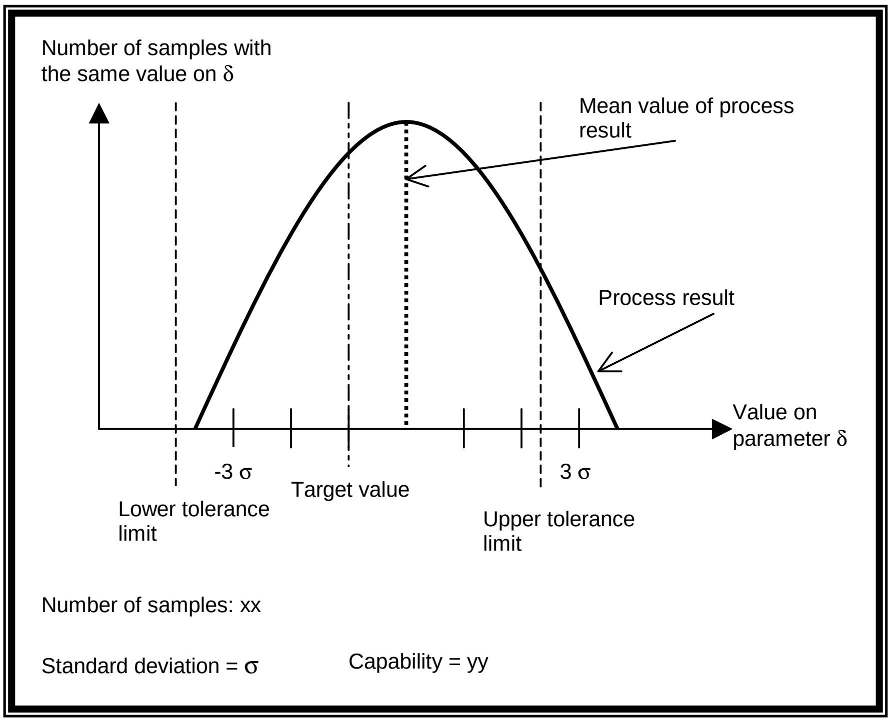
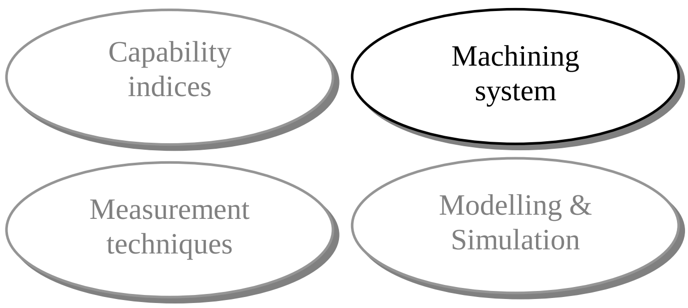


Figure 7.10. An illustration of process result compared with target value and standard deviation.

7.5 Accuracy in a Machining System

The second group is about machining systems and their accuracy. The overall accuracy in a machining system is the result of the characteristics of the assembled parts as well their interactions during machining.



The geometry in a machine tool is built by the aid of three axes; x, y and z. An important property of these axes is the mutual relationship to achieve a correct tool path of movement in the three-axis space. The characteristic of success is for example repeatability and positioning. These characteristics are usually measured on an unloaded machine tool, i.e. not during machining. As a result the measured values are valid for an unloaded machine tool, and for a prediction of the actual behaviour of the machine tool during machining.

A capability index, as an overall accuracy of a machining system, is measured on a machined part, thus reflecting the accuracy of a machining system affected by the forces from cutting. But to get knowledge about the factors that accumulate in accuracy of the system, it is necessary to learn details of each module in the system.

The accuracy of a machining system described as a capability index, is a result of co-operation of all modules included in the machining system, see figure 7.11. They act and change due to forces, temperature deviations and vibrations originated from rotating parts, motors and cutting process within the machining system, as well as from the environment.

If the resulting capability indices do not prove to be sufficient, one or several parameters of the machining system have to be altered. This is a task requiring thorough knowledge and experience of machining systems.

7.5.1 Test on a Machine Tool with DBB

This test is an illustration of measurement of the behaviour of a machining system. The test on a machining centre was performed with the aim of detecting if the ability of the machine tool to make geometric shapes is dependent on the position of the working table, the feed rate and or the size of the shape.

For detecting the assumed difference a Double Ball Bar [Renishaw] is used as measuring tool. Robust design is used as a method for experimental design. For more information about the method, see Phadke [1989] and appendix A.

Double Ball Bar, DBB

DBB is a measuring method for evaluation of machining systems. The method detects deviations from moving along the geometric shape of a circle. The equipment used for performing the test is a telescopic arm attached to two magnetic spheres, one placed on the machine table and the other in the tool holder. The circle interpolation test can be made with different radiuses in both lathes and turning machines.

The equipment detects the difference in radius from a perfect circle by the movements of the telescope arm while it is turned around making a circle. The test is performed both clockwise and anti-clockwise.

The equipment can be used both for static and dynamic tests. Dynamic test gives information of the ability of machining systems to move in a perfect two-dimensional circle. The software evaluates the result and presents the size of the errors. Examples of errors are scaling errors and deviations from perpendicularity between machine axes.

Static test gives information about geometric accuracy and repeatability. Figure 7.11 shows an illustration of the DBB equipment [Renishaw Ballbar Diagnoshandbok].

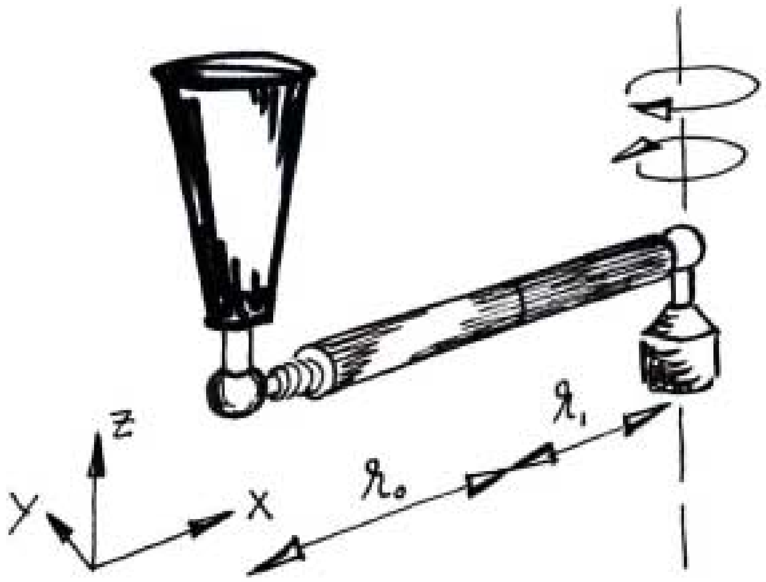


Figure 7.11. The figure shows DBB equipment from Renishaw. Changing r1 into a longer piece, or not using it at all, alters the length of the arm and so attain different radiuses.

Performed experiments

The experiments are performed in a three-axis machine tool, a Mazak, at the Royal Institute of Technology, KTH. The machining center has a maximum spindle speed of 4000 rpm.

The measuring equipment made circles at three different positions at the worktable, with three different radiuses and three different feed rates. The number of possible combinations of these three parameters each with three levels is quite substantial, why **parameter design** has been used. For further details about parameter design, see appendix A.

The used radiuses are 100, 150 and 250 mm and the feed rates are 500, 3000 and 4000 mm/minute. The positions at the worktable are described in figure 7.12.

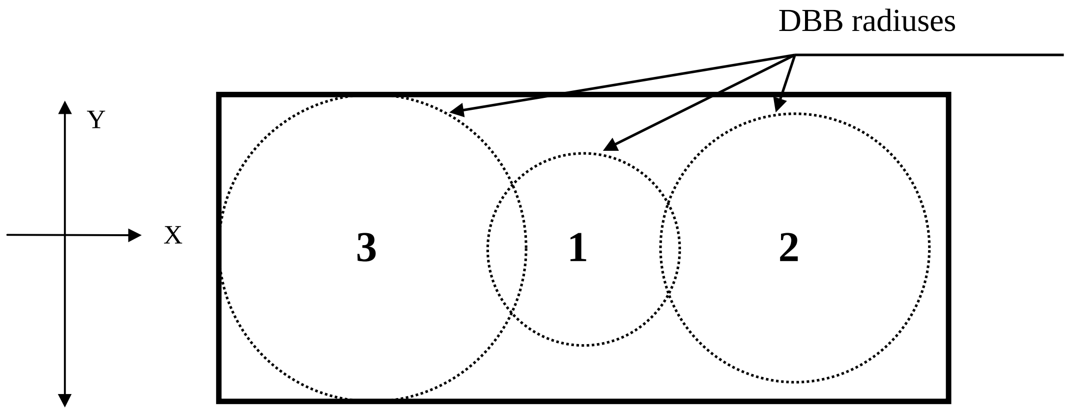


Figure 7.12. Position 1, 2 and 3 at the worktable.

