



## Improving process capability database usage for robust design engineering by generalising measurement data

Okholm, A.B.; Rask, M.; Ebro, Martin ; Eifler, Tobias; Holmberg, M.; Howard, Thomas J.

*Published in:*  
13th International Design Conference - Design 2014

*Publication date:*  
2014

*Document Version*  
Publisher's PDF, also known as Version of record

[Link back to DTU Orbit](#)

*Citation (APA):*  
Okholm, A. B., Rask, M., Ebro, M., Eifler, T., Holmberg, M., & Howard, T. J. (2014). Improving process capability database usage for robust design engineering by generalising measurement data. In *13th International Design Conference - Design 2014* (pp. 1133-1144). Design Society.

---

### General rights

Copyright and moral rights for the publications made accessible in the public portal are retained by the authors and/or other copyright owners and it is a condition of accessing publications that users recognise and abide by the legal requirements associated with these rights.

- Users may download and print one copy of any publication from the public portal for the purpose of private study or research.
- You may not further distribute the material or use it for any profit-making activity or commercial gain
- You may freely distribute the URL identifying the publication in the public portal

If you believe that this document breaches copyright please contact us providing details, and we will remove access to the work immediately and investigate your claim.

## **IMPROVING PROCESS CAPABILITY DATABASE USAGE FOR ROBUST DESIGN ENGINEERING BY GENERALISING MEASUREMENT DATA**

A. B. Okholm, M. Rask, M. Ebro, T. Eifler, M. Holmberg and T. J. Howard

*Keywords: process capability database, robust design, tolerance*

### **1. Introduction**

All manufacturing processes produce parts with variation from the specified dimensions. There is a widespread agreement in engineering design that a better understanding of this process variance and an early consideration are necessary for the success of a development project. Several approaches related to production variation exist, e. g. Design for Manufacture and Assembly (DfMA), Design for Six Sigma (DfSS) or Robust Design (RD) [Taguchi 1986], [Chowdhury 2005], [Boothroyd et al. 2010]. The goals are a reduction of manufacturing costs and designs which are in the best case insensitive to occurring variance, leading to improved product quality and increased user satisfaction.

However, all existing approaches rely on information about the variation in actual production processes that are often not available in early design stages. To overcome this challenge, many major American companies followed a trend of robust design during the 1990s and created process capability databases (PCDB). Even though these offer valuable insight into the expected performance of single processes, they were largely unused for mechanical design purposes due to the lack of practical tools for accessing information relevant to the designer [Tata and Thornton 1999]. While further research in PCDBs followed [Bauer 2002], [Kern 2003], [Delaney and Phelan 2008], it still seems that there are challenges to be solved before widespread adoption in industry is possible.

The purpose of this paper is an identification of both, challenges as well as the potential value for an application of PCDBs in early design stages. Based on an overview about existing approaches, a modified indexing scheme for PCDBs is proposed and coupled with a new measure of process capability, which is easily understood and directly applicable for the mechanical design engineer. The accuracy of corresponding measurements, the ease of use and the benefit to the designer are illustrated using a test database generated for the example case of an anemometer.

### **2. Background**

To cope with variation in production processes, manufactured parts are designed with an allowable geometric variation. These tolerances, i. e. the tolerable minimal/maximal limit for geometrical properties, make sure that the product will assemble and function as intended during use. However, especially in the early stages of new product designs possible deviations of a nominal shape and the resulting effects are often taken into account solely by means of DfMA guidelines [Boothroyd et al. 2010] or qualitative risk assessment approaches [Thornton 2004]. Due to the lack of information, detailed geometric tolerances are often not specified until the near final design is passed to manufacturing or quality departments. This leads to very tight tolerances, which are very difficult and expensive to maintain in production [Tata and Thornton 1999], [Arvidsson and Gremyr 2008].

Consequently, there is an obvious need for accurate data on the achievable process performance or actual production processes in early design stages to predict the functional behaviour of products or to improve product robustness [Tata and Thornton 1999].

