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Research

Another Look at the Process Capability Index

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Process capability indices (PCIs) have been widely used in manufacturing industries. In this paper, we take a very specific view that a proper value of the process capacity index (PCI) represents the true yield of the process. Following this logic, a universal PCI, C_y, is proposed and derived. The superiority of the new PCI is presented in theory and demonstrated through examples. Copyright © 2005 John Wiley & Sons, Ltd.

KEY WORDS: C_p index; C_{pk} index; C_{pm} index; yield

INTRODUCTION

Capability analyses often required for purchasing process equipment. The process capability index (PCI) is widely adopted in the manufacturing industry[1,2]. The most well-known PCI is probably the C_p index, introduced by Juran *et al.*[3]:

$$C_p = \frac{USL - LSL}{6\sigma} \tag{1}$$

where *USL* is the upper specification limit, *LSL* is the lower specification limit, and σ is the process standard deviation. Equation (1) represents the ratio of the length of the specification interval (the engineering tolerance) to the natural tolerance 6σ, which is also defined as the 'process capability' by Juran. Thus, a value of $C_p = 1.33$ implies that the specification interval is 33% wider than the natural tolerance to assure a yield of 99.73%. Note that a $C_p = 1.33$ is generally used in practice for an ongoing process[4].

Two specific assumptions were made for C_p to be appropriate: (a) the underlying quality characteristic $\mathbf{X}$ is a random sample from a normal distribution $N(\mu, \sigma^2)$, and (b) the population mean μ is at the midpoint of the interval [*LSL*, *USL*]. When a process satisfies both (a) and (b), we say that the process is under the 'ideal situation'. In this case, the actual proportion of product that falls within the specification interval [*LSL*, *USL*] is $2\Phi(3C_p) - 1$, where Φ denotes the cumulative distribution function (cdf) of the standard normal distribution. See Appendix A for the derivation.

If either assumption (a) or (b) is invalid, i.e. when the situation is less than ideal, then C_p only measures the potential capability index in the sense that the actual proportion of products that falls within the specification interval [*LSL*, *USL*] is less than $2\Phi(3C_p) - 1$. Various adjustments have been proposed in the literature.

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The most well-known are

$$C_{pk} = \min\left\{\frac{USL-\mu}{3\sigma}, \frac{\mu-LSL}{3\sigma}\right\} \quad \text{and} \quad C_{pm} = \frac{USL-LSL}{6\sqrt{\sigma^2+(\mu-T)^2}}$$

The C_{pk} index was developed in Japan and utilized by Japanese companies[4], while the C_{pm} index was independently introduced in Chan *et al.*[5] and Hsiang and Taguchi[6]. For other third-generation generalizations, such as C_{pmk}, $C_p(u, v)$ or C_{pw}, see Vännman[7] and Spiring[8]. A common feature of all these corrected versions is that they all satisfy the inequality

$$C_{p*} \le C_p \tag{2}$$

where C_{p*} includes C_{pk}, C_{pm}, C_{pmk}, $C_p(u, v)$, C_{pw}, etc. This is also demonstrated in Sommerville and Montgomery[1].

What does PCI really try to measure? If two processes have an identical PCI, does this imply they are equally good? If one process has a higher PCI than another process, what does this really mean? More importantly, are they *compatible*? If so, in what sense? It is fair to claim that, except for some qualified descriptions[9], an unambiguous definition of PCI is still lacking. In this paper, we believe that a meaningful PCI must have a meaningful physical support. We first discuss the relationships between yield and other PCIs. A PCI based on yield, C_y, is then defined, some of its properties are discussed. Simulative studies are conducted, followed by some concluding remarks.

PCI IMPLIES YIELD

One of the most important reasons for all these adjustments is due to the concern that the C_p may be higher than it should be. This is mathematically reflected in Equation (2). It is generally agreed that the original motives underlying the introduction of PCIs were related to the proportion of non-conforming products[10]. Sommerville and Montgomery[1] make use of C_p to draw conclusions about the process performance expressed in parts per million (ppm). So when we have a value of $C_p = 1$, it is known that under the ideal situation the yield is 99.73%; and if the situation is less than ideal, the yield is less than 99.73%. Instead, if we see C_{pk} (or C_{pm})= 0.9, what can we say about the true yield? Most PCIs do not provide a precise meaning of yield. In this paper, we take a very specific view that a proper value of PCI should represent the true yield of the process.