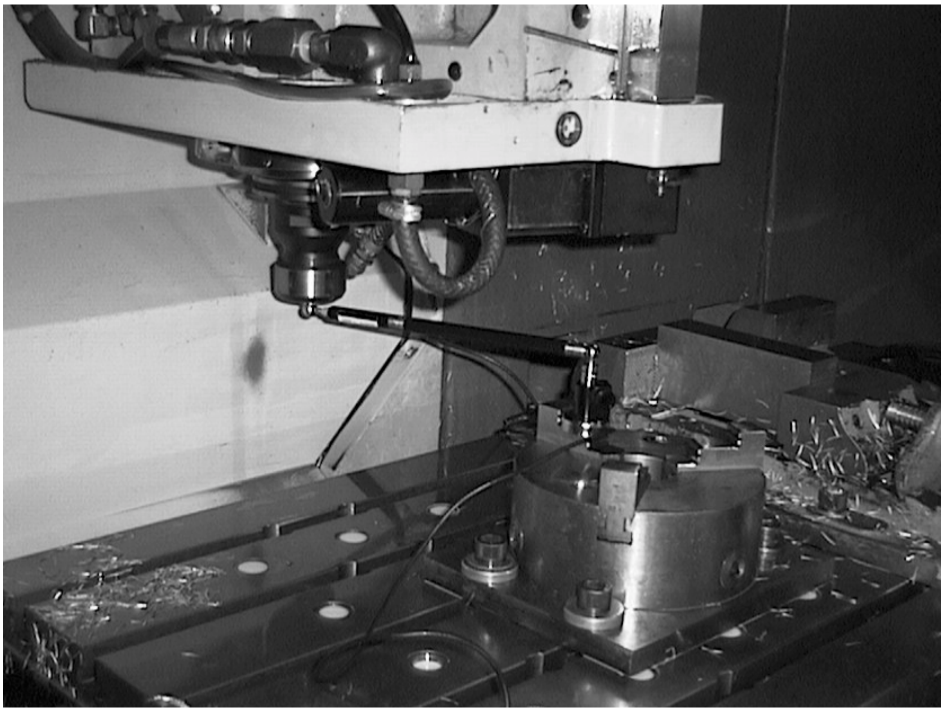


Figure 7.13. The DBB equipment placed in the machine tool.

Choice of factors

Signal factor: Order the Numerical Control system (NC-system) to make a circle in the XY-plane.

Noise factor:	Geometry, kinematics (positioning). Temperature deviations. Static and dynamic stiffness.
Control factor:	Feed rate. Position at the worktable. Radius of the circle.
Control factor:	Feed rate.
Response factor:	A perfect circle in the XY-plane.
Process:	Interpolation of a circle.

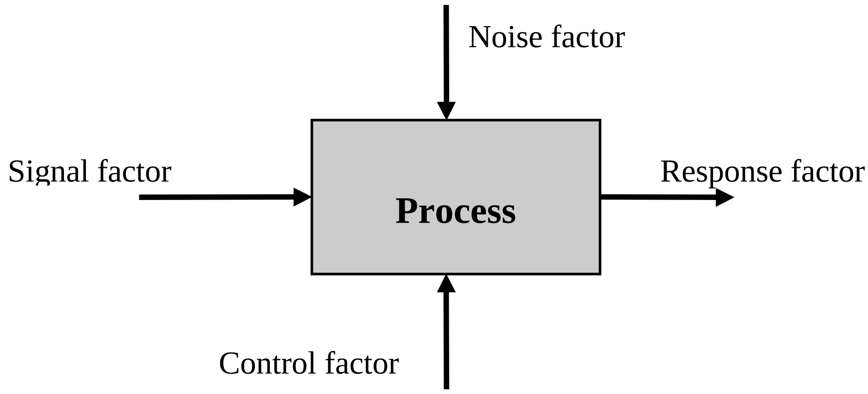


Figure 7.13. A P-diagram describing the factors in relation to the process, [Phadke, 1989, p 30].

- Signal factor

In this case the signal factor is the order given to the machine tool to move in a perfect circle with specific radiuses, positions on the working table and speeds. The signal is programmed by the operator and transmitted by the NC-program to the machine tool.

- Noise factor

These are the factors that can not, or is chosen not be possible to control. A machining systems is affected both of internal and external factors. Some of them are known and others are not. The interplay between factors is also mostly unknown. Noise factors on a machine tool can be divided into four groups as the following:

Geometry affects from the mechanical parts of the machine toll, e.g. scale and servo engines.

Temperature differences are induced in the machine from both internal and external sources. Room temperature and heat from chips affects the machine tool, as well as heat induced when running its engines motors and friction between parts when running the machine.

Dynamic factors are vibrations from both external and internal sources.

Static factors are the stiffness or rigidity of the machine tool, i.e. how much it flexes during load.

- Control factor

The three control factors of this test are position on the worktable, rate of speed and radius of the circle. The worktable is mostly used in the middle, i.e. position 1, see figure 7.14.

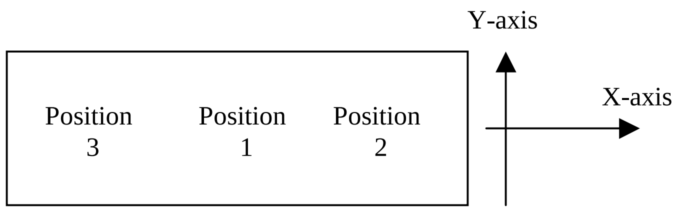


Figure 7.14. The three positions at the worktable.

- Response factor

In this case the response factor is a perfect circle, independent of feed rate, radius or position. In this test the level of "perfect" circle is evaluated as circularity. Circularity is defined as the difference in radius between two concentric circles encircling the measured circle.

- Process

A signal factor will be transformed into a response factor by a process. The process in this case is to take the signal factor and convert a radius, feed rate and position to the response factor a circle.

Delimitation

The measurements are done in XY-plane of the machine tool, i.e. the working table. Measurements can be done in XZ- and YZ-plane, but in this case the XY-plane is considered the most interesting.

The maximum radius that is used is 250 mm; this lead to a limitation in possible positions in Y-axis since the working table is 500 mm wide.

Since the working table has fixtures mounted to it the sphere of the DBB-equipment attached to the working table ended up being on different height from the working table (Z-axis). Tests are performed on three different positions along the X-axis.

These tests are performed in a cold machine tool i.e. the machine tool was not warmed up the tests began. This might somewhat affect the result.

Choice of orthogonal array

The orthogonal array L_9 (3^4) is an array with nine rows and four 3-level columns, see table (7.1), and it is suitable for this experiment.

Experiment No.	Factor 1	Factor 2	Factor 3	Factor 4
1	1	1	1	1
2	1	2	2	2
3	1	3	3	3
4	2	1	2	3
5	2	2	3	1
6	2	3	1	2
7	3	1	3	2
8	3	2	1	3
9	3	3	2	1

Table 7.1. This table shows an L_9 (3^4) orthogonal array.

This array corresponds to the experiment layout in table (7.2).

Experiment No.	Positioning	Feed rate	Radius	Factor 4
1	1	500	100	empty
2	1	3000	150	empty
3	1	4000	250	empty
4	2	500	150	empty
5	2	3000	250	empty
6	2	4000	100	empty
7	3	500	250	empty
8	3	3000	100	empty
9	3	4000	150	empty

Table 7.2. The layouts of the experiment showing the three parameters that are altered (position, feed rate and radius).

The experimental layout is design in order to reduce the number of necessary experiments but still achieve a reliable result.

Circularity

The resulting circularity is the software defined according to the ISO 230 standard. Circularity is defined[3] as the difference in radius between two concentric circles encircling the measured circle, see figure 7.15. Circularity is here measured in µm (10^{-6} m).

[3] ISO 230-1:1996 (E), 6.6 Circularity, 6.61 Definition, (in Swedish).

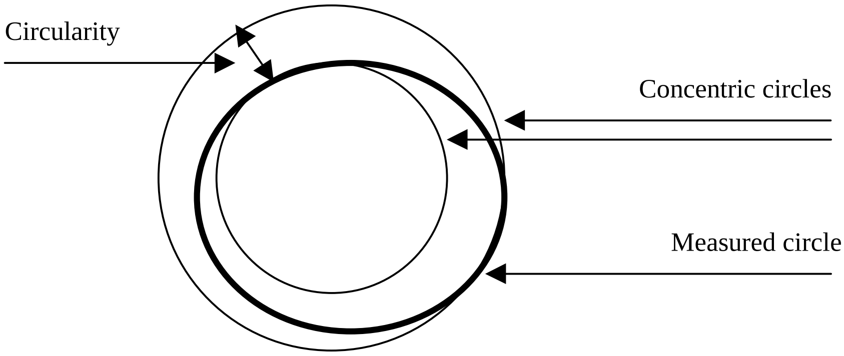


Figure 7.16. Circularity is defined as the difference in radius between two concentric circles encircling a measured circle.

Result from measuring circularity

The software of the DBB equipment calculates the errors and states these in percentage of the total error. Figure 7.16 is the result from one of the measurements. The printout shows the result from both the clock wise and counter clockwise measurement, which are shaped more like a peanut than a perfect circle. In this test the servo mismatch is 49% of the total error and the circularity in this case is 72.8 µm. All test results are shown in appendix C.

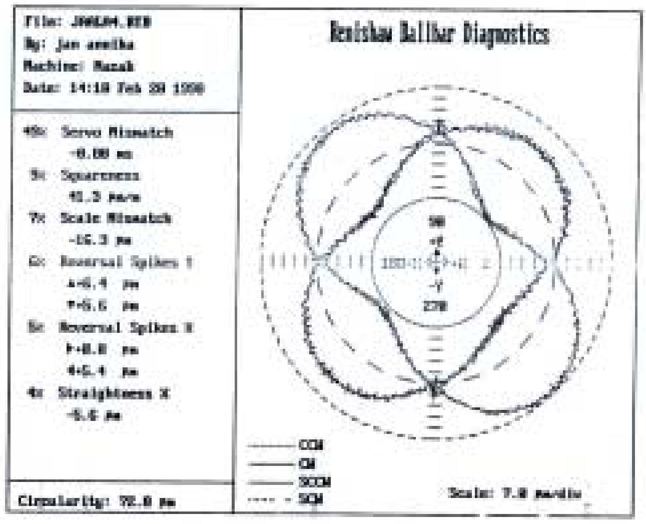


Figure 7.16. This is the result from one of the DBB measurements. CW is clockwise and CCW is counter clockwise.

From each of the nine performed experiments the resulted circularity has been used to calculate a result. The result is calculated as a signal to noise ratio, S/N (dB). S/N = -10·log10(circularity), see table (7.3).

Experiment No.	Position	Feed rate	Radius	Cicularity	S/N
1	middle (1)	500	100	21,5	-13,3244
2	middle (1)	3000	150	55,5	-17,4429
3	middle (1)	4000	250	72,8	-18,6213
4	right (2)	500	150	27,5	-14,3933
5	right (2)	3000	250	60,6	-17,8247
6	right (2)	4000	100	66,9	-18,2543
7	left (3)	500	250	51,2	-17,0927
8	left (3)	3000	100	58,2	-17,6492
9	left (3)	4000	150	73,4	-18,657

Table 7.3. The layout of the nine performed experiments shows the values of the parameters.