## 2.1 Process Capability Data

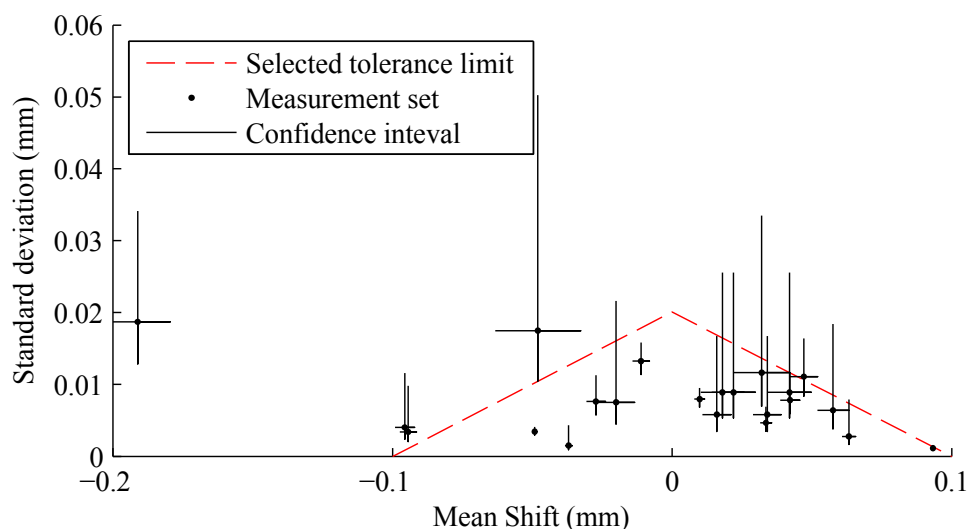
Several papers have been published on methods to predict the occurring process variation using process models [Thornton and Tata 2000]. However, creating process models can be very complicated and impractical for many manufacturing processes. Another option for acquiring the necessary information about production variance is to measure the actual process performance and store it in a database. This so called process capability data is defined "as the expected and obtained standard deviations and mean shifts for a feature produced by a particular process and made of a particular material" [Tata and Thornton 1999]. For a systematic use of corresponding PCDBs in early design stages, the accuracy as well as the structure and the accessibility of data play a decisive role.

### 2.1.1 Generating Process Capability Data

In a typical manufacturing process multiple parts are measured during a first article inspection and subsequently during routine process checks. From the measurement reports the mean shift  $|\mu - m|$  and the standard deviation  $\sigma$  of the measurement set are calculated. Where  $\mu$  is the process mean and  $m$  the target dimension. This data is stored in the database along with the nominal size from a technical drawing and an index, which makes it possible to find the given data based on a combination of the feature, the features' geometry, process and material attributes [Tata and Thornton 1999], [Bauer 2002], [Kern 2003], [Delaney and Phelan 2008].

[Thornton 2004] combines the feature and its geometry/dimension into one index, e.g. a hole and its depth or a chamfer and its angle. The index scheme proposed by [Kern 2003] differs slightly. Whereas the feature types are more abstract such as a front face or inner diameter, the geometry attribute is more generalized and loosely based on geometric product specification (GPS), e.g. the position or concentricity. This allows the engineer to easily search for a geometry attribute such as concentricity across many different feature types.

In order to do more advanced analyses, more data is often added to the PCDB, including stock (the material stock type before processing), lower specification limit (LSL), upper specification limit (USL), machine, operator number, batch size and part volume. However, with a growing amount of data existing indexing schemes are losing clarity and it is even ambiguous how to index a measurement set. As a solution [Kern 2003] developed an assistance tool to guide the designer to select suitable index attributes.



**Figure 1. Graphical display of process capability data as proposed by [Thornton and Tata 2000]**

### 2.3.2 Displaying Process Capability Data

One possibility for a more efficient use of PCDBs is a clever graphical display, which provides quick overview of important characteristics. [Thornton and Tata 2000] describe  $x$ - $y$  plots of mean shifts and standard deviation to illustrate actual process capability data. As an example, Figure 1 shows a measurement set of a diameter [ $3\text{mm} \leq x \leq 4\text{mm}$ ] for an injection moulded part from the test case described in section 4. The diagram shows if the mean shift  $|\mu - m| \neq 0$  of the measurement sets displayed on the  $x$ -axis maintain a tolerance of e.g.  $\pm 0.1$  mm despite the occurring variation, described by the standard deviation  $\sigma \neq 0$  on the  $y$ -axis. Confidence intervals of both mean shift and standard deviation are shown additionally to visualise the statistical significance.

The view is great for the process engineer, showing overall process capability and indicating areas where easy gains in process capability are possible by adjusting the mean shift. However, for the designer the plot is tedious to interpret. He is concerned with the actual tolerances possible for the given design and not the mean shifts and standard deviations.

## 2.2 Application of PCDBs in engineering design

Especially for an efficient use of PCDBs in early stages of engineering design, the accessibility of process capability data pertinent to a particular design, corresponding production processes and a specific company is a critical success factor [Tata and Thornton 1999], [Delaney and Phelan 2008]. In this context, it seems that indexing schemes have become too complicated and abstract to be used efficiently. The issue of selecting the correct attributes arises every time a new design has to be evaluated. Moreover, a flexible adaptation of PCDBs to specific combinations of product features and connected production processes as well as a focus on data relevant for design decisions instead of process optimization must be provided.

In this way, suitable PCDBs also support the tendency in Robust Design methodology towards applying quantitative or formalised Robust Design methods as early as possible in the design process [Ebro et al. 2012]. While in a robust solution, insensitive to geometric variation, the tolerances can generally be widened maintaining the same output performance, the goal is to find an optimum, which balances the cost of increased tolerance requirements, design complexity and the quality loss associated with design parameters being off target [Arvidsson and Gremyr 2008]. Consequently, accurate and easy-to-use process capability data is essential to estimate the optimum level of tolerances and could create a shift in design methodology, from ‘Design of Tolerances’, to ‘Design to Process Capabilities’ (DtPC).