C_{pk}, C_{pm} and yields

Suppose that $LSL = -3\sigma$, $USL = 3\sigma$ and $C_{pk} = \min\{(USL-\mu)/3\sigma, (\mu-LSL)/3\sigma\} = 0.9$. This implies that $\mu = \pm 0.3\sigma$. The true yield is then $\Pr(-3.3 < Z < 2.7) = \Phi(2.7) - \Phi(-3.3) = 0.996$. If the adjusted PCI should represent the true process capability, then it should indicate the yield under the ideal situation. Now, if the standard C_p value is 0.9, the true yield should be $2\Phi(3 \times 0.9) - 1 = 0.993$. In terms of ppm defective, the difference is $10^6 \times (0.996 - 0.993) = 3000$. In fact, for the true yield of 0.996 under the ideal situation, we need C_p to be 0.9594. In other words, C_{pk} over-adjusts the true yield by under-reporting the equivalent C_p value. In fact, C_{pk} does not imply the yield. The same value of $C_{pk} = 0.9$ may imply different yields, depending on the value of USL and LSL.

For the case of C_{pm}, the interval is given by $T \pm L$ with $\sigma = 1$, it can be shown that the true yield is given by $\Pr(T+L < X < T-L) = \Phi(L-a) - \Phi(-L-a)$, where $a = \sqrt{L^2/(3C_{pm})^2 - 1}$. Note that the true yield depends on both L and C_{pm}. Thus, the same C_{pm} may give different values of yield (depending on the value of L). This is observed by Pearn *et al.*[10]. As a matter of fact, this phenomenon is true for almost all C_{p*} values.

A PCI based on yields

A PCI called C_y, where y stands for yield, is defined in such a way that when we encounter $C_y = 1$, then the process yield is 0.9973, whereas $C_y = 0.9$ represents a process yield of 0.993, etc. In general, we have

$$\text{process yield} = 2\Phi(3 \times C_y) - 1 \tag{3}$$

This equation should be true under any situation: whether or not the mean or the process target coincides with the center of the specification interval [LSL, USL] and whether or not the process follows a normal distribution. Under the ideal situation, the C_y index is indeed equivalent to the C_p index. We believe that this is a sensible approach if the role of PCIs is to monitor the proportion of non-conforming products[4,10].

The meaning of the classical C_p is clear only when the underlying distribution is normal and its mean is the midpoint of the tolerance limits. Under the not-so-ideal situations, however, it is not clear how to properly generalize the standard index C_p. For example, if the population is Gamma, then an interval of length 6σ no longer covers 99.97% of the area under its density function[1]. Furthermore, it is questionable whether an equal amount of probability should be assigned to each tail for such an interval. An alternative approach is to use the shortest possible length of the interval that contains 99.73% of the area[12].

The main difference between our C_y and all other C_{p*} is that we make no effort to generalize C_p to cover all different situations, neither do we suggest an additional family of indices to further confuse the managers. We do precisely the opposite—we only narrow down our search by linking with the basic simple concept: the true yield.

THE PROPOSED PCI: C_y

Let F be the distribution of the process. Based on the fundamental idea that PCI implies yield, we propose a universal PCI as

$$C_y = \tfrac{1}{3}\Phi^{-1}[\tfrac{1}{2}(F(USL) - F(LSL) + 1)] \tag{4}$$

where Φ denotes the cdf of the standard normal distribution, i.e.

$$\Phi(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{x} \exp\left(-\frac{1}{2}t^2\right) dt$$

This seemingly complicated formula can be easily evaluated via any computer software. We next discuss the theoretical reason behind the formulation and show how to apply C_y in reality through an example.