The signal to noise ratio can be used to visualise the result. The average of the three S/N-values of each factor is calculated and then compared in a diagram, see table (7.4).

Feedrate	S/N	S/N average
500	-13,3244	
	-14,3933	
	-17,0927	-14,9368
3000	-17,4429	
	-17,8247	
	-17,6492	-17,6389333
4000	-18,6213	
	-18,2543	
	-18,657	-18,5108667

Table 7.4. The S/N-value for the three different feed rates.

Position and radius is calculated in the same way. Thus the resulting values can be visualised and evaluated in figure 7.17.

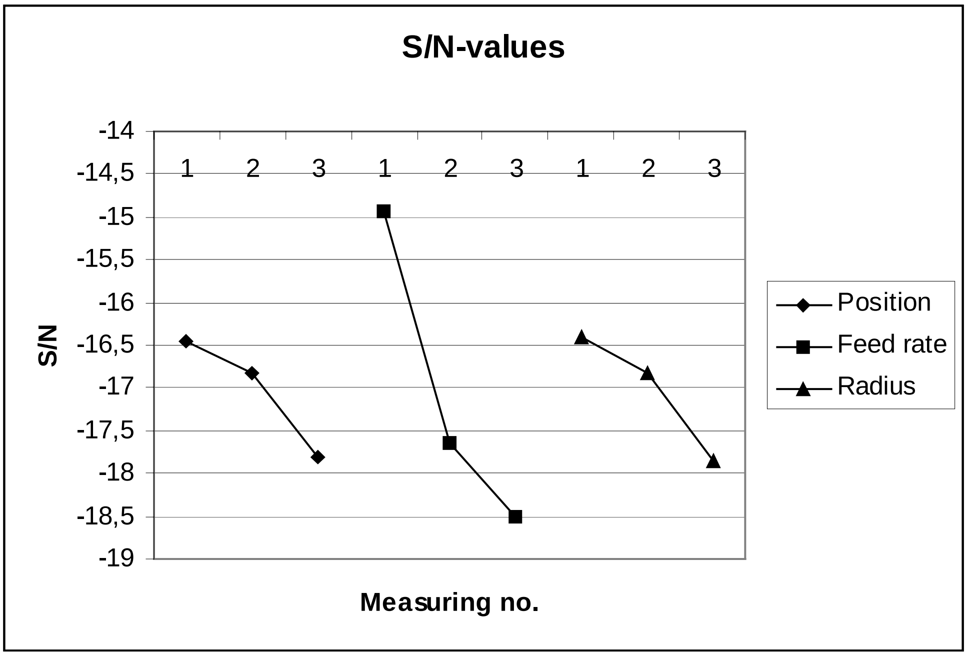


Figure 7.17. S/N-values of each factor is calculated and then compared.

The first three values shows the effect of the position on the worktable, the three values in the middle the feed rate and finally, the last visualises the effect of the radius. This result implies that the ability of the machine tool to move in a circle is best:

- In position 1, i.e. the middle of the worktable
- With the slowest feed rate
- With the smallest radius.

This result gives some guidance on performance of the machine tool. It can also be interesting to know, or to estimate to what degree the three factors affects the total difference from a perfect circle. This can be done with ANOVA, Analysis of variance, which is used to determine the significant effects in a fractional factorial experiment.

No.	Circularity x	S/N (=10*log(X))	(=S/N-medel)^2	
1	21,5	-13,32	13,72	
2	55,5	-17,44	0,171	
3	72,8	-18,62	2,536	0,961
4	27,5	-14,39	6,946	
5	60,6	-17,82	0,633	
6	66,9	-18,25	1,501	0,1257
7	51,2	-17,09	0,004	
8	58,2	-17,65	0,038	
9	73,4	-18,65	2,651	1,7822

Table 7.5. The quadric average for circularity.

The quadric average for each factor is the "square sum" divided my "degrees of freedom", see table 7.6. The F for the three factors, position, feed rate and radius is calculated by dividing the "quadratic average" with the "square sum" of the error. The bigger the value of F, the bigger affect on the resulting circularity. In this case the feed rate affects the resulting circularity more than the position on the worktable and the radius.

Factor	Degrees of freedom	Square sum	Quadratic average	F
Position	2	2,869	1,435	1,824
Feed rate	2	20,836	10,418	13,244
Radius	2	3,273	1,637	2,081
Error	2	1,573	0,787	
Total	8	28,551		

Table 7.6. This is the result of the ANOVA-test.

The result of the test
All in all, the result of the test is:

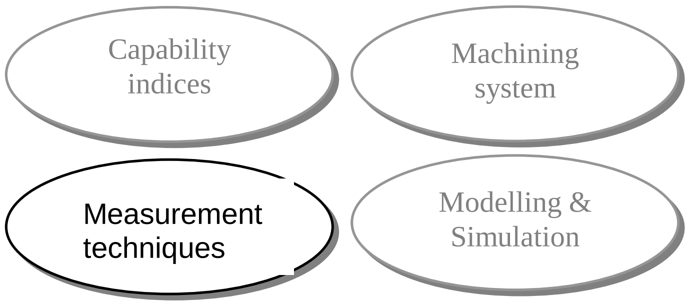
- The machine tool has the highest value of circularity at position 1, i.e. the middle of the worktable.
- The slower the feed rate, the better value of circularity.
- The smaller the radius, the better value of circularity.

The result of the test is analysed by Analysis of variance, ANOVA. This showed that the feed rate affects the resulting circularity more than the position on the worktable and the radius.

The result of the test is not per se the real result; but it is knowledge of how to perform tests in order to increase the understanding of the behaviour of the machining system. Understanding and experience of machine tools is the basis for a well thought-out alternation of the machining system to optimise accuracy or capability indices.

7.6 Measurement

The behaviour of a machining system and its affecting factors can be quantified in numbers i.e. measured. These numbers are used as input parameters in a model and thereby used for analysing and verifying the accuracy of a machining system. This analyse of the system can be used for optimisation and improvements of the accuracy.



The relationship between a machining systems and the corresponding model, are measurements. Input values describing the properties of the machining system, or its modules, is measured on either the system itself or from a similar system.

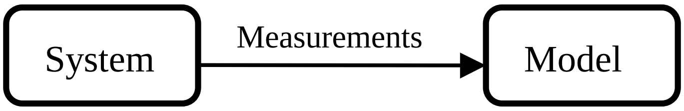


Figure 7.18. Measurements are the link between a machining system and its model.

A machining system is a system of modules connected to co-operate as a machining system. What is considered as a module and a system depends on the situation, e.g. a machine tool can be considered as one module or a system consisting of several modules.

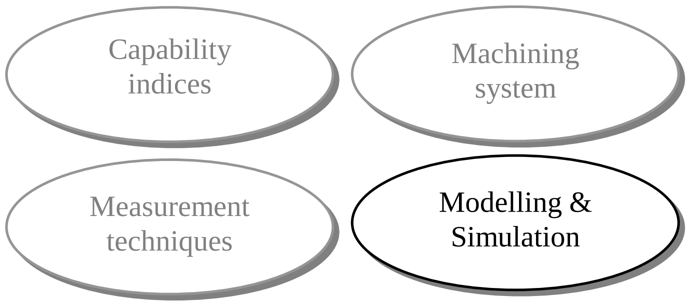
The reliability of predicted capability indices estimated by a model is dependent on the reliability of input values. These input values are either measured on a complete system or part of a system, see figure 7.18. When judging the reliability some aspects has to be taken into consideration, for example:

- A measured value has a normal deviation.
- To know what property is being measured, if it is affected by its environment and in that case how much it is affected.
- The measuring error and its effect on the resulting value.

The data used to calculate capability indices originates from machined parts. As a result a capability index represents an indirect value of the accuracy, i.e. a value including all errors in the co-operating machining system. Measurements performed on machined parts have a restricted use for optimisation of the machining system since they have a limited possibility to show individual errors in the system. This is due to the fact that it is difficult or impossible to extract sources of errors in the machining system from results on a machined part.

7.7 Models of a Machining System

By the use of a model of a machining system it is possible to evaluate the accuracy of parts and changes in the machining system. This is an effective way of experiencing a system without having to perform expensive and time-consuming test on real machining systems.



As it is difficult to make a model as an exact fingerprint of the system, it is instead designed to resemble; thus, the model will be a simplification. But in accordance with more knowledge about the behaviour and properties of the modules and the machining system, the more reliable the model will be. The reliability of a model is also improved with increased knowledge about the rules and regulations determining the behaviour of a module or system. In addition to this, it is important with a clearly defined aim of the use of a model and its included characteristics of the system.

The more useful a model of a machining system is the more reliable will the model be. The possibility to simulate the effect of affecting properties on a machining system or parts of it is essential, for example:

- Getting knowledge and experience of the behaviour of a machining system by alternating properties of the system and compare the result.
- Learning about the co-operation of several properties when functioning together.
- Making cost effective tests in order to reduce the number of mistakes due to for example wrong tolerance setting and sensitivity to temperature changes.
- Making it easier to discuss a suggested solution on improvements of a machining system by visualising its consequences.
- Reducing the number of test. Using simulations of a model is less expensive and time-consuming compared to full size tests.
- Evaluating maintenance of a machining system to make it cost and time effective.

'Usefulness' is a descriptive word describing the overall demands on a tool for making models and for simulating environments. Demands on a tool for making models for predicting capability indices are for example:

- The model of a machining system needs to be sufficient accurate to give reliable capability indices.
- Tools for making a model of a machining system need to be easy to use.
- The result from simulating a model has to be easy to understand and draw conclusions from.
- It needs to be easy to alter a model when optimising the system; i.e. to alter properties of included modules for example part, tool, cutting process or fixture.
- Both modules and machining systems are individuals, which is to be taken in account when considering a model.