## 3. Improving the Process Capability Database

In the following, a new, generalised concept of data indexing, processing and presentation is presented, which tries to ease the efficient application of PCDBs and make it faster and easier for the designer to efficiently use process capability data for new designs. The indexing scheme is simplified, and made more flexible by using a tagging system. Instead of providing the designer with statistical information, the recommended tolerances based on actual process capability are shown directly. Moreover, the tolerances are normalised in regard to the specified dimension making more use of each dataset and minimising the risk of process capability requests not returning any results. Examples of the generated test database, further explained in section 4, clarify the chosen concept.

### 3.1 Indexing

As seen in section 2 PCDBs need to be indexed to efficiently retrieve process capability data of relevance to the current design. We propose to use *material*, *process* and *geometry* as the primary attributes. The material and process is defined as in previous work, e. g. material ABS treated in an injection moulding process. The geometry is the tolerance type, which is specified on the technical drawing. This includes the GPS tolerance options (e.g. concentricity or position) or just simple tolerances (e.g. distance, diameter). The direct relationship between the information on the drawings and the index attributes makes the selection of the correct geometry unambiguous. Another benefit of the standard tolerance options is that the designers are already familiar with the terminology.

This is combined with a tagging system, where additional tags can be added. Measurement sets affected by additional properties such as high length to width ratios or special surface treatment could be optionally tagged by the user. Tags are not stored in the same manner in the database table as primary index and regular attributes, but in a separate table, which allows none or multiple tags to point to the same measurement set.

An example of a complete database record for a measurement set can be seen in table 1, showing relevant aspects of the corresponding input data. The tagging system allows indexing design attributes that are specific to a single production method or material. E.g. for injection moulding it is possible to index the following design attributes:

- Mould material type: aluminium, steel, hardened, etc. to find the effect of mould material
- Mould/Process iterations (T0, T1, T2...) could give valuable insights of which specification limits require mould rework or process adjustment.
- Tagging dimensions measured across parting lines could potentially show a general increase in desired specification limits.

**Table 1. Measurement set - As stored in the PCDB**

Material	Process	Geometry	Target	USL	Mean Shift	Std.
Thermoplastic	Moulding	Diameter	3,00	3,01	-0,0486	0,0032
- ABS, PC blend	- injection moulding					
General Tag (1)	General Tag (2)	General Tag (3)	Mesh. Equipment	LSL	Measurement date	Num. Samples
Mould type	Production run	Inside	CT scanning	2,99	13. oct 2013	12
-steel	- PR3		-Zeiss			
-- NAK 80			metrotom 800			

### 3.2 Processing Capability Data

Based on the index attributes and the additional tags, processing the capability data consists of three subsequent steps. The data made accessible to the designer is explained in the following sub sections:

1. Compute the process capability specification limit (*PCSL*).
2. Normalise the *PCSLs* so it is independent of dimension.
3. Fit operating curves to the *PCSL* data grouped by different design attributes.

#### 3.2.1 Process Capability Specification Limit

Process capability indices, e. g. described by [Kane 1986] or [Wu et al. 2009], have been widely adopted in statistical process control. Instead of looking at process mean  $\mu$ , standard deviation  $\sigma$  and specified upper and lower limits *USL*, *LSL*, these values are transformed into a unit less number. This process capability index provides a quick overview of how a process is performing. An example is the commonly used  $C_{pk}$  index, where  $d = (USL - LSL)/2$  is half the specification window and  $m = (USL + LSL)/2$  is the midpoint between the specification limits. This can also be reversed for a known  $C_{pk}$  to calculate the desired symmetric tolerance:

$$C_{pk} = \frac{d - |\mu - m|}{3\sigma} \text{ or } d = 3 \cdot C_{pk} \sigma + |\mu - m| \quad (1)$$

