Proposal of a New Process Capability Index Based on Dollar Loss by Defects*

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Abstract

The process capability indices have been widely used to measure process capability and performance. In this paper, we proposed a new process capability index which is based on an actual dollar loss by defects. The new index is similar to the Taguchi's loss function and fully incorporates the distribution of quality attribute in a process. The strength of the index is to apply itself to non-normal or asymmetric distributions. Numerical examples were presented to show superiority of the new index against C_p, C_{pk}, and C_{pm} which are the most widely used process capability indices.

Key Words: Process Capability Indices, Expected Dollar Loss, Taguchi's Loss Function

1. Introduction

Growing global competition has requested companies adopt various statistical techniques for analyzing process capability, improving quality of output, and reducing cost due to rework or scraps. Although there is no standard definition for the term "process capability," it is broadly accepted that the primary objective of process capability is to determine how well a process produces output conforming to design specifications for a product and service (Krajewski *et al.*, 2007).

In recent years, process capability indices (PCIs) have received significant attention as process capability measurement. The most widely used indices are C_p, C_{pk}, and C_{pm}. These capability indices determine the current ability to meet design specification for a product and service. The underlying rationale of introducing PCIs is to monitor the proportion of output outside the specification limits and determine capability of the process in use (Kane, 1986).

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* This work was supported by INHA UNIVERSITY Research Grant.

However, there is a considerable weakness in PCIs. Because the process location (μ) and process variability (σ) are unknown and have to be estimated from a sample, the sampling variability can result in incorrect values of the capability indices. To resolve this weakness resulting from the use of a point estimate, various authors have attempted to develop techniques and tables for constructing the lower 95% confidence limits for each capability index. Chou, Owen and Borrego (1988) presented tables for developing 95% confidence limits for C_p and C_{pk}. Boyles (1991) proposed a statistical procedure for finding lower confidence limits for C_{pm} and contrasted C_{pk} and C_{pm}, to note that the former could fail to distinguish between off-target and on-target processes. Likewise, Kushler and Hurley (1992) studied various confidence intervals for C_{pk} and C_{pm} and compared the performances of a variety of confidence intervals in terms of plotting "miss rates" of the confidence bounds for two capability indices. Another drawback of using the PCIs, which is more critical than the former one, is that the assumption of the process distribution. PCIs assume that the measurements are independent and reasonably normally distributed (Chen and Chen, 2004; Franklin and Wasserman, 1992; Gunter, 1989; Spring, 1997). For example, Gunter (1989) indicated that many practical processes in a real world violate the assumption that the process is normally distributed and that unless the process distribution is normal, the application of C_{pk} leads to serious errors. Franklin and Wasserman (1992) also questioned whether PCIs are valid if a process is non-normal. They showed that 95% lower confidence limits developed in terms of the methods of Chou, Owen and Borrego (1988) for C_p, Bissell (1990) for C_{pk}, and Boyles (1991) for C_{pm} can lead to 75% or 80% lower confidence limits for skewed or heavy tailed process. Because PCIs fail to measure process capability accurately for non-normal process data, many companies heavily restricted the use of process capability indices to accompanying normality test of the measurement data or a large size of sample (Andrew, 1994). A different approach to process quality control is initiated by Genichi Taguchi (1987). Taguchi's quality philosophy can be regarded as target-oriented quality control rather than conformance-oriented quality control because it assumes that any deviation of product characteristics form the target creates customer dissatisfaction, and this dissatisfaction can be expressed as dollar loss to the company in terms of a quadratic loss function (Kackar, 1988). Thus, the objective of loss function approach is to improve the product or process quality by reducing the mean squared deviation of the produced quality characteristics form the target which is the sum of the square of the difference between the mean of a quality characteristic and the target value and the pure variance of the quality characteristic.