7.8 Summary

The research question guiding this work is:

- *What is required to give a reliable simulated value of capability and accuracy?*

A method of structuring the research question is to make a schematic picture of the process, see figure 7.19. The processes of interest are modelling and simulation of a machining system. Input data to the process is properties of the machining system and its environment. The accuracy on a machined part is the output from the processes. These estimated values are then used to calculate capability indices

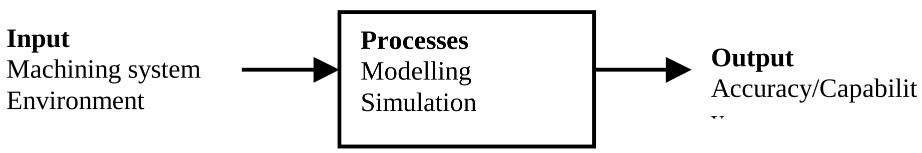


Figure 7.19. The process of modelling and simulation requires inputs to deliver the desired output.

To achieve reliable simulated values of the accuracy of a machining system, four areas have to be mastered.

- Capability indices as a statistical method
- Machining system and their characteristics
- Measurement techniques
- Modelling and simulation

A thorough understanding of the possibilities and limitations of each of the four areas is necessary to achieve a reliable and useful result from a simulation of a model.

The accuracy of machined parts can, depending on the situation, be evaluated either by capability indices or by the average value combined with a standard deviation. In whatever way the accuracy is presented, it is important to carefully plan and clearly define the aim of the evaluation in order to be able to make the most use of it.

Predicting the accuracy of machined parts give a possibility to optimise the machining process to increase the accuracy of the part. This can be used for several cost-effective activities:

- Evaluating changes of included modules in machining systems.
- Optimising defined tolerances on parts.
- Optimisation of the use of machining systems.
- Improve capability and increase quality on machined parts.
- Evaluating a machining system during the design.

With other words, a tool for evaluating the accuracy from a complete model of a machining system would be very useful to have.

8 Summary and Conclusions

8.1 Summary

The vision of simulating capability indices is derived from the vehicle industry where machining by cutting processes is common. The accuracy of these machined parts is important since they are assembled into a product with high demands on functionality. When assembling parts into a product the tolerances of the parts co-operate and the result of this gives the final functionality.

The accuracy of a machined part is the result of properties of the total machining system and its environment. Properties of machined parts will always slightly differ due to natural deviations, but to improve accuracy in a machining system it is important to master the deviations caused by every other reason than the natural deviation.

The vision of simulating a model of a machining system with the aim of predicting capability is a comprehensive task. The research question derived from the vision, which also guides this thesis, is to be looked upon as a beginning for further studies concerning the subject. This thesis consists of investigations of required areas to achieve a reliable capability index.

8.1.1 Scientific Value

The first three steps in the method used in this thesis is:

- Analyse what is.
- Imagine what should be.
- Create what has never been.

An analysis of the research question gives the answer that there is a need to be able to simulated a machining system in order to achieve a reliable value of accuracy, in this case a capability index, on machined parts. A further analysis of the research question results in the fact that a combination of four areas is necessary when predicting reliable accuracy values and capability indices.

Continuing with the second step, imagine what should be, gives simulation as a tool for predicting the accuracy of a machining system. The thesis combines two fields, firstly, capability indices as a statistical tool and secondly, simulation as a tool for predicting accuracy and thereby the capability.

8.1.2 Novel Aspects of This Work

The novel aspect of this work is the approach to the subject by combining the two fields of capability indices and of simulation as a tool for predicting capability indices. The thesis comprises several relevant research areas, both from a scientific and an industrial point of view, well worth further research.

8.2 Conclusions

This work concerns the subject of predicting capability indices of a machining system by the use of a simulation system. The aim of the present thesis was to increase the understanding of the research question defined as:

"What is required to give a reliable simulated value of capability and accuracy?"

From the result obtained in the present study, the following conclusions can be drawn:

1. Accuracy of machined parts is an important subject for industry since the accuracy affects the properties of the part. By having control over a machining process in a machining system the yield will improve. It is a challenge to fully control the characteristics (including accuracy) of machined parts due to the large number of affecting properties as well as due to the high demand on reliability. To be able to predict properties in a reliable way is of great importance for industry because it results in improvements and better control of tolerances on a certain part, which in turn leads to better properties of the assembly.

2. The possibilities and advantages with a simulation system predicting the outcome of a machining process are numerous, for example:

- Optimisation of cutting processes and thereby the machined part.
- A more robust design of machining systems.
- Error detection in a machining system.
- Concurrent engineering i.e. reduces the number of mistakes and unforeseen courses of events when designing a machining system.

3. To be able to predict capability indices for both existing and future machining system it is necessary to have thorough knowledge in four areas; *capability as a statistical tool*, *accuracy in machining system*, *measurement tools and methods* and *modelling and simulation*.

Short summary of the theoretical studies of each area.

➢ Capability indices

To achieve a reliable capability index, the capability study needs to be properly planned, performed and evaluated. The statistical method of capability indices needs to be well known in order to choose index, to compare different indices and to be able to make comparisons between indices from several machining systems.

➢ Machining system and their properties

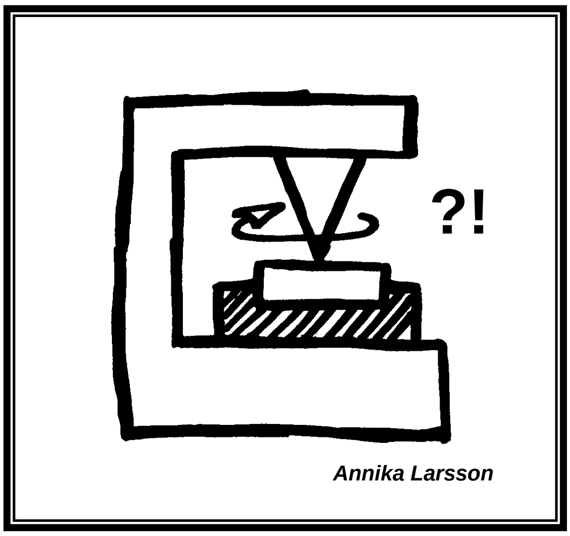
A machining system can be described as a system consisting of five modules: workpiece, fixture, machine tool, tool and cutting process. Properties of the whole machining system are depending on properties from each module and the interface between them. The cutting process, the environment and the machining system itself effects the properties of the machining system and thereby the machined part. The machining accuracy of a machining system is dependent on four groups of characteristics: temperature influence, geometry and kinematics as well as static and dynamic stiffness.

➢ Measurement tools and methods

The measurable result of a cutting process, i.e. the properties of a part, is an indicator of how well the process corresponds to given tolerances. Input values to be used in a model of a machining system need to be measured, i.e. characteristics of each module (including the machined part), the machining system and its environment. Different tools and methods can be used. For reliable results the measurement activities need to be planned, performed and evaluated with the forthcoming use in mind.

➢ Methods and tools for making models and for simulation

For a reliable and useful result, the model as well as the simulated environment need to be sufficiently consistent with the machining system in question. There are a great number of models available for cutting processes, process state variables (e.g. cutting force and temperature) and different modules of a machining system. Usually, these models can only be used discretely since there is almost no relationship between the structures, required data and assumptions of the models. It is therefore not yet possible to model and simulate a machining system and take into consideration all of its characteristics (e.g. temperature influence, static and dynamic stiffness) to achieve a reliable accuracy value.



8.3 Future Research

In this thesis you will find questionable and or inspiring sections, which might lead to future research. This section includes a few indications for future studies to be performed.

- Capability indices

Today there is no standardised way as to acquire a capability value, i.e. which indices that should be used and in which situation. It will be useful for the industry to have standardised ways to choose and calculate capability indices. A standardisation will for example make it possible to compare capability studies performed by different companies.

- Modelling of a machining system

It is highly desirable to be able to model and simulate a machining system and take into consideration all of its characteristics (e.g. temperature influence, static and dynamic stiffness). A complete and reliable model will give the possibility to achieve a reliable accuracy value corresponding to a real outcome on machined parts.

- Machining system

It is desirable to get knowledge of the characteristics of machining system as to increase the robustness of systems. By increasing the knowledge of the connections between noise and signal factor and how they affect the response factor, it might be possible to design machining systems, which are less effected by factors that can not be controlled. This will also give a system with a high repeatability on the characteristics of the part. A robust machining system will also be easier to model.

9 References

Bergman, B., Klefsjö, B., (1991), *Kvalitet från behov till användning* (In Swedish), Studentlitteratur, ISBN 91-44-33411-7

Boyles, R. A., (1991), *The Taguchi Capability Index*, Journal of Quality Technology, Vol 23: 17-26

Breyfogle, F. W., (1991), *Statistical methods for testing, development and manufacturing*, John Wiley & Sons, Inc., ISBN 0-471-54035-8

Carlsson, T., (1998), *Modern Verkstadsmätteknik* (In Swedish), Royal Institute of Technology, Inst. för Materialens Processteknologi, Produktionsteknisk mätteknik.