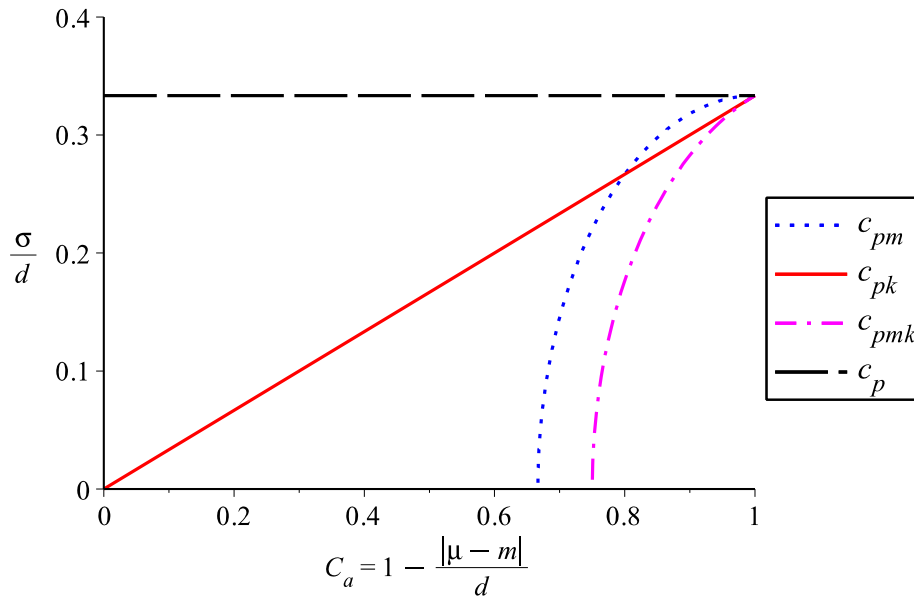
To highlight the difference between  $d$  used to calculate the  $C_{pk}$  value, and  $d$  used as an estimator for symmetric tolerances based on available process capability data, the variable is renamed to *Process capability specification limit (PCSL)* in the following. Using the data from table 1 and an intended process capability index of  $C_{pk} = 1,66$ , the PCSL is computed leading to a tolerance of  $\pm 0,0645$  mm around the target value of 3 mm:

$$PCSL = 3 \cdot 1,66 \cdot 0,0032 \text{ mm} + |-0,0486 \text{ mm}| = 0,0645 \text{ mm} \quad (2)$$

However, there are several commonly used process capability indices, each serving their own purpose [Taguchi 1986], [Wu et al. 2009]:

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

The difference between the different indices can more clearly be understood by looking at Figure 2, where the relationship between closeness to target  $C_a$  and the standard deviation  $\sigma$  normalized using the half specification width  $d$  is shown. The line for  $C_{pm}$  is 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  $C_{pk}$ .  $C_{pmk}$  combines the value loss function  $C_{pm}$  with the relation to yield of  $C_{pk}$ .  $C_{pmk}$  is very conservative. For higher values this effect is more pronounced.



**Figure 2. Comparison of the different process capability indices**

For the purpose of our database we have chosen to use  $C_{pk}$ , since it provides the most understandable result directly related to the yield of the process. The yield of a process is within

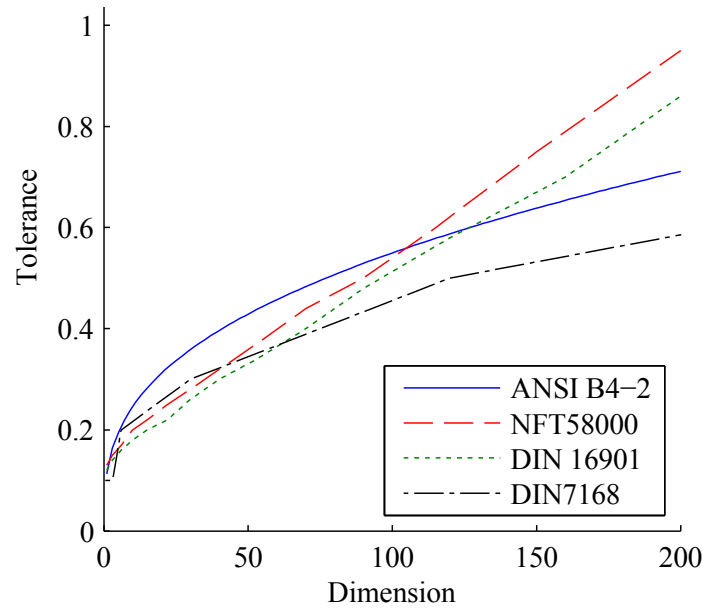
$$2\Phi(3C_{PK}) - 1 \leq \text{yield} \leq \Phi(3C_{PK}) \quad (3)$$

where  $\Phi(x)$  is the cumulative distribution function of the standard normal distribution  $\mathcal{N}(0,1)$  [Boyles 1991]. The optimal process capability index value depends on the application. However, Six Sigma ( $6\sigma$ ) as well as DfSS approaches advocate a target of  $C_{pk} = 2$  (equivalent to  $6\sigma$ ) for short term process capability, which has been shown to generally improve manufacturing quality and profits [Koch et al. 2004]. It is assumed that the process drifts over time up to  $1,5\sigma$  (effectively resulting in a sigma level of 4,5), which still results in an acceptable 3,4 ppm defects. For the PCSL to reflect six sigma production capability, the  $C_{pk}$  input for each measurement set should be varied from 2,0 to 1,5  $C_{pk}$  depending on whether the measurement set reflects the short or long term capability. For simplicity we propose to use a general value of  $C_{pk} = 1,66$  to account for a mixture of long term and short term measurements.

### 3.2.2 Normalisation

The PCSLs are normalised in regard to dimension. This means that we only need a few measurements at different dimensions before a designer can use this to calculate the tightest achievable tolerance for any nominal dimension (for the same production process and material).