PCI under normality

To illustrate the proposed C_y index, first assume that the underlying process is $N(\mu, \sigma^2)$, the ideal situation. By defining a PCI with yield, we have a common basis for comparison under various situations. When two products claim they have the same $C_y = 1.2$, for example, their yields are $2\Phi(3 \times 1.2) - 1 = 0.999\,68$, or their ppm non-conforming is 318. Theoretically, assuming X is $N(\mu, \sigma^2)$, then

$$\text{process yield} = \Pr[LSL \le X \le USL] = \Phi\left(\frac{USL - \mu}{\sigma}\right) - \Phi\left(\frac{LSL - \mu}{\sigma}\right)$$

Equating the above relation with Equation (4) and solving for C_y, we obtain

$$C_y = \frac{1}{3}\Phi^{-1}\left[\frac{1}{2}\left(\Phi\left(\frac{USL - \mu}{\sigma}\right) + \Phi\left(\frac{\mu - LSL}{\sigma}\right)\right)\right] \tag{5}$$

A few remarks can be made about the C_y index.

- It reduces to the classical formula for C_p when $\mu = \frac{1}{2}(LSL + USL)$.
- It gives the exact yield of the process.
- It is a function of only two quantities, $x_1 = (LSL - \mu)/\sigma$ and $x_2 = (USL - \mu)/\sigma$. Note also that C_y attains its maximum at $x_1 = x_2$, hence $C_y \le C_p$, so $2\Phi(3C_p) - 1$ still represents the potential yield if the process is centered.
- By its construction, C_y is the only PCI that gives the correct yield of the process as implied by the classical value of C_p under an ideal situation.
- The formula for C_y is complicated in its appearance. However, the function Φ and its inverse are available in almost any statistical software. The computation effort for C_y is rather straightforward. A simple line of computer code will be sufficient.

PCI under the non-normal population

Now, for a general case, assume the process follows an arbitrary continuous distribution F and let $Y = \Phi^{-1}[F(X)]$, then Y is distributed as $N(0, 1)$. Let m denote the median of F, that is,

$$\Pr[X \ge m] = \Pr[X \le m] = \tfrac{1}{2} = F(m)$$

The function $g(x) = \Phi^{-1}[F(x)]$ is monotone increasing, since both F and Φ are. The median of Y is then $g(m)$, which is precisely equal to 0. Moreover, $X \in [LSL, USL]$ if and only if $Y = g(X) \in [g(LSL), g(USL)]$. It follows that

$$\text{process yield} = \Pr[LSL \le X \le USL] = \Pr[g(LSL) \le Y \le g(USL)] = \Phi(g(USL)) - \Phi(g(LSL))$$

Hence, the proper definition for C_y is

$$C_y = \tfrac{1}{3}\Phi^{-1}[\tfrac{1}{2}(\Phi(g(USL)) - \Phi(g(LSL) + 1)] = \tfrac{1}{3}\Phi^{-1}[\tfrac{1}{2}(F(USL) - F(LSL) + 1)]$$

as displayed in Equation (4). Note that F is not necessarily symmetric. Moreover, the parameters are hidden in the function g, which depends on the distribution function F. For example, if F is $N(\mu, \sigma^2)$, then

$$g(x) = \Phi^{-1}\left[\Phi\left(\frac{x-\mu}{\sigma}\right)\right] = \frac{x-\mu}{\sigma}$$

and in this case the formula of C_y reduces to C_p when $\mu = (USL + LSL)/2$, as it should.

Our main idea is to first transform the original data to normality and then apply the formula for C_y designed under normality. The exact yield is preserved since a monotone transformation changes the specification limits monotonically. Rodriguez[11] introduces the concept of the 'robust capability index' which indicates the need of a capability index whose interpretation is insensitive to the departure from normality, unlike that of a standard C_p or C_{pk}. Our C_y, as defined in Equation (4), is probably the most robust capability index among all PCIs.