Taguchi's quality loss function is helpful for a decision marker not only to understand quality loss is a continuous function (not a step function classifying things as being good or bad), but also to justify investment for quality improvement (Maghsoodloo *et al.*, 2004). This approach can also develop a cost and quality effective guideline for supplier selection because any measured value of product characteristic ties in a monetary loss which would be directly transferred into management decision making process (Maghsoodloo *et al.*, 2004). In addition, Taguchi's approach does not need normality assumption which is a required condition in the traditional process capability index because the quality loss is estimated by deviation from the target value regardless of the type of distribution. However, Taguchi's approach could sometimes mislead the decision maker because it is difficulty to understand whether the origin of the loss is due to process variance or departure of process mean from the target. Another weakness is that Taguchi's approach is somewhat inappropriate to determine whether the process is operating in an acceptable level or not because dollar loss computed from Taguchi's loss function has no benchmarking point to judge if the process is acceptable or not. Finally, Taguchi's approach often fails to identify which process has more serious problem in quality. Let us suppose two processes producing parts, A and B. The dollar loss when the part A is out of specification is only $20 while that for part B is $200. Even though the deviation of part A from the target becomes larger than the deviation of part B, total dollar loss of part A can be smaller than that of part B because the dollar loss of out-of-specification for part A is significantly smaller than that of part B ($20 vs. $200). If this case happens, decision making based on Taguchi's loss function can be misled. To resolve these weaknesses inherent in the traditional PCIs and the Taguchi's loss function, we need o develop a unitless measure incorporating a dollar loss. Hsiang and Taguchi (1990) and Chan, Cheung and Spiring (1988) proposed a unitless process capability index C_{pm} modifying Taguchi's loss function which would help track the potential process capability regardless of the process centering. However, like other PCIs, C_{pm} only indicates engineers what has happened in quality of the product or process, not how to make it happen and what effect would follow if it happens in the process capability (Kotz and Johnson, 2002). Thus, there is a need to develop a unitless process capability index so that it can help engineers to relate the causes of a quality problem and the dollar loss due to the causes. In the next section, we explore the Taguchi's loss function and its variants and suggest a modified loss function. Then, we develop a unitless capability index incorporating dollar loss for the normal distributed process. Finally we compare the quality index developed in this study with the traditional PCIs, C_p, C_{pk}, and C_{pm} which are the most widely used process capability indices.

2. Modification of Loss Functions

Taguchi's quality philosophy can be thought as target-oriented quality. It assumes that loss is incurred as a product's quality characteristic deviates from its target value, regardless of the degree of deviation. The quality loss is expressed as a dollar loss equal to the cost of the product's scrap or manufacturing. Taguchi's loss function is approximately proportional to the square of the deviation of the quality characteristic from its target value, which stems from an extension of Taylor series. It is formulated as $L_i(y_i) = c(y_i - T_i)^2$ where c is a proportionality constant and T_i is the target value and y_i is an observed quality characteristic. c is determined by dividing the loss when the deviation of a product's quality characteristic is the tolerance limit(δ) from the target value by the squared tolerance limit(δ^2). Variants of Taguchi's loss function have been proposed by many authors (Kackar, 1986; Pearn *et al.*, 1992; Stevens and Baker, 1994). Kackar (1986) mathematically formed an asymmetric quadratic loss function. Pearn, Kotz and Johnson (1992) also showed an appropriately modified loss function when the loss is assumed to be bounded if the response (y_i) of a product's quality characteristic falls outside the specification limits. But, they did not consider the situation where the loss function becomes asymmetric. Stevens and Baker (1994) developed a generalized loss function incorporating the different degree of penalty on the quality loss when a product's quality characteristic is deviated from the target value. The underlying rationale of the generalized loss function is that a product's quality loss resulting from the deviation from the target value can be not only approximately proportional to the linear deviation but also proportional to the exponential deviation from the target. The penalty on the quality loss would depend on a product's quality characteristic which a firm produces. In fact, Taguchi neglected the terms with powers higher than 2 in the expansion of Taylor series when he developed the quality loss function. Even though he did so, the quadratic loss function is widely accepted in the past research. Therefore it would not be a serious problem to use the quadratic loss function in this paper. Taguchi *et al.* (2004) exhibited several types of loss functions: the-nominal-the-best (*N* type), the-smaller-the-better(*S* type), and the-large-the-better (*L* type). The nominal the best system allows variation in both directions from the target value. If one can desire variation in both directions around the target value, it ends up a symmetric nominal the best type loss function. On the other hand, when tolerance limits are needed to set at unequal distance from the target value, the loss function should be asymmetric and the target value is not the midpoint of the tolerance interval. The smaller the better type loss function involves nonnegative in the quality characteristic whose ideal target is zero. A typical example is the amount of impurity. When the ideal target is a positive infinity, one can use the larger the better type loss function. A typical example is the strength of materials. In this case, the stronger, the better. Taguchi's loss function addresses that the quality loss is the societal loss resulting from a product, from the time the product is shipped to customers (Kackar, 1986). The societal loss can include failure to meet the customer's expectation of fitness for use, future loss of goodwill, harmful effect caused by the defective product and the cost of the product disposal or manufacturing unusable products. The societal loss is assumed unbounded in the Taguchi's loss function. Even though this concept is attractive to ones taking a long-term view, it is, in fact, not easy to measure some of the societal loss such as future loss of goodwill, harmful effect of the defective product, or failure to meet the customer's expectation. In addition, it is somehow unrealistic that the societal loss increases quadratically without a bound as the response of a product's quality characteristic deviates far more from the target value. Therefore, we assume that the total loss is constant(K) if a product's quality characteristic falls outside of the specifications. K is determined by the cost of the product disposal or manufacturing.