A number of existing industrial standards used for manufacturing describe the normal relationship between linear dimensions and tolerances. The authors have analysed the most commonly used standards for general tolerances: American [ANSI B4.2 1978], European [ISO 286 1993] and the German [DIN 7168:1991-4 1991]. The ANSI and the ISO standards use the same formula and are quite close to the German DIN standard. These standards display a non-linear relationship between tolerance and dimension. For the same level of precision, the tolerances of large dimensions are relatively smaller than for small dimensions. In contrast, the German [DIN 16901:1982-11 1982] and the French [NFT 58-000:1987-10 1987] standard, specifically addressing moulded plastic parts, present an almost linear relationship between tolerance and dimension for values above 10 mm (see Figure 3). This might be due to creep which is a major contributor to production error in moulded parts.



**Figure 3. Standards for relation of dimension and tolerance**

These standards are all described in technical reports using tables to show the tolerance for a given dimension interval and precision. In a note for [ANSI B4.2 1978] and later mentioned in [ISO 286 1993] a continuous function is described for international tolerance (IT) grades (precision levels) between IT6 and IT16 for dimensions from 2 mm to 500 mm. This function is for unknown reasons not included in newer versions of ISO 286 yet table values still seem estimated using this function. The relationship is as follows

$$d = \frac{10^{0,2(ITG-1)} \cdot i}{2} \quad \text{with} \quad i = 0,45\sqrt[3]{T} + 10^{-3}T \quad (4)$$

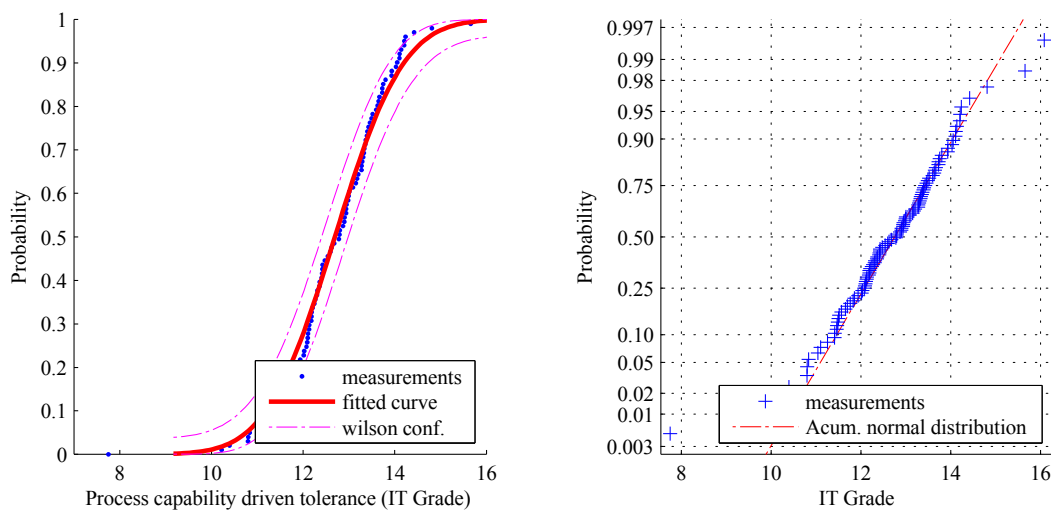
where  $i$  is the standard tolerance factor,  $T$  is the target dimension in [mm] and  $d$  half specification width in [ $\mu$ m]. We use said function to normalize the *PCSL* because the ISO 286 is widely used in the industry. Further work on improving the normalisation of tolerances or simply choosing the best tolerance specification standard requires more data than we have been able to generate in our test case described in section 4. The IT grade (ITG) for the measurement set presented in table 1 can be computed:

$$\begin{aligned} ITG &= 5 \cdot \log_{10} \left\{ \frac{2d \cdot 10^3}{0,45\sqrt[3]{T} + 10^{-3}T} \right\} \text{ [IT grade]} \\ ITG_{specified} &= 13,4 \quad \text{[IT grade]} \\ ITG_{actual} &= 12,5 \quad \text{[IT grade]} \end{aligned} \quad (5)$$

$ITG_{actual}$  is based on the process capability by replacing  $d$  with  $PCSL$ , the process capability driven symmetric tolerance.  $ITG_{specified}$  is the IT grade specified in the design documentation. A lower actual IT grade than the specified IT grade means that the process is performing within the tolerance limits.

### 3.2.3 Analyse normalised data

A further analysis of the underlying measurement sets is done to present the user with an easier to use data view. Relevant measurement sets are aggregated based on design attributes selected by the user. Then, an accumulated frequency plot of the process capability IT grade distribution is proposed to help the user determining which tolerance to use. This gives an overview of the current process capability for the selected design attributes. The plot shows the probability to produce the selected part at the specified  $C_{pk}$  and tolerance. An example for this aggregated view on different features of injection moulded parts is displayed in Figure 4a (see also example product in section 4).