Estimation of C_y

When the observations $X_1, X_2, \ldots, X_n$ are given, the C_y index is simply a parameter to be estimated. The general idea is to first estimate the unknown parameter θ (a finite-dimensional parameter) by $\hat{\theta}$ and then substitute it into the formula of C_y. For example, in all previous works of estimating C_{p*}, the standard practice is to use

$$\hat{\mu} = \bar{X} \quad \text{and} \quad \hat{\sigma}^2 = \frac{1}{n-1}\sum_{i=1}^{n}(X_i - \bar{X})^2$$

for $\theta = (\mu, \sigma^2)$. This can be used to estimate C_y for the ideal case. In general, the distribution of the process F can be modeled by a parametric family indexed by a vector-valued unknown parameter θ, we may write F

as $F(x;\theta)$. Using Equation (4), our estimate for the parametric case is simply

$$\hat{C}_y = \tfrac{1}{3}\Phi^{-1}[\tfrac{1}{2}(F(USL;\hat{\theta}) - F(LSL;\hat{\theta}) + 1)]$$

If F is completely unspecified, very little is known on how to estimate $F(LSL)$ and $F(USL)$. The conventional approach is to use a parametric method to fit F to a certain family of distributions to obtain an estimator of θ. See, for example, Clements[13] for techniques with respect to the fitting of Pearson curves and Rodriguez[11] for an example from the log-normal family. Rodriguez[11] appears to be the only work that makes reference to using a kernel density estimate to deal with the estimation of PCIs (although no specific estimator is suggested).

For the non-parametric case when F is completely unspecified, we use

$$\hat{C}_y = \tfrac{1}{3}\Phi^{-1}[\tfrac{1}{2}(\hat{F}(USL) - \hat{F}(LSL) + 1)]$$

As a general-purpose non-parametric estimate for our use, we suggest

$$\hat{F}(x) = \frac{1}{n}\sum_{i=1}^{n}\Phi\left(\frac{x - X_i}{1.06sn^{-1/5}}\right)$$

where s is the sample standard deviation. This is obtained by integrating a kernel density estimate with the bandwidth $h = 1.06sn^{-1/5}$ determined by the normal reference rule[13]. Such a choice of h is asymptotically optimal if the underlying distribution is normal. Since $\Phi(x)$ goes to 0 and 1 at a rather fast rate as x goes to extreme values, we see that the values of $\hat{F}(USL)$, $\hat{F}(LSL)$ are generally determined by the values of several extreme observations. Hence the non-parametric estimator does not provide an accurate estimator at the points of our need. This is indeed the problem of tail distributions with all non-parametric estimators. In actual application, we suggest that every effort be made to use the classical parametric approach, and the non-parametric version of $\hat{C}_y$ only be used as a last resource.

SIMULATION COMPARISONS

In this section, we compare four PCIs: C_p, C_{pk}, C_{pm} and C_y in various situations:

- Case A: when the process is normal and $\mu = T$ (the target value);
- Case B: when the process is normal but $\mu \neq T$; and
- Case C: when the process is non-normal, the popular Gamma distribution is used to demonstrate the basic idea.

Case A is the ideal case and we expect that all four PCIs should perform well and be similar to each other. Case B is less than ideal and we expect that C_y and C_{pm} which take into account the bias between μ and T will perform well, while C_{pk} and C_p will not. When the normality assumption is violated, Case C shows the case of Gamma distribution under different settings of parameters. Here, we follow the procedure previously described, assuming the underlying distribution is unknown.

In each case, we generate $n = 30$ random variates $(x_1, \ldots, x_{30})$ and calculate the corresponding PCIs. For graphical reasons, any PCI larger than four is set to be four (meaning large). We then repeat this for $k = 10\,000$ iterations and summarize using boxplots for the 10 000 PCIs. Table I shows the underlying values for simulations, where 'True PCI' is evaluated via Equation (3) as a benchmark for comparisons. Boxplots are given in Figures 1–3.

