Concept of using General Process Capability Data

Andreas Bruun Okholm, s082562
Mathias Rask Møller, s082536[1]
Technical University of Denmark

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A approach to generate Generalised Process Capability Data in order to populate and add functionality to a Process Capability Database. A description of the concept of generalisation, uses and implementation.

A Process Capability DataBase (PCDB) is a tool for mechanical designers to get information of what is possible to achieve in the companies production. This is done by storing and displaying statistical information about features on produced components. By applying Process Capability (PC) information in the design process it is possible to reduces: rework, cost, failure rate, assembly problems and increases product performance (Tata and Thornton, 1999).

As mentioned in (Tata and Thornton, 1999; Tata, 1999; Rask Møller and Okholm, 2013) and a number for key challenges has to be addressed to expand the use of PCDB.

- Data Communication: The databases are typically not easily searchable which makes it very difficult to find the correct data and in many cases the data sought after data does not exists. Further more the data is not presented in a way which is easily understandable by mechanical designers.
- Fragmented Organization: Development department are dependent on data from production.
- Information Technology: Make a database which is fast, live, global, self populating, up to date and live up to the industry criteria of security and anonymity.

There has been a couple of attempts in academia to solve some of these difficulties (Thornton and Tata, 2000; Kern, 2003; Thornton, 2004), but there hasn't much attention on the subject since indicating there is still issues to resolve before it can be efficiently used in the industry.

In this article we present a concept of data indexing, processing and presentation which tries to make it faster and easier for the mechanical designer to efficiently use process capability data in new designs. The general principle is to provide a interface where the data is presented in a much more generalised than typically done in PCDB interfaces. The core indexing scheme is simplified, but details are retained or improved using a flexible tagging system. Instead of presenting the designer with statistical information, recommended specifications limits based on actual PC is shown directly. The specification limits is normalised in regards to the specified dimension making more use out of each dataset, minimising the risk of PC requests not returning any results.

Combined with advances in Information Technology we hope this will help make PCDBs a viable tool in the mechanical design process.

I. INDEXING

PCDB data needs to be indexed to efficiently retrieve data of relevance to the current design. The data stored in a PCDBs is typically measurement sets; the statistical result of a number of measurements from a given part dimension combined with the Design Characteristics (DC). Feature, geometry, material and process is suggested by Kern (2003) to be the primary DC's. For each primary DC there exists a tree structure of possibilities. An example of an index using Kerns proposed design index could be "Plane", "Position", "Aluminum", "Turning" as feature, geometry, material and process respectively.

For our index, *material* and *process* should be only required DCs. This is combined with a tagging systems, where additional tags can be inputted. Common tags can be selected from tree structure. Tags gives more flexibility since more than one tag can be applied to one measurement set and it is possible to index for DC's that are specific to a single production method or material.

Example: For injection moulding it would be interesting to index the material type of the mould - aluminium, steel, hardened, ... Indexing the mould iterations (T0, T1, T2) could also give valuable insights of which specification limits requires mould rework or process adjustment. Another example: To tag if the dimension measured crosses a parting line in the mould potentially showing a general increase in desired specification limits.

In casting and injection moulding which are some of the most used processes for mass produced part, feature and geometry is not necessarily important DCs. In mould making the individual geometries are manufactured in the same CAM milling machine. The variation in the product from the mould is most likely independent of geometry with exceptions of features that have high length to width ratios and small deep holes that are hard to manufacture. PC data for different geometries such as diameters, positions, thickness, radii are pooled together but can be marked with an exception-tag.

In a fully integrated robust design process interaction between component are reduced to as small and simple surfaces as possible. The need for indexing geometry of components should decrease.

What you measure and index is what you can analyse from. Since the index limits the possible conclusions, which can be mades when extracting the data. If the goal is to understand the long term process capability impact of an injection mould process it is either necessary to have measurement sets from many products at different stages of their lifespan or multiple measurements through the lifespan of a couple of products.

II. PROCESSING CAPABILITY DATA

Processing the capability data consists of three steps:

1. Compute Process Capability Specification Limit (PCSL).
2. Normalize PCSL.
3. Interpret normalised PCSL data.

A. Process Capability Specification Limit

The process capability indices (C_p and C_{pk}) described by Kane (1986) has been widely adopted in statistical process control, been extended and further researched for better understanding (Wu, Pearn, and Kotz, 2009). Instead of looking at process mean μ, standard deviation σ and specification upper and lower limits USL, LSL using Process Capabilities Indices (PCIs) transforms these values into unit less numbers, which provides a quick overview of how a process is performing.