**Figure 4. a) Accumulated frequency of IT grade distribution with Wilson score confidence intervals, b) Normality investigation of IT grade of measurement data**

To even out random effects in the measurements sets, a normal distribution is fitted and Wilson score confidence intervals are added based on the number of measurements sets, to show statistical certainty. The IT grades distribution is assumed to be normally distributed due the central limit theorem, which from our sample data seems to be correct, see Figure 4b. Based on the experience gained from our test data the 90% cumulative probability should be the standard tolerance grade used for designing new parts. The reason for choosing 90% cumulative frequency and not 100% is due to a large degree of exceptions in the upper 10% of the measurements sets. These exceptions include dimensions of long and slender objects, unnecessary tight tolerances in non-critical areas and dimensions where specifications have become desynchronised from manufacturing targets.

As a designer it is often tempting to use an IT grade at a lower cumulative probability, however statistically this will result in errors. Instead the designer should try to specify the given design characteristics more precisely for the given task, hoping these will result in a tighter permissible tolerances. If a tolerance associated with a low probability of occurrence is chosen generally this will impact the price of production since it either: Increases risks of rework to hit the target  $C_{pk}$  or requires more precise machines than what is used for the measured components.

### 3.3 Statistical Validity

The user needs to trust the information provided by the PCDB. The uncertainty of the resulting distribution of IT grades is influenced by several factors, of which sample size and number of measurement sets are the only two possible actionable variables:

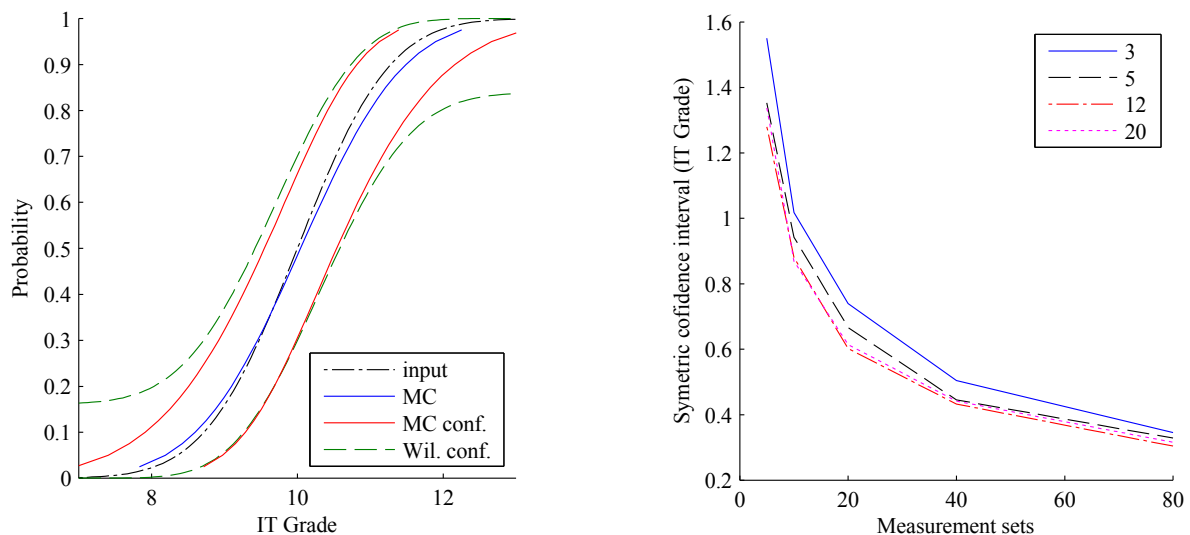
- More samples in each measurement set will increase certainty.



- More measurements sets increase certainty.
- Lower standard deviation of the IT grade distribution will increase certainty.
- Higher mean deviations from target  $C_a$  will increase certainty especially at low sample sizes.

To model the uncertainty and accuracy of the IT grade distribution, we have chosen to use Monte Carlo simulation, since it would be very difficult to accurately model analytically. We assume that the IT grade from each measurement set is a continuous random variable with mean  $\mu_{ITG}$  and standard deviation  $\sigma_{ITG}$  giving  $ITG \sim \mathcal{N}(\mu_{ITG}, \sigma_{ITG}^2)$ . The randomly generated ITG is converted into a normal distribution of individual measurements  $x$  using a fixed target dimension of  $T = 100$  [mm] and closeness to target  $C_a = 0.6$ . The standard deviation  $\sigma_x$  and mean shift  $|\mu - m|$  can be calculated yielding the distribution parameters  $x \sim \mathcal{N}(|\mu - m|, \mu_x^2)$ . Each measurement is generated from the measurement set distribution. When all measurements have been generated the process is reversed and the distribution parameters of the ITG are estimated. The simulation is run  $n$  times.