Figure 1 shows the results of Case A when the standard deviation $\sigma = 2$, 1.33, 1, 0.75 and 0.5. All four PCIs have a similar behavior—the median is close to the true PCI value (indicated in Table I), but the distribution is slightly skew to the right. Furthermore, C_y is (nearly) identical to C_p. Figure 2 shows the results of Case B when the standard deviation $\sigma = 2$, 1.33, 1, 0.75 and 0.5. Only C_y and C_{pm} which take into account the bias are close to the true values. As the standard deviation increases, however, C_y is consistently closer to the true value than C_{pm}. For the non-normal (Gamma) case, as indicated in Figure 3, C_y outperforms other PCIs: C_y is rather stable, while C_{pm} and C_{pk} over-adjust C_p to present a misleading signal (in terms of yield).

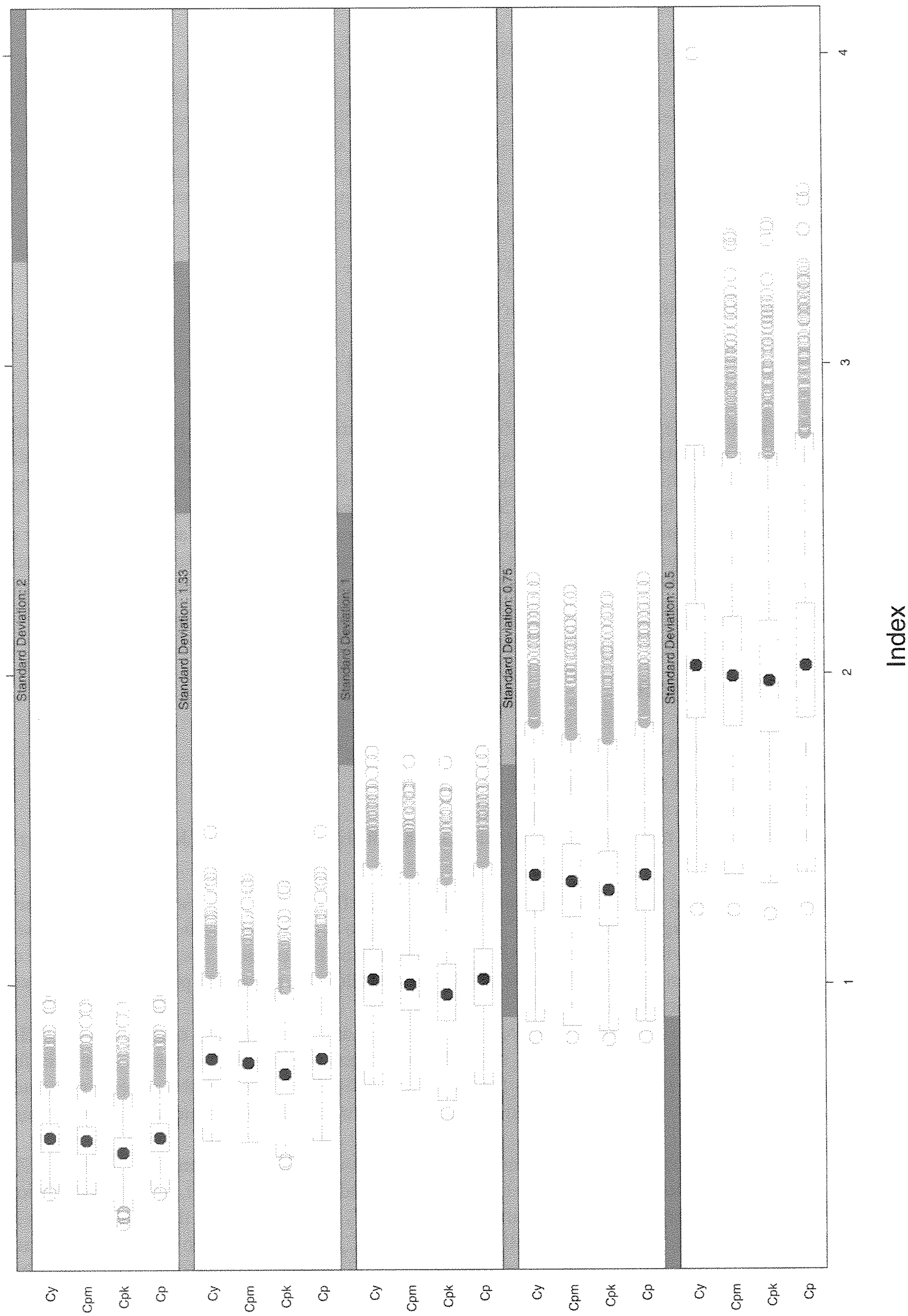

Figure 1. Boxplots for various PCIs: Case A (normal and $\mu = T$)