The PCIs ability to transform process variables of any object into unit less capability index can be reversed to calculate desirable specification limits. For en example the commonly used CPI C_{pk}

$$C_{pk} = \frac{d - |\mu - m|}{3\sigma} \tag{1}$$

can be reversed

$$d = 3C_{pk}\sigma + |\mu - m| \tag{2}$$

where $d = (USL - LSL)/2$ is half the specification limit and $m = (USL + LSL)/2$ is the midpoint between the specification limits. Since the d is the required tolerance to achieve the desired process capability index value we call this the Process Capability Specification Limit (PCSL).

There are several commonly used PCIs each serving their purpose (Wu, Pearn, and Kotz, 2009; Taguchi, 1986)

- C_a : Closeness of process mean to target
- C_p : Relative size of variation
- C_{pk} : Amount of nonconforming (%NC)
- C_{pm} : Value loss (Taguchi loss function)
- C_{pmk}: Version of C_{pm}, sensitive to mean shift.

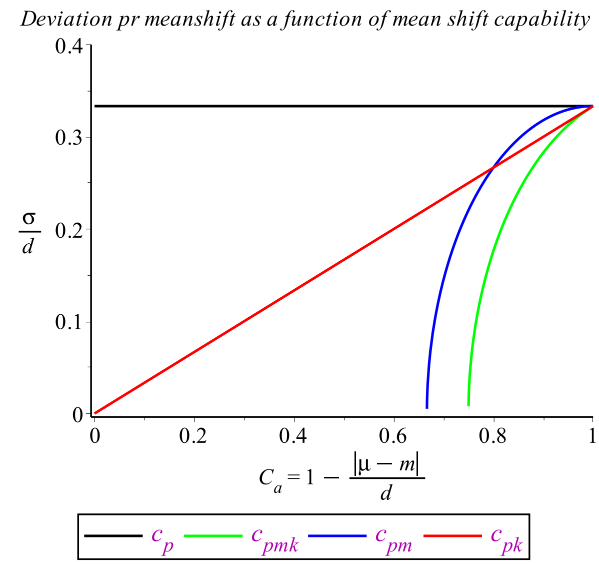

FIG. 1. C_p referens only to the variance of the process. C_{pk} is related to the yield of the product. C_{pm} takes a loss function in to account relates to a target dimension. C_{pmk} takes both the yield of the product and a loss function.

TABLE I. C_{pk} Non-conformaties

$\mathbf{C}_{pk}$	σ level	$\mathbf{NC}_{\max}$ (ppm)	$\mathbf{NC}_{\min}$ (ppm)
1.00	3	2699.8	1349.9
1.33	4	63.3	31.7
1.50	4.5	6.7	3.4
1.66	5	0.6	0.3
2.00	6	0.002	0.001

Visualising the $CPIs = 1$ shows how a process on target $C_a = 1$ allows the same variation for all PCIs see figure 1. The line for C_{pm} is in below that of C_{pk} except for values of C_a close to 1. Using C_{pm} will in general be more conservative resulting in larger specification limits than C_{pk}. The plot shown is for a capability equal to one for higher values this effect is even more pronounced.

For the purpose of our database we have chosen to use C_{pk}, since it provides the most easily understandable result - directly related to the yield of the process. The yield of a process is within $2\Phi(3C_{pk}) - 1 \leq$ yield $< \Phi(3C_{pk})$ where $\Phi(\cdot)$ is the cumulative distribution function of the standard normal distribution N(0,1) (Boyles, 1991). For typical capability levels the resulting nonconforming products in parts per million (ppm) is listed in table I

The optimal process capability index values depends on the application, however there exists a practice in quality control called six sigma (6σ), which advocates the use of six sigma ($C_{pk} = 2$) for short term process capability will generally improve manufacturing quality and profits Koch, Yang, and Gu (2004). It's assumed that the process drifts over time up to 1.5σ (effectively resulting in a sigma level of 4.5), which still results in an acceptable 3.4 ppm defects. Depending wether the data inputed into the PCDB are mostly from newly setup processes or long term samples the C_{pk} should be varied from 2.0 to 1.5 to achieve six sigma for the process. We propose to use a value of $C_{pk} = 1.66$, which would result in six sigma levels of performance if the inputed datasets are a mixture of long term and short term measurements. Alternatively it would be possible to set an acceptable C_{pk} value when inputing each measurement set depending weather the measurement set reflects the short or long term capability.