The Monte Carlo simulation predicts that the standard deviation of the IT grade distribution is overestimated especially at lower sample sizes due the increased uncertainty of these. Even at sample sizes of 10 it is still overestimated by 10%. This effect can also be seen on Figure 5a, the results of a simulation run with the following parameters:  $ITG \sim N(10, 1)$ , sample sizes = 10, number of sample sets = 20,  $n = 10\,000$ .



**Figure 5. a) Monte Carlo cumulated frequency plot, b) Symmetric confidence interval size at 90% probability as a function of sample size and number of measurement sets**

The Monte Carlo simulations were also used to estimate the confidence intervals at different cumulative probabilities using the percentile method. The percentile method interval is the interval between the  $100 \cdot \alpha$  and  $100 \cdot (1 - \alpha)$  percentiles of the Monte Carlo distribution. To verify the simulation we compared the confidence intervals to a simple approximation of the interval based on the Wilson score interval, as seen in Figure 5a. The Monte Carlo interval width is very close to the Wilson score at midsection of the probability curve. The confidence intervals for the Wilson score deviates at the top and bottom section, which is a property of the Wilson approximation.

The effects of sample size and number of measurement sets is displayed in Figure 5b, which shows the symmetric confidence interval at a cumulative probability of 90% as a function of sample size and number of measurement sets. Increasing the sample size only have an effect up to about 12 samples, additional sample measurements do not increase accuracy. The amount of measurement sets is the main factor for reducing the confidence intervals. If the purpose is to differentiate between design attributes then the number of measurement sets is going to limit how small the differences between design attributes can be resolved with statistical certainty.

## 4. Results

The elaborated structure for a PCDB was evaluated using an example product consisting of injection moulded parts. The generated test database, populated with measurement of 75 different samples from 4 different parts using a variety of different measurement techniques, thereby showed the applicability as well as the value of process capability data in comparison to specified tolerances in the underlying technical drawings.

### 4.1 Test Case

To test the elaborated PCDB concept an experimental database was generated. *Vaavud*, a small company making anemometers, provided technical drawings, samples and inspection reports for the example product, a non-stationary wind meter for smart phones shown in Figure 6. Danish Technological Institute provided additional measurements made using their Zeiss CT scanning equipment. The tested parts were all injection moulded. Three parts were made of POM (PTFE filled) in a multi cavity mould. The last part was made using a blend of PC and ABS.



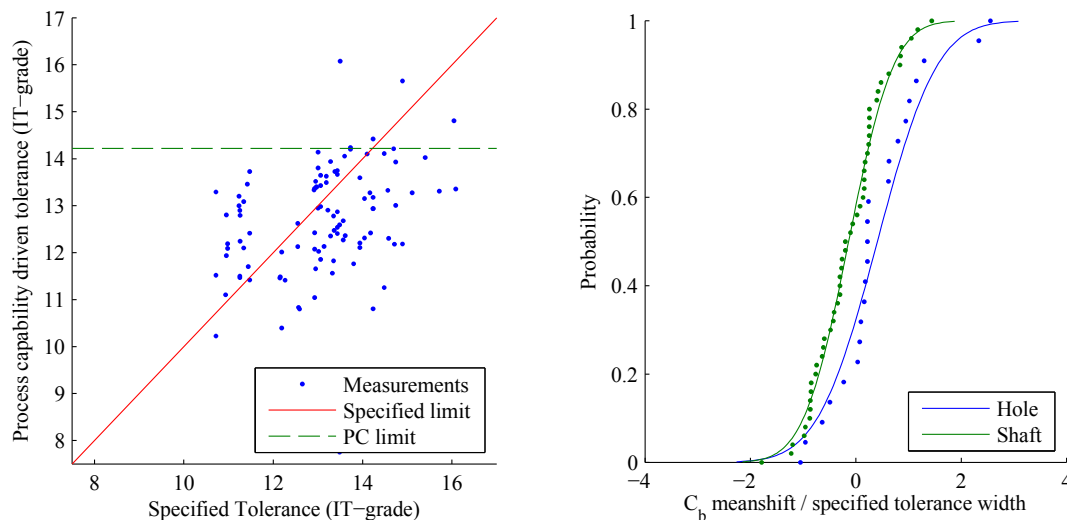
**Figure 6. Example product: anemometer**

### 4.2 Discussion of results

As seen in Figure 4a, the 90% cumulative frequency of all measurements corresponds to a  $14.2 \pm 0.4$  IT grade. Already this value, aggregated for different geometry features, offers valuable information to the designer. Moreover, the indexing/tagging scheme allows a systematic search for design attributes with lower permissible tolerances. Exemplarily, mould properties, materials, geometries etc. were investigated, leading to the following conclusions:

- Linear dimensions within a single mould half did not show significant better performance than dimensions across mould split lines.
- Linear dimension performed to the same IT grade level as radii and diameters.
- Internal and external diameters and radii showed no significant difference.
- Small (0-5 mm), medium (5-10 mm) and large dimensions (10+ mm) performed to the same required tolerance, though the largest dimension were only 80 mm.