Figure 2. Boxplots for various PCIs: Case B (normal and $\mu = T$)

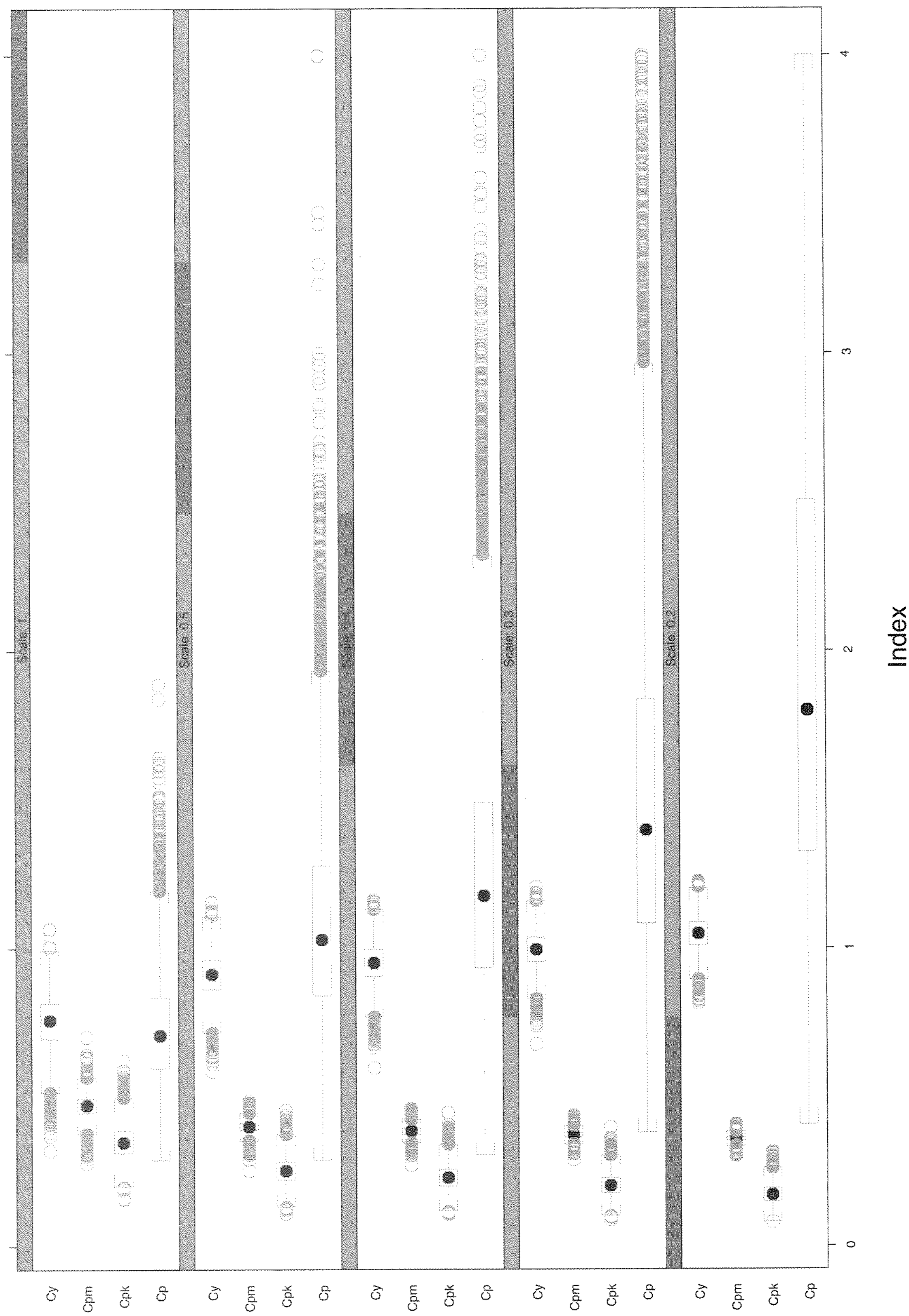

Figure 3. Boxplots for various PCIs: Case C (non-normal)