CIRP, (1990), Nomenclature and Definitions for Manufacturing Systems (English Language Version), Annals of the CIRP, Vol. 39/2/1990

Deleryd, M., (1995*), Duglighetsstudier i svensk industri – resultat från en enkätstudie* (In Swedish), Research Report 1995:6, Division of Quality Technology & Statistics, Luleå University

Deleryd, M, (1996), *Process Capability Studies in theory and Practice*, Licentiate Thesis 1996:06 L, Luleå University of Technology, ISSN 0280-8242

Doty, L. A., (1996), *Statistical process control*, Industrial Press Inc., ISBN 0-8311-3069-5

Ejvegård, R., (1993), *Vetenskaplig metod,* (in Swedish), Studentlitteratur, Lund, ISBN 91-44-36612-4

Hallendorff, C. J. H., (1979), *Verktygsmaskiner* (In Swedish), Karlebo-serien 8, ISBN 91-85026-26-3

Johnson, L. T., Tisell, J. (1989), *En dugligare tillverkning*, (in Swedish), Studentlitteratur, Lund, ISBN 91-44-30551-6

Juran, J. M., (1988), *Juran's quality control handbook*, 4th ed., McGraw-Hill Inc, ISBN 0-07-033176-6

Karlebo Handbok, Utgåva 14, (1992), Liber Utbildning, ISBN 91-21-13273-9

Kjellberg, A., Rundqvist, B., Sohlenius, G., (1996), World Class Manufacturing Education, New Conditions – New Requirements, ISSN 1104-2133

Larsson, S., (1993), *Utrustningar för att mäta vektygsmaskiners noggrannhet* (In Swedish), Faktarapport Nr 105, Sveriges Verkstadsindustrier, Ordering nr. V030022

Lundin, M., (1993), Duglighetstester av verktygsmaskiner (In Swedish), Faktarapport Nr 101, Sveriges Verkstadsindustrier, Ordering nr. V030012

Luttervelt, van, C. A., (1997), *A report from the CIRP working group on modelling of machining operations*, Machining Science and Technology, 1(1): 163-169

Luttervelt, van, C. A., Childs, T. H. C., Jawahir, I. S., Klocke, F., Venuvinod, P. K., (1998), Present Situation and Future Trends in Modelling of Machining Operations Progress Report of the CIRP Working Group 'Modelling of Machining operations', Annals of the CIRP, Vol. 47/2/1998: 587-626

McLaughlin, G. C., (1988), *Designing an effective process capability study*, ASQC Quality Congress Transactions: 524-529

Phadke, M. S., (1989), *Quality engineering using Robust Design*, P T R Prentice-Hall, Inc, ISBN 0-13-745167-9

Pillet, M., Rochon S., Duclos E., (1997-98), *SPC–Generalization of capability index C_{pm}: Case of unilateral tolerances*, Quality engineering, 10(1): 171--176

Sohlenius, G., (1990), Presidential Address, Incentives for CIRP, Annals of the CIRP Vol. 39/2/1990: 685-688

Weck, M., (1984), *Handbook of Machine Tools*, Volume 4, ISBN 0-471-26225-0

Ju mer jag tänker på saken,
dess tydligare tycks det mig
att livet helt enkelt
är till för att levas.

Goethe

Appendix A: Robust Design – A Brief Introduction

A.1 Principles of Quality Engineering

When the reconstruction efforts after World War II started Japan was facing the challenge to produce high-quality products and to continue to improve the quality. As a result of this work Dr. Taguchi developed the foundations of Robust Design during the 1950s and the early 1960s. This method draws on many ideas from statistical experimental design to plan experiments in order to obtain reliable information about variables involved in making engineering decisions. The method of Robust Design has since Taguchi wrote the basic philosophies developed through research and applications in industry. The method is claimed not just to be useful for engineering applications, but also for other kinds of business as well [Phadke, 1998]. Dr. Madhav Phadke, a mechanical engineer, who has worked at AT & T Bell Laboratories for several years has had extensive experience in applying the Robust Design method to engineering problems [Phadke, 1998, foreword].

A.1.1 Quality and Fundamental Principle of Robust Design

Phadke [1989] states that "The ideal quality a customer can expect is that every product delivers the target performance each time the product is used, under all intended operating conditions, and throughout its intended life, with no harmful side effects." This ideal quality can serve as a reference point for being able to measure a quality level. The basic idea of quality of a product or a process according to Taguchi is that it is measured in terms of the total quality loss to society. Products breaking down or malfunctioning are not just expensive for the owner or the user, it also cost money for the society. For example, a car crash due to malfunctioning tiers costs money for the driver, the owner and the society. In relation to ideal quality, the total loss would be zero and the greater the loss the lower the quality.

The fundamental principle of Robust Design is according to Phadke [1989] "… is to improve the quality of a product by minimising the effect of the causes of variation without eliminating the causes". To achieve this parameter design is used, which means that the design of products and processes are designed to minimise the sensitivity to various variations during performance. An optimisation like this might not always lead to the desired quality and further improvements on the causes of variation might be necessary. Naturally, an improved quality must justify the increased product cost.

A.1.2 Quality Loss Function

When a part has parameters outside given tolerance limits, it burdens the financing of manufacturing due to costs of re-work or waste. But it also becomes a financial burden for the customer if the incorrect part fails to be found and sorted out and thereby sold. In most cases it makes no difference if the characteristics of the parts in an assembled product are barely within, or just out of, the tolerance limits, assumed the product still fulfils its function. But according to Phadke [1989] "…products that meet tolerance also inflict a quality loss, a loss that is visible to the customer and that can adversely affect the sales of the product and the reputation of the manufacturer".

A quadratic loss function can approximate the quality loss in most cases and is given by equation (1).

$$L(y) = k \cdot (y-m)^2 \tag{1}$$

Here k is a constant called quality loss coefficient and it is plotted in figure A.1.

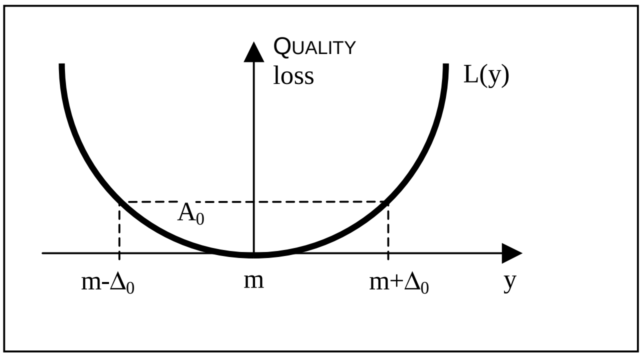


Figure A.1. Illustration of the quality loss equation L(y) [Phadke, 1989].

y is the studied characteristic of a product, A_0 is the cost of repair or replacement of the product. A functional limit, m+Δ_0, is the value of *y* at which the product would fail in half of the applications. In the picture above the loss at m+Δ_0 is A_0. By substitution in equation (1) *k* is obtained, see equation (2).

$$k = \frac{A_0}{\Delta_0^2} \qquad (2)$$

A.1.3 Variations of The Quadratic Loss Function

The quadratic loss function given by equation (1) is valid whenever the quality characteristic y has a finite target value and the quality loss is symmetric on either side of the target value. This equation is thereby called nominal-the-best type quality loss function [Phadke, 1989, p 20]. When a parameter only can be a positive value, and the ideal value is zero and its performance becomes progressively worse as the value increases, then it is a smaller-the-better type quality characteristic (see equation (3)). Larger-the-better type characteristic can not be a negative value. But in this case zero is the worst value and the performance becomes gradually better as the values increases, see equation (4). In some cases a deviation of the quality characteristic in one direction is more harmful than the other direction, this makes an asymmetric loss function, see equation (5).

$$L(y) = k \cdot y^2 \qquad (3)$$
$$L(y) = k \cdot (1/y^2) \qquad (4)$$
$$L(y) = k_1 \cdot (y-m)^2 \text{ or } k_2 \cdot (y-m)^2 \qquad (5)$$

A.1.4 Noise Factors

As the fundamental principle of Robust Design is to minimise the effect of the causes of variation it is of vital importance to identify important noise factors (definition, see section A.1.7). To be able to do this, engineering experience and efficient experimentation for defining important noise factors is necessary. Noise factors, or causes for variations, can be divided into three different groups for both products and manufacturing processes [Phadke, 1989].

- Products

External sources can be divided into two main sources, the environment and the forces to which products are subjected.
Unit-to-unit variation is the inevitable variation on products produced in a manufacturing process.
Deterioration causes changes in product performance as time passes.

- Manufacturing processes

External noise factors related to the environment in which the process is carried out.
Process uniformity occurs when many products are processed at the same time.
Process drift occurs when several units are produced due to wear of equipment.

A.1.5 Non-linearity of Product Characteristics

The principal goal of Robust Design is to exploit the non-linearity with the aim of finding a combination of product parameter values, which gives the smallest variation in the value of quality characteristic. A product's quality characteristic is related to various product parameter and noise factors through a non-linear function. As a result; several combinations of product parameter values can give the desired target value of the product's quality characteristic under nominal noise conditions. Due to this non-linearity these different product parameter combinations can give quite different variation in the quality characteristic. By exploiting non-linearity the quality loss can be reduced without increasing the product cost. The work of exploiting is divided into two different actions; *parameter design* and *tolerance design* as illustrated in figure A.2.

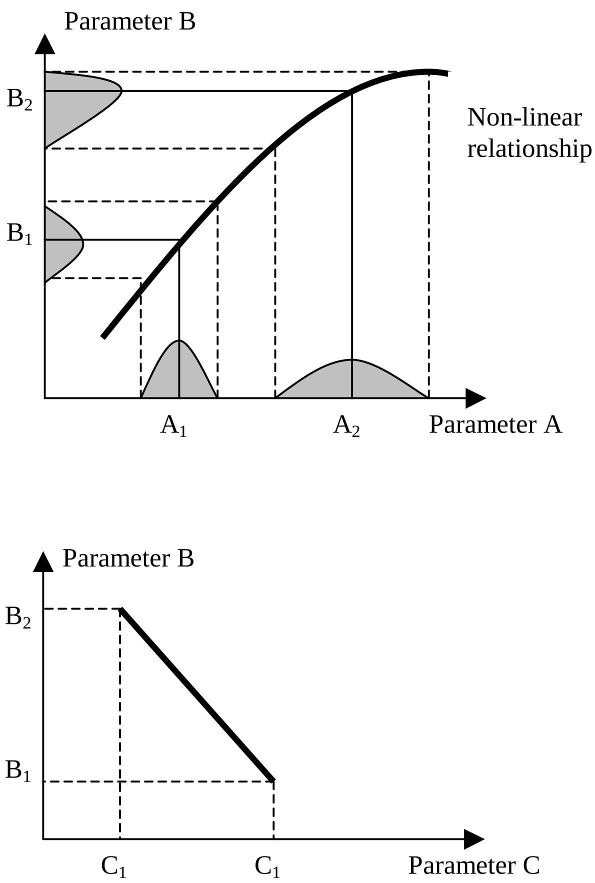


Figure A.2. Non-linear relationship is useful for attenuating sensitivity to noise and a linear relationship is useful for shifting the process mean to the target value [Phadke, 1989].