Another interesting finding is the a very small (or non-existent) correlation between the tolerance, specified in drawings, and the actual process capability driven tolerance, as seen in figure 6a. It seems that it makes little or no difference if tolerances are specified for each measurement on a part drawing. This clearly shows the need for process capability driven tolerances as a part of robust design. Given the available data, a new part produced using the same production method and materials should be given a tolerance no tighter than 14.2 IT grade.



**Figure 7. a) Correlation between specified tolerances and actual tolerances, b) Comparison of two different design attributes**

Having a database with easy sortable production data can also be used for finding information about general trends, which support the designer and will be valuable to the production directly. For example, holes were larger than specified compared to shafts using the mean shift normalised with the specification limit, see figure 5b. This is likely a deliberate choice by the mould maker, since subsequent tool wear will reduce this systematic deviation from target. Furthermore, corrections will be cheap since it does not require the making of a new mould part.

## 5. Conclusion

In this paper, an overview of existing approaches has shown problems in using process capability databases for design purposes. An efficient indexing scheme and easy to use user interface are two key factors to a functional process capability database.

We have proposed a statistical approach for making process capability independent of dimension and an approach for calculating a process capability driven tolerance. The statistical uncertainty has been estimated using Monte Carlo simulation and compared to known statistical approximations.

In the test case we compared different design attributes and in general no significant differences were found. For new designs using the same process and material the minimum tolerance should be 14.2 IT grade. Failure to design for the available process capabilities of production leads to additional cost for rework or larger failure rate of products.

When designing a new component the generalised process capability database will provide easy access to information of the process capability of the given material and process.

## References

- ANSI B4.1-1967, "Preferred limits and fits for cylindrical parts", Tech. Rep., United States of America Standards Institute, 1967.
- Arvidsson, M., Gremyr, I., "Principles of robust design methodology", *Quality and Reliability Engineering International*, 24, 2008, pp. 23–35.
- Bauer, L. W., "Process Capability Modeling", *General Electric Corporation - Technical Information Series*, 2002GRC038, 2002.
- Boothroyd, G., Dewhurst, P., Knight, W. A., "Product Design for Manufacture and Assembly", 3rd edition, CRC Press Boca Raton, USA, 2011.
- Boyles, R. A., "The taguchi capability index", *Journal of Quality Technology*, 23, 1991, pp. 17–26.
- Chowdhury, S., "Design for Six Sigma", Dearborn Trade Publishing, USA, 2002.
- Delaney, K. V., Phelan, P., "Design improvement using process capability data", *Journal of Material Processing Technology*, 209, 2008, pp. 619–624.

DIN 16901:1982-11, "Plastics mouldings; tolerances and acceptance conditions for linear dimensions", Tech. Rep., German Institute for Standardization, 1982.

DIN 7168:1991-4, "General tolerances for linear and angular dimensions and geometrical tolerances", Tech. Rep., German Institute for Standardization, 1991.

Ebro, M., Howard, T. J., and Rasmussen, J. J., "The foundation for robust design: Enabling robustness through kinematic design and design clarity", in *Proceedings of the 12th International Design Conference DESIGN 2012*, 2012, pp. 817–826.

ISO 286:1993,, "Geometrical product specifications (gps) – isocode system for tolerances on linear sizes", Tech. Rep., International Organization for Standardization, 1993.

Kane, V. E., "Process capability indices", *Journal of Quality Technology*, 18, 1986, pp. 41–52.

Kern, D. C., "Forecasting manufacturing variation using historical process capability data: applications for random assembly, selective assembly, and serial processing", Ph.D. thesis, Citeseer, 2003.

Koch, P., Yang, R.-J., Gu, L., "Design for six sigma through robust optimization", *Structural and Multidisciplinary Optimization*, 26, 2004, pp. 235–248.

NFT 58-000:1987-10, "Nft58000 plastics - tolerances applicable to moulded plastic parts", Tech. Rep., Association française de normalisation, 1999.

Taguchi, G., "Introduction to quality engineering: designing quality into products and processes", *Quality Resources*, 1986.

Tata, M., Thornton, A., "Process capability database usage in industry: myth vs. reality", in *ASME Design Engineering Technical Conferences*, 1999.

Thornton, A. C., "Variation risk management: focusing quality improvements in product development and production", Wiley Hoboken, 2004.

Thornton, A. C., Tata, M., "Use of graphic displays of process capability data to facilitate producibility analyses", *AI EDAM*14, 2000, pp. 181–192.

Wu, C.-W., Pearn, W., Kotz, S., "An overview of theory and practice on process capability indices for quality assurance", *International Journal of Production Economics* 117, 2009, pp. 338 – 359.

Dr. Thomas Howard, Associate Professor  
 Technical University of Denmark  
 Department of Mechanical Engineering  
 2800, Lyngby, Denmark  
 Email: thow@mek.dtu.dk  
 URL: <https://sites.google.com/site/thomasjameshowardhomepage>