Table I. Values used in simulation study

Case	Distribution	(*LSL*, *USL*)	Target	Parameter	True PCI
A	Normal	(10, 16)	13	$\sigma = 2.00$	0.50
	($\mu = 15$)			$\sigma = 1.33$	0.75
				$\sigma = 1.00$	1.00
				$\sigma = 0.75$	1.33
				$\sigma = 0.5$	2.00
B	Normal	(10, 16)	11	$\sigma = 2.00$	0.3351
	($\mu = 15$)			$\sigma = 1.33$	0.4029
				$\sigma = 1.00$	0.4699
				$\sigma = 0.75$	0.5630
				$\sigma = 0.5$	0.7592
C	Gamma	(0, 4)	2	scale = 1.0	0.7864
	(shape = 1)			scale = 0.5	0.9428
				scale = 0.4	0.9828
				scale = 0.3	1.0290
				scale = 0.2	1.0856

CONCLUDING REMARKS

We believe that a meaningful PCI must have a meaningful interpretation and take a very specific view that PCI represents the true yield to derive a general PCI, called C_y. It may be argued that if yield is so important why not just report the yield directly[14,15]? This is a very legitimate question. We agree that C_y and the true yield imply each other and they provide equivalent information. C_p has established its role as the single-number summary for process capability, which is irresistible to managers responsible for hundreds of process capabilities running concurrently[11]. Here, we take the original C_p and derive the C_y to provide a common ground so that all processes can be compared. Furthermore, since yield is only a percentage, we can combine various yields to derive an overall yield. In this way, we can define a company-wise value of PCI. For the same reason, we can extend C_y to higher dimensions.

The extension of C_y to a multivariate process capacity index is straightforward: using multiple integration for a multivariate distribution. However, unless we have a clear definition of what a multivariate PCI really attempts to measure, such an extension may be meaningless for practitioners (apart from some theoretical exercise).

The study of PCI has received a great deal of attention in the recent literature, notably in Polansky[16], Deleryd and Vännman[17], Pearn and Chen[18], Tang and Than[19], Shiau *et al.*[20], Noorossana[21], Bordignon and Scagliarini[22], Pearn and Lin[23] and Chang *et al.*[24]. Kotz and Johnson[25] provides an excellent review and many research possibilities. It is our hope that this paper will contribute to this important subject. A rather complete collection of papers in this area is given in Spiring *et al.*[26].

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APPENDIX A

Proof of process yield $= 2\Phi(3C_p) - 1$ is given below:

$$\begin{aligned}
\text{process yield} &= \Pr[LSL \le X \le USL], \quad \text{where } X \sim N(\mu, \sigma^2) \\
&= \Pr\left[\frac{LSL-\mu}{\sigma} \le Z \le \frac{USL-\mu}{\sigma}\right], \quad \text{where } \mathbf{Z} \sim N(0, 1) \\
&= \Pr[-3C_p \le Z \le 3C_p] \\
&= \Pr[Z \le 3C_p] - \Pr[Z \le -3C_p] \\
&= \Phi(3C_p) - \Phi(-3C_p) \\
&= \Phi(3C_p) - (1 - \Phi(3C_p)) \\
&= 2\Phi(3C_p) - 1
\end{aligned}$$

Authors' biographies

Min-Te Chao is a research fellow at the Institute of Statistical Science, Academia Sinica, Taiwan. Dr Chao received his PhD in Statistics from University of California-Berkeley in 1967. He is an elected fellow of the Institute of Mathematical Statistics (IMS) and an elected member of the International Statistical Institute (ISI). He was the founding director of the Institute of Statistical Science, Academia Sinica (Taiwan) and currently serves as the editor of *Journal of Data Science*.

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