A.1.6 Parameter and Tolerance Design

The quality of a product or a process is the result of various parameters and noise factors, which form a complicated and non-linear function. According to Phadke [1989] "The principal goal of Robust Design is to exploit the non-linearity to find a combination of product parameter values that gives the smallest variation in the value of the quality characteristic around the desired target value". If the requirements on the variation of the output need to be altered, that is if a tolerance needs to be either tightened or widened, it can be done by two distinct actions. Taguchi refers to these two actions as parameter design and tolerance design [Phadke, 1989]. Parameter design means that the nominal value on a noise factor is changed in order to reduce the tolerance interval of the outcome factor. The relationship between these two parameters (noise and outcome factor) is a non-linear relationship and by this gives the possibility of this action. Tolerance design is the next step. This will make sure that the noise factor, which has been altered during the previous step, will give the correct target value on the output. This step is performed using a linear relationship. In other words, the standard deviation of the outcome is reduced through a non-linear relationship and then the process mean value is transferred to the target value using a linear relationship. According to Phadke [1989, p. 29] "Typically, no manufacturing cost increase is associated with changing the nominal values of product parameters (parameter design). However, reducing a tolerance interval (tolerance design) leads to higher manufacturing cost."

A.1.7 P-Diagram

To be able to succeed with a Robust Design project it is important to identify important factors that affects the machined part or the machining process. It is equally important to recognise what control factors change the manufacturing cost, and which do not. Factors that are related to a product or process can be classified in three groups and be shown in a P-Diagram. According to Phadke [1989, p. 31] is the word parameter equivalent to the word "factor" in most of Robust Design literature.

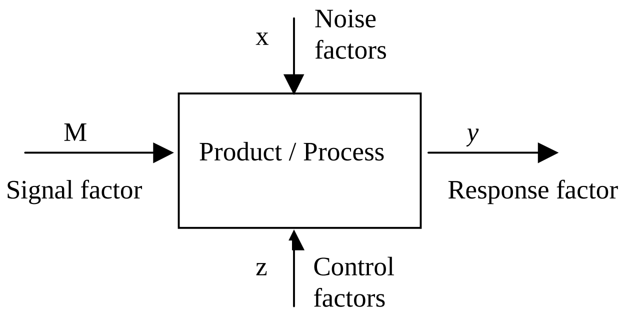


Figure A.3. Block diagram of a product/process, i.e. a P-Diagram.

- Response factor

The response is the output of a product or a process. The actual output is a characteristic that is important for the specific product or process. The response used for optimisation in a Robust Design experiment is called a quality characteristic.

- Signal factor

This factor expresses the intended value of the response. Sometimes a combination of more than one signal factor is used to express the desired response.

- Noise factor

Factors that cannot be controlled or are unknown are called noise factors. This class also contains factors that are expensive or difficult to control. The only known characteristics, which changes during time due to alternations in environment, of the noise factor is statistical, e.g. it has a standard deviation and mean value. It is the noise factor that causes the response to deviate from given values by the signal factor, which lead to quality loss.

- Control factor

Factors to be specified and determined by the designer are called control factors. A control factor can have different values, called levels.

A.1.8 Engineering Design

The engineering problem of optimising a product or process with the aim of gaining a specific quality level and a low manufacturing cost is difficult. Phadke [1989, p. 33] describes a strategy consisting of three steps;

- concept design
- parameter design
- tolerance design

The first step, *concept design*, consists of a decision on product architecture or process technology to achieve the desired function of the product. Concept design is an important step towards reducing the sensitivity to noise factors as well as reducing the manufacturing cost. The second step, *parameter design*, determines the best levels of the control factors that do not affect manufacturing cost. This step also includes the work with minimising the sensitivity of the product or process to noise factors. The third step, *tolerance design*, means that the tolerance interval is reduced. In other words, a reduction in quality loss due to performance variation and an increase in manufacturing cost. Robust Design focuses on how to perform parameter design effectively. For more detailed information, see Phadke [1989].

A.2 Steps in Robust Design

Robust design is a methodology to optimise the levels of control factors to make a product or process as insensitive as possible to noise factors. This methodology consists of eight steps, which can be classified into three groups [Phadke, 1989].

- **Planning the experiments**

1. Identify the main function, side effects, and failure modes.
2. Identify noise factors and the testing conditions for evaluating the quality loss.
3. Identify the quality characteristic to be observed and the objective function to be optimised.
4. Identify the control factors and the alternative levels.
5. Design the matrix experiments and define the data analysis procedure.

- **Performing the experiment**

6. Conduct the matrix experiment.

- **Analysing and verifying the experiment results**

7. Analyse the data, determine optimum levels for the control factors, and predict performance under these levels.
8. Conduct the verification experiment and plan future actions.

For more information about matrix experiments and how to analyse and verify the experiments, see Phadke [1989].

Appendix B: Statistical Process Control

W. A. Shewhart who worked at Bell Laboratories introduced Statistical Process Control, SPC, in 1924. He developed a statistical chart, which today is called control chart, for control of product variables as well as the procedures and mathematical proof that make the use of these charts scientifically viable. The procedure introduced by Shewhart was to analyse chart averages of small sample sizes rather than individual values. When developing the mathematical proof for his procedure, he used the Central Limit Theorem, (1), which states that the distribution of sample averages will be normal or almost normal. Using this system, quality can be controlled according to Leonard A. Doty with a sampling procedure rather than using 100% inspection. He emphasises the statistical process control on the technical portion of the subject [Doty, 1996].

$$S_x = \sigma / \sqrt{n} \qquad (1)$$

S_x = standard deviation of the sample means
σ = standard deviation of the individual values
n = sample size (should be 4 or greater)

D. Shainin and P. D. Shainin describes Shewharts chart in Quality Control Handbook by Juran [1988], which is a comprehensive book about quality and methods associated with quality. The book includes both theory and practical examples. Shewhart analysed a number of different processes and concluded that all manufacturing processes vary. He identified two different components of variation. One is random variation (unknown and insignificant causes). Shewhart attributed it to chance and un-discoverable causes, and the other variation is intermittent variation attributed to assignable causes. In conclusion Shewhart stated that random causes can not be economically discovered and can thereby not be removed without making basic changes to the process. Assignable causes, on the other hand, can be economically discovered and removed with a tenacious diagnostic program. [Juran, 1988].

B.1 Definitions

Definitions according to D. Shainin and P. D. Shainin [Juran, 1988, p. 24.2]:

Statistical process control: The application of statistical techniques for measurement analysing the variation in processes.

Process: Any specific combination of machines, tools, methods, materials and/or people employed to attain specific qualities in a product or service. A change in an of these constituents results in a new process. These qualities (e.g. dimension, material property) will be called “quality characteristics” to avoid being mistaken for levels of quality. Some processes are manufacturing processes; some are service processes; others are support operations often used in manufacturing industry as well as in service industry.

Control: The control process is a feedback loop, in which we measure actual performance, compare it with standard, and influence on the difference. The quicker the response is to deviation from the standard, the more uniform is the produced quality.

B.2 Charts

The variation of a specific quality characteristic can be quantified by sampling the output of the process and estimating the parameters of its statistical distribution. Plotting these parameters versus time can reveal changes of a process. The most common types of charts are ξ and *R* charts. The quality characteristic x is measured on each individual processed part. The mean, ξ, and the range, *R*, are calculated for each subgroup and plotted in the chart. The *grand average* and the average range, *–R,* is drawn on each chart. When this is done, control limits are established at ±3 standard deviations (SD) which represents the upper and lower control limits, UCL and LCL, respectively. An example is shown in figure B.1 [Juran, 1988].

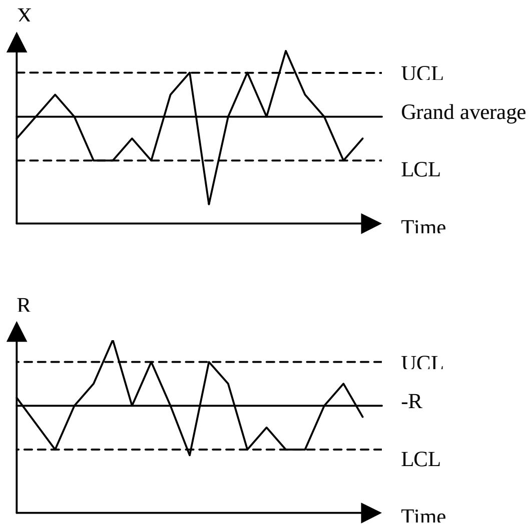


Figure B.1. Grand average and range charts. Upper and lower control limits equals ±3 standard deviations (SD).

The area between the two control limits defines the *random variation* in the process. Values outside the UCL and LCL limits indicate one or more assignable causes of variation. A process that is in “statistical control” shows only random variations, i.e. only values within the control limits. A process in statistical control is considered to be economically feasible [Juran, 1988].

Shewhart’s charts came into use in the 1940's as a result of efforts to improve quality and productivity of war production. “When Shewhart developed his theory, the concept of statistically analysing the variation of a process in order to improve quality was unheard of. His work was truly pioneering.” [Juran, 1988].

The Quality Control handbook [Juran, 1988] claims that control charts are commonly used to:

1. attain a state of statistical control (all subgroup averages and ranges within control limits; therefore, no assignable causes of variation present),
2. monitor a process,
3. determine process capability. After the process is in control, the limits of process variation can be determined. Since the control

limits are established for averages, they must be multiplied by $\sqrt{n}$ (n = subgroup size) before they can be compared to tolerances.

A control chart controls the process, not the product. Statistical control verifies the stability of the process and also the homogeneity of the product. A process that is capable of meeting specifications and is in statistical control is thereby suitable for taking samples on products for product acceptance [Juran, 1988].

Appendix C: DBB

The DBB tests were performed in March 1998 at the Royal Institute of Technology, KTH, Sweden. Annika Larsson and Tekn Lic Jan Ackalin performed the test.