We have focused on C_{pk} through most of this section. In situations where the desired tolerances directly influence product performance, for instance in lens optics construction, using the more abstract C_{pm} might make more sense.

B. Normalization

The calculated Process Capability Specification Limits (PCSL) are normalised so it can be used to predict PCSLs for any dimension within the limit of the normalisation algorithm. This reduces the required amount of data in the database before it's useful for mechanical design since it is possible to use PC information from components of different sizes.

There exists industrial standards used for manufacturing which describe the 'normal' relationships between linear dimensions and tolerences. We have analysed the most commonly used standards for general tolerences: American ANSI B4-2 (1978), European ISO 286-2 (1997) and the German standard DIN7168 (1991). and the

and have slight difference but all present a nonlinear curve. For the same level for precision the tolerance of big dimensions is smaller relative to size than for component of a small dimension.

The german standard DIN 16901:1982-11 and the French NFT58000 are standards that specifically relates to moulded plastic parts. These standards present an almost linear function. The difference can be a result of the creep in moulded plastic that is a percentage of volume and not a function of dimension.

In figure 2 both the standards for general and moulded plastic specific linear tolerances are shown.

The descriptions of the standards presents the data as tables for tolerances in dimension intervals. This poses a problem when trying classify the specific tolerance dimension to a precision level. In a note for ANSI B4-2 and later mentioned in ISO 286:1993 a continues function is described for IT-grades between IT6 to IT16 for dimensions from 2mm to 500mm. This function is not included in newer versions of ISO 286.

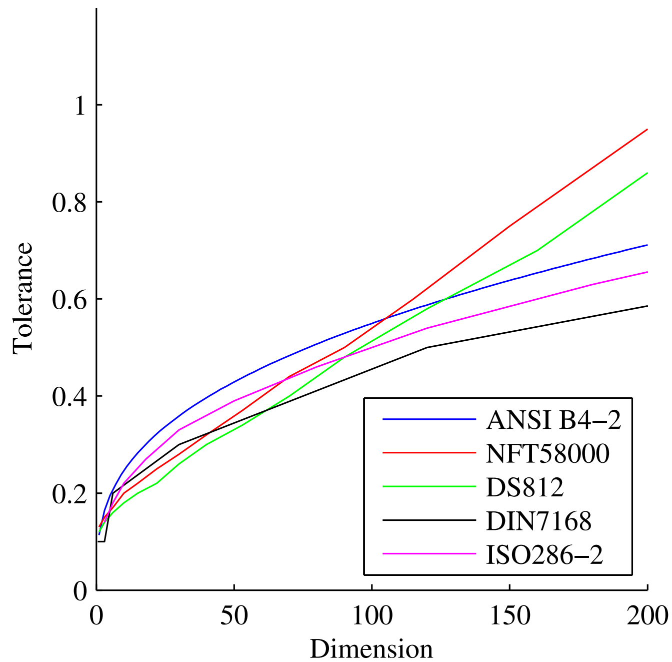

FIG. 2. The danish standard DS812 (POM 120) and the French NFT58000 (normal) are standards specifically for moulded plastic components. They are almost linear for sizes above 10mm The American ANSI B4-2 (gr. 13) and the german DIN7168 (medium) and Europaen ISO 286-2 (IT13) describes the linear tolerances dimension relation. The tolerance is smaller for

$$tol = 10^{0.2(ITG-1)} \cdot i \tag{3}$$

$$i = 0.45\sqrt[3]{D} + 10^{-3} D \tag{4}$$

Where i is standard tolerance factor, D is the nominal dimension $D = \sqrt{D_1 D_2}$ and T is the international tolerance in μm.

In the generalized PCDB the data is normalized using said function because ISO 286 is general practice in the industry. Future improvements to find formulation for normalization for the different process could be analyzed from a populated PCDB.