Likewise, we modify Taguchi's nominal the best type loss function as follows:

$$L(y_i) = \begin{cases} K & y_i < T_i - \delta_1 \\ c_2(y_i - T_i)^2 & T_i - \delta_1 \le y_i < T_i \\ c_2(y_i - T_i)^2 & T_i \le y_i < T_i + \delta_2 \\ K & T_i + \delta_2 < y_i \end{cases}$$

$$\text{where } c_1 = \frac{K}{\delta_1^2} \text{ and } c_2 = \frac{K}{\delta_2^2}.$$

δ_1 and δ_2 are the tolerance limits. K is the total dollar loss when the product is scrapped. The values of c_1 and c_2 can be determined if the tolerance limits are set and K is measured. If the loss function is symmetric, the target value lies in the midpoint of the tolerance interval and c_1 and c_2 have the same value. However, if it is asymmetric, the target value should not be the midpoint of the tolerance interval. A the-smaller-the-better type loss function is similar to the above equation. The difference is the product's quality characteristic should be nonnegative, therefore no loss arise when the quality characteristic is less than zero. The loss function is

$$L(y_i) = \begin{cases} c_2(y_i)^2 & 0 \le y_i < \delta_2 \\ K & \delta_2 < y_i \end{cases}$$

$$\text{where } c_1 = \frac{K}{\delta_2^2} \text{ and}$$

Under a the-larger-the-better type loss function, the target value is positively infinite and only the lower tolerance limit exits. As a result, to formulate a loss function, we need to transform this type of tolerance to a the-smaller-the-better type tolerance by letting $t = \frac{1}{y}$.

3. Proposed Process Capability Index

Taguchi's approach is somewhat inappropriate for determining whether the process making a product is operating in an acceptable level or not because it does provide no cut-off line for a capable process. For example, suppose that a manufacturer of ball bearings used in gas turbines collects data regarding the diameter of the bearing and that the quality loss derived from Taguchi's approach is $6.25 per unit. Does this loss successfully tell the manufacture whether the process making the ball bearing is capable or not?

In addition, Taguchi *et al.* (2004) addressed that the loss function approach can be used to compare the quality levels of the various processes with different attributes. However, if the defect costs of two attributes (for example, the diameter and the hardness of ball bearings) are different and the tolerance limits for each attribute are not the same, the dollar loss derived form the loss function approach would fail to indicate which attribute is really a problem. In this light, we must develop a unitless measure for the process capability.

In a manufacturing environment, an acceptable process can be defined as such that at least 99.73% of the observed product's quality characteristics falls within the predetermined tolerance limits. 99.73% is the probability of the distribution area within $\pm 3\sigma$ about the mean in a normal distribution. This can be used as a base in determining whether a process is capable or not. If an actual process distribution is known, the expected loss of the process is obtained from the given loss function.

Let us suppose a process distribution is normal. We can obtain the expected quality loss of the actual process by computing $E(L(y_i)) = \int L(y_i)dF(y)$, where F is a normal distribution with μ and σ. Let us consider a process having a normal distribution with mean 10 and variance 1 with the loss function as follows:

$$L(y_i) = \begin{cases} 100 & y_i < 9 \\ 90(y_i - 10)^2 & 9 \le y_i < 10 \\ 80(y_i^2 - 10)^2 & 10 \le y_i < 11 \\ 100 & 11 < y_i \end{cases}$$

Given the loss function above, $E(L(y_i))$ can be computed as follows:

$$E(L(y_i)) = 100\int_{-\infty}^{9} \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(y-\mu)^2}{2\sigma^2}\right)dy$$
$$+\int_{9}^{10} 90(y-10)^2 \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(y-\mu)^2}{2\sigma^2}\right)dy$$

$$+\int_{10}^{11} 80(y-10)^2 \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(y-\mu)^2}{2\sigma^2}\right) dy$$
$$+100\int_{11}^{\infty} \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(y-\mu)^2}{2\sigma^2}\right) dy$$

We denote the expected loss of the actual process by $E_a(loss)$. Then, we need to minimize the expected loss function to find a benchmarking expected loss for the actual process. First, we minimize the expected loss over the mean. This means that the mean of actual process is adjustable to the mean value so that the expected loss can be minimized. Let $f = \min_{\mu} E_{(\mu,\sigma)}(loss)$. Then, the f becomes a function of the standard deviation and the $f(\sigma)$ is a monotonically increasing function. Since the capable process should encloses at least 99.73% of the process distribution within the tolerance limits, we can obtain the maximum allowable standard deviation (σ_o) for the current process to be capable such that exactly 99.73% of the process distribution falls within the tolerance limits. With this σ_o, the benchmarking expected loss for the capable process $f(\sigma_o)$, can be computed. We denote this expected quality loss by $E_o(loss)$. If the expected quality loss ($E_a(loss)$) for a quality attribute is greater than $E_o(loss)$, then the process is not capable. In this logic, we can develop a measure which is comprised with a proportion of $E_a(loss)$ and $E_o(loss)$, called the primary quality index (PQI). If the proportion is less than 1, the process is capable. If the proportion is greater than 1, the process producing the product is not capable.