C.1 Double Ball Bar, DBB

DBB is a measuring method for evaluation of machining systems. The method detects deviations from moving along the geometric shape of a circle. The equipment used for performing the test is a telescopic arm attached to two magnetic spheres, one placed on the machine table and the other in the tool holder, se figure C.1. The circle interpolation test can be made with different radiuses in both lathes and turning machines.

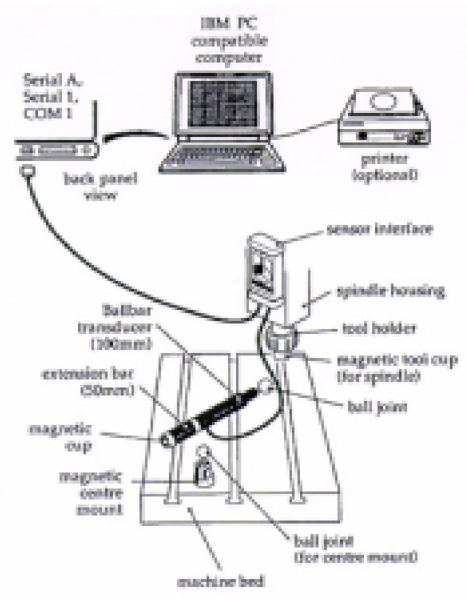


Figure C.1. The figure shows DBB equipment from Renishaw [www.Renishaw.com].

The DBB telescopic arm is moved in a circle by a machine tool and it registers the deviations in length of the telescope arm while it is making the circle. The test is performed both clockwise and anti-clockwise as described in figure C.2. The overshoot arc is to guarantee an invariable speed during the measurement.

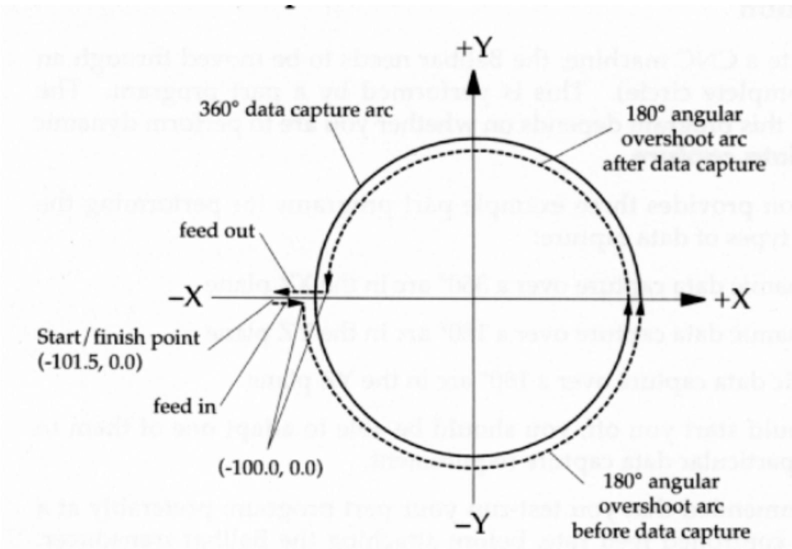


Figure C.2. The circular movement performed by a machine tool during a DBB measurement.

C.2 Results

The resulting circularity is calculated by the DBB software, according to circularity defined by the ISO 230 standard. Circularity is defined as the difference in radius between two concentric circles encircling the measured circle, see figure C.3. Circularity is here measured in µm.

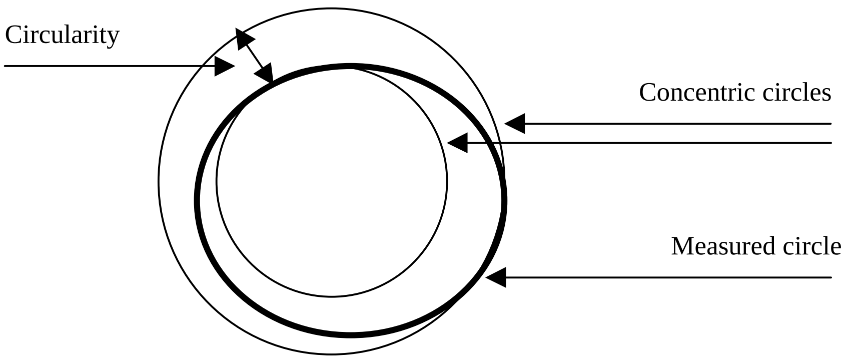


Figure C.3. Circularity is defined as the difference in radius between two concentric circles encircling the measured circle.

Result from measuring circularity

The results of the DBB measurement are presented in figure C.4. to C.12. The printout of the result can be explained by the following. To the right is a drawing of the circles performed by the machine tool, one circle is done clock wise, CW, and one is done counter clock wise, CCW. The scale has an interval of 7 µm. The lower area to the left shows the result of the measurement in circularity, the unit is µm. The middle area to the left shows the major errors in percentage.

The result of the measurements are unfortunately printed on a printer with low level of toner, hence the bad quality. The missing text is written below each figure.

The result of the nine performed experiments has been used to calculate the resulted signal to noise ratio, S/N (dB), see table C.1.

$$S/N = -10 \cdot \log_{10}(\text{circularity})$$

Experiment No.	Position	Feed rate	Radius	Cicularity	S/N
1	middle (1)	500	100	21,5	-13,3244
2	middle (1)	3000	150	55,5	-17,4429
3	middle (1)	4000	250	72,8	-18,6213
4	right (2)	500	150	27,5	-14,3933
5	right (2)	3000	250	60,6	-17,8247
6	right (2)	4000	100	66,9	-18,2543
7	left (3)	500	250	51,2	-17,0927
8	left (3)	3000	100	58,2	-17,6492
9	left (3)	4000	150	73,4	-18,657

Table C.1. The nine performed experiments showing the values of the three parameters and the resulting circularity as well as the calculated S/N ratio.

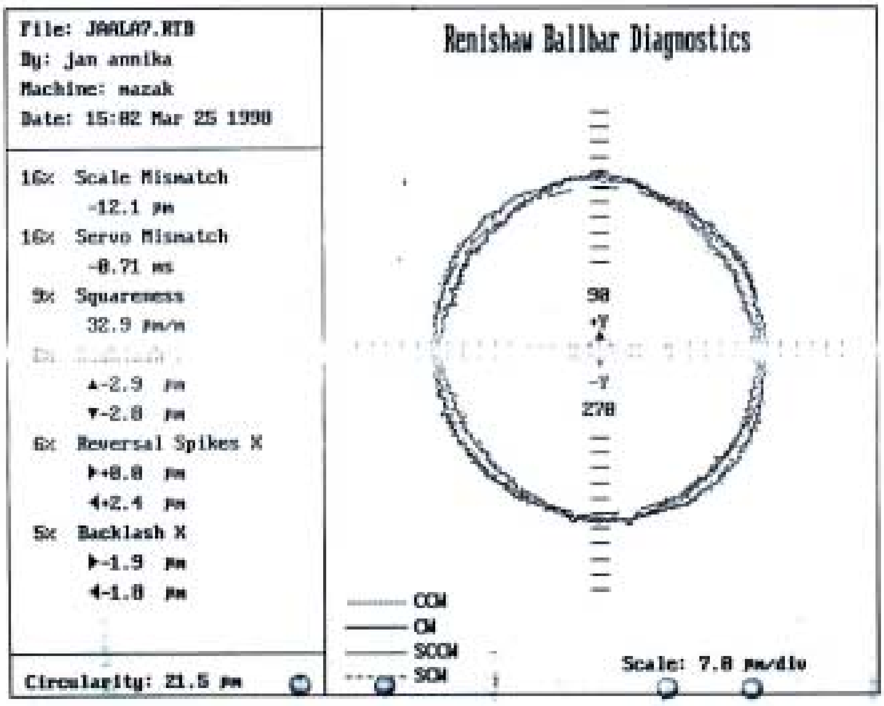


Figure C.4. Measurement no. jaala7. Circularity 21.5 µm. Position 1, feed rate 500 rpm, radius 100 mm. [8% Backlash Y].

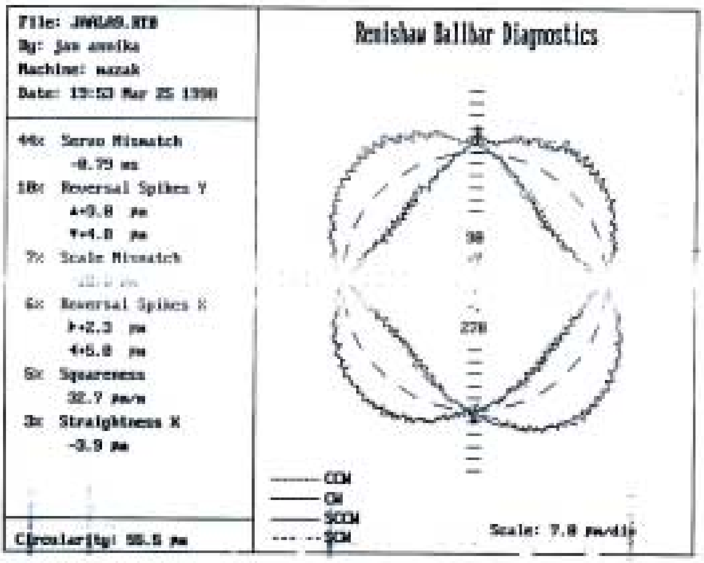


Figure C.5. Measurement no jaala9. Circularity 55.5 µm. Position 1, feed rate 3000 rpm, radius 150 mm. [7% Scale Mismatch].