C. Analyze normalized data

fit normal distribution of sub groups. find subgroups
extracting data
robustness
visible confidence intervals of interpertation

III. USER INTERFACE

Readability of accumulated normal distribution compared to a bell curve.

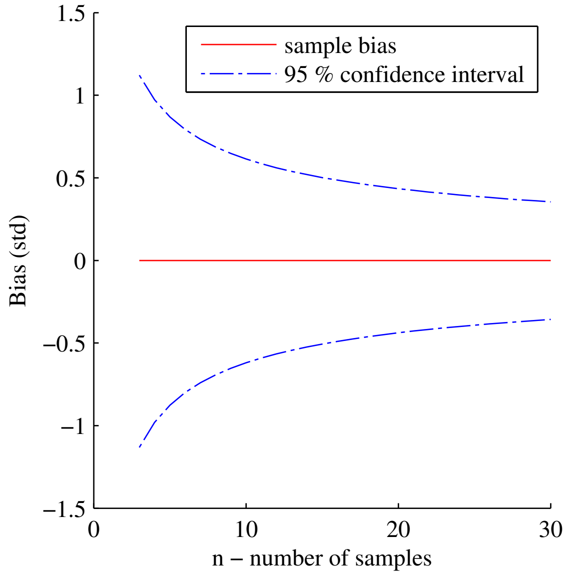

FIG. 3. The uncertainty of the standard deviation estimate is reduced as the number of samples is increased. The increase in accuracy gained per additional decreases with more samples. From the graph we have chosen 12 to be the optimal point for general process capability use.

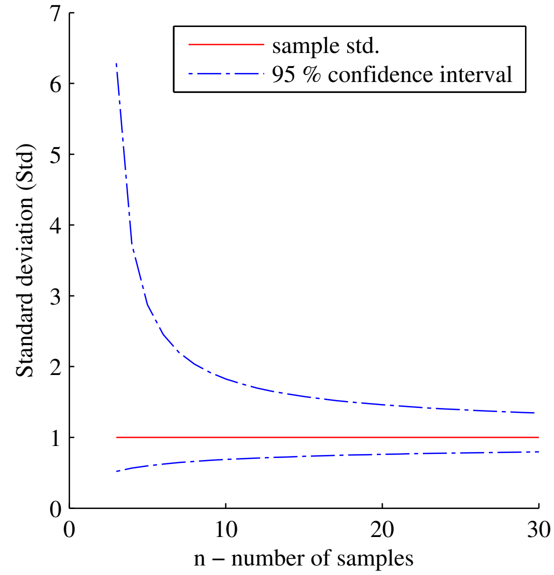

FIG. 4. The uncertainty of the standard deviation estimate is reduced as the number of samples is increased. The increase in accuracy gained per additional decreases with more samples. From the graph we have chosen 12 to be the optimal point for general process capability use.

Two figures showing the actual interface

General Interactivity in plots Special courses comment of measurement sets.

Group sorting Reference to Thornton graphical display article.

Visible confidence intervals

User can set tolerance (from IT to specific dimentions)

Two views General charts inspired by ANSI Process view inspired by Thornton Graphical display

IV. STATISTICAL VALIDITY

measurement sets are assumed to fit a normal distribution.

What you measure is what you get. Each product in the sample set, produces a measurement. From the sample set is a measurement set created.

Confidence intervals - sample size of each measurement set.

Number of measurement sets to predict process capability.

show current production capability in terms of it-grade

V. USING THE GENERAL PROCESS CAPABILITY DATA

apply tolrance, By looking at normalized data of the variance of products of the same material and process, it is possible to find a suitable tolerance improvement per rework material selection

VI. DISCUSSION

Using todays techonolgy, generalization of PC data upon request from the user i feasble. A proposed techincal setup is described in **?**.

Initiating PCG is a tough process. The reward for doing robust design engineering is long reach The reward for using PCDB or robust design in general to make changes in early design is a long term and might only benefit the company and not feedback to the designers compared the reward for the hero in production solving the expensive errors in design.

Implementing GPC requires a change economical barrier big company incement from quality department gain: knowlegde of own PC high precision data Extensive knowlegde on causes and problem loss: cross companies diverse data gain: Alot of data knowlegde of processes and matrial outside your field knowlegde of possible to achive in industry Index storing of own data and partially analysed loss: Indusry espiange concerns loss of information due to anonymity

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