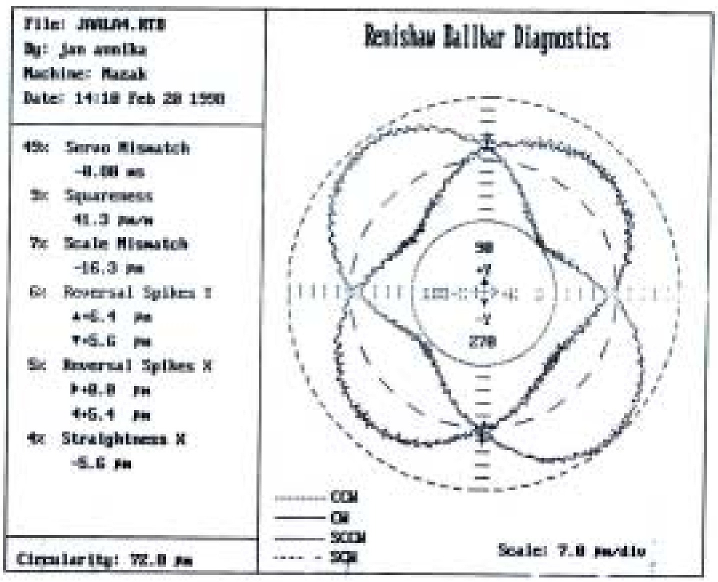


Figure C.6. Measurement no. jaala4. Circularity 72.8 µm. Position 1, feed rate 4000 rpm, radius 250 mm.

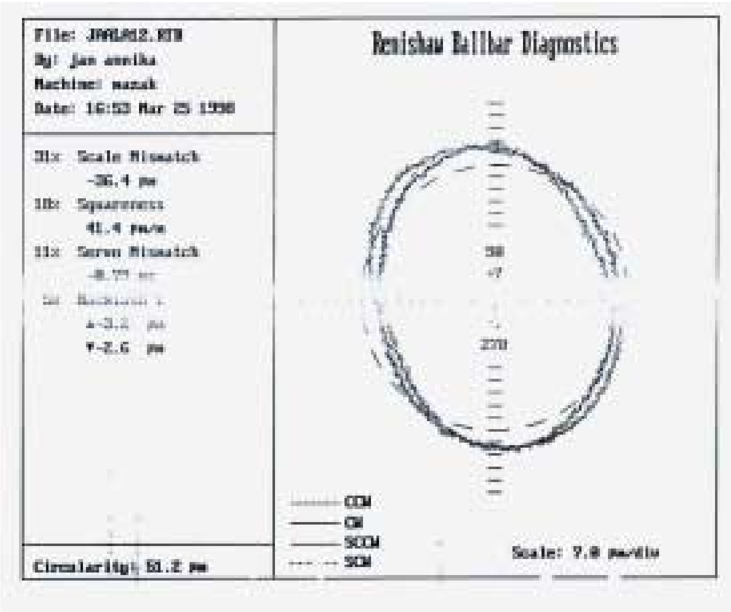


Figure C.7. Measurement no. jaala12. Circularity 51.2 μm. Position 2, feed rate 500 rpm, radius 150 mm. [5% Backlash Y].

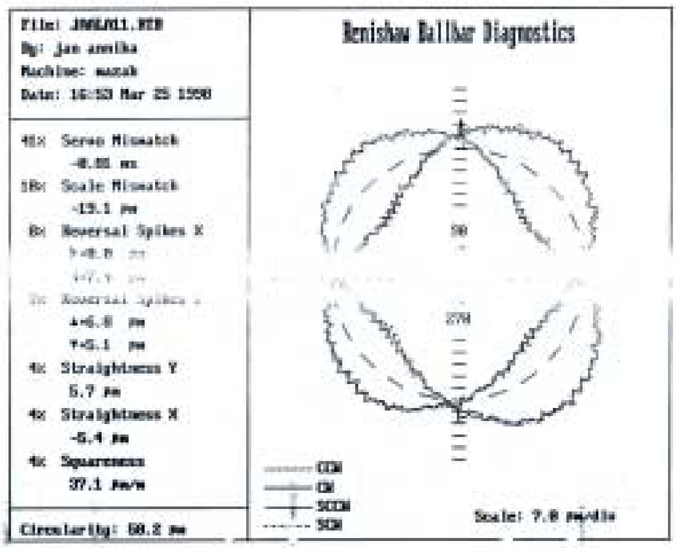


Figure C.8. Measurement no. jaala11. Circularity 58.2 μm. Position 2, feed rate 3000 rpm, radius 250 mm. [<+7.4 μm, 7% Reversal spikes Y].

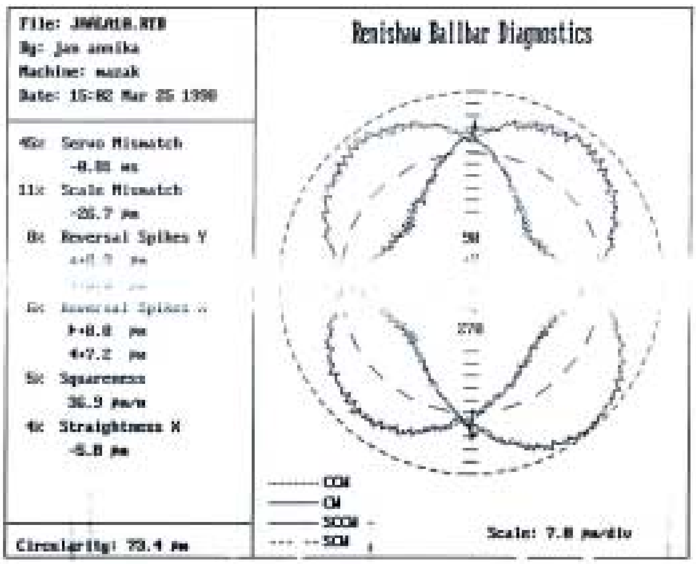


Figure C.9. Measurement no. jaala10. Circularity 73.4 μm. Position 2, feed rate 4000 rpm, radius 100 mm. [v+9.0 μm, 6% Reversal Spikes X].

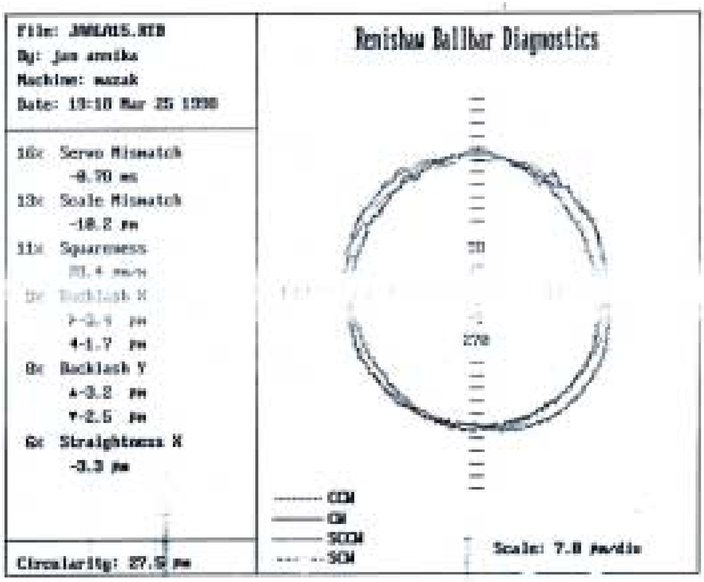


Figure C.10. Measurement no. jaala15. Circularity 27.5 μm. Position 3, feed rate 500 rpm, radius 250 mm. [9% Backlash X].

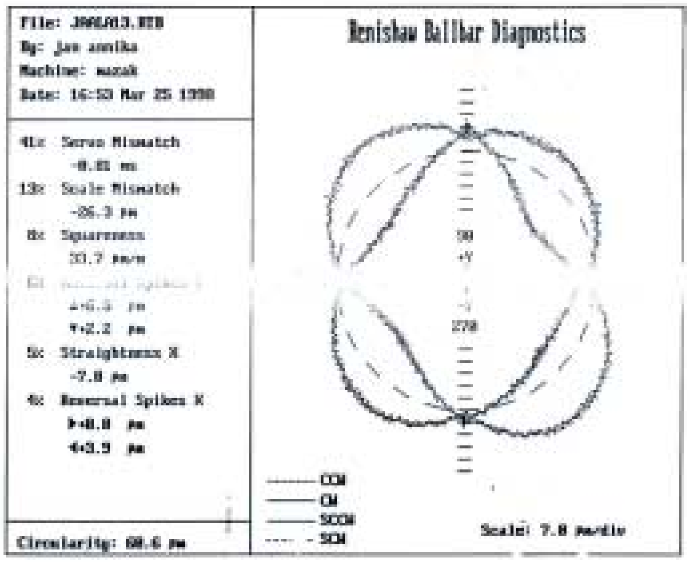


Figure C.11. Measurement no. jaala13. Circularity 60.6 μm. Position 3, feed rate 3000 rpm, radius 100 mm. [6% Reversal Spikes Y].

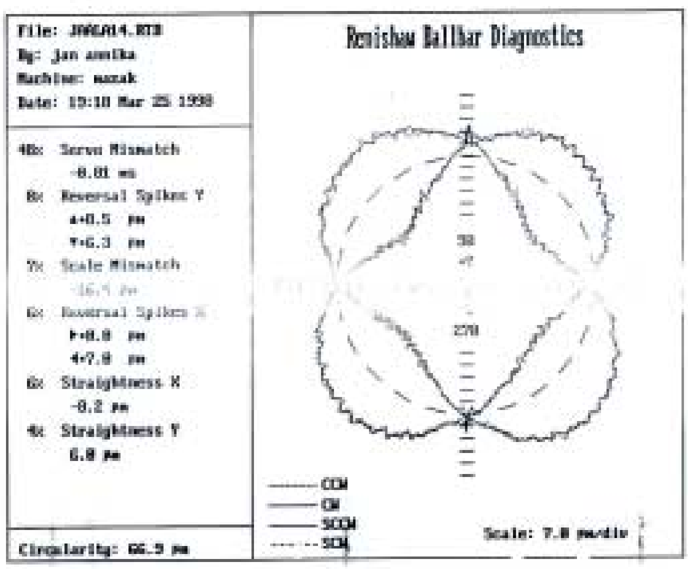


Figure C.12. Measurement no. jaala14. Circularity 66.9 μm. Position 3, feed rate 4000 rpm, radius 150 mm [7% Scale Mismatch -16.4 μm].