In many engineering application, the deviation of process from the target value is usually adjustable without a fundamental change. On the other hand, the process variability is not easily adjustable unless a significant physical improvement is made. Taguchi (1987) suggested a two-step procedure for reducing the total variance of process in a nominal-the-best situation: reducing process variability fist and then increasing precision by shifting process mean toward the target value. This implies that process variability would be a primary concern in quality improvement. Therefore, in addition to the primary quality index (PQI) mentioned before, a supplementary measure reflecting the sole impact of process variance on the entire quality level will help engineers correctly diagnose the potential of the process. The sole impact of the process variance can be measured by adjusting the mean to the point where the expected loss is minimized with keeping the actual process variance intact. With shifting the mean of the process distribution to the point, we can compute the expected loss which is due to only the variability of the process. We denote this expected quality loss by $E_s(loss)$.

An advantage of the supplementary measure is exhibited in the examples in Table 1. The table includes two processes and the target value is 4. The first process (Process 1) indicates its mean of the process distribution is deviated from the target value, but its variance is relatively smaller than that of the second process. The second process (Process 2) shows the opposite case where its mean is close to the target value but its variance is larger. At the first glance, Process 2 seems to be better than Process 1 because $E_a(loss)$ of Process 2 is smaller than that of Process 1. However, if the process mean can be adjusted with low cost, one may conclude that Process 1 has more potential to become a capable process than Process 2 because $E_s(loss)$ of Process 1 is smaller than that of Process 2.

Table 1. Expected dollar loss by different means and variances

Process	Mean	Variance	$E_a(loss)$	$E_s(loss)$
Process A	2.1	0.98	\$45.32	\$8.13
Process B	4.2	1.78	\$38.27	\$25.30

The supplementary quality index (SQI) can be developed by computing the proportion of the quality loss due to only the variance, $E_s(loss)$ over the expected quality loss, $E_o(loss)$. We developed two quality indices which indicate the process capability: primary quality index (PQI) which is computed by dividing $E_a(loss)$ by $E_o(loss)$, and supplementary quality index (SQI) which is computed by dividing $E_s(loss)$ by $E_o(loss)$. PQI and SQI should be used together to determine the overall capability of the process.

Based on the logic mentioned before, a procedure to compute PQI and SQI can be described for two different scenarios: a normal distribution and a skewed distribution. A lognormal distribution is used for a skewed process distribution because its shape is reasonably flexible. Weibull distribution can also be used with a little modification. Given a loss function and a process distribution, it is infeasible to find an optimal expected dollar loss, so that we develop a simple heuristic procedure to compute PQI and SQI values. The following cases include heuristic procedures for a normal distribution (Case 1) and for a lognormal distribution (Case 2).

Case 1: The quality attribute of a process Y is normally distributed with a mean μ and a standard deviation σ.

1. Compute $E_{(\mu,\sigma)}(loss)$. Set $E_a(loss) = E_{(\mu,\sigma)}(loss)$.
2. Shift μ to the target value (i.e., μ = target) and compute $E_s(loss)$.
3. Find σ_o such that $P(T - \delta_l < Y < T + \delta_2) = 0.9973$ where μ = target (T).
4. Compute Eo(loss) = E(μ=T, σo)(loss).
5. Compute PQI and SQI: PQI = Ea(loss)/Eo(loss), SQI = Es(loss)/Eo(loss).

Case 2: The distribution of the process Y is lognormal with μ and δ.

1. Compute $E_{(\mu,\sigma)}(loss)$. Set $E_a(loss) = E_{(\mu,\sigma)}(loss)$.
2. Let $\alpha_o = \max\{P(Y < T - \delta_l), P(Y > T + \delta_2)\} - 0.0013$. Compute $P_{\alpha o} = \exp\{\sigma\Phi^{-1}(\alpha_o) + \mu\}$ where Φ^{-1} is an inverse standard normal distribution function. Shift $P_{\alpha o}$ to a tolerance limit. (For instance, $\alpha_o = P(Y < T - \delta_l) - 0.0013$, then $P_{\alpha o} = T - \delta_l$.) Compute $E_s(loss)$.

3. Find μ and σ such that $P(T - \delta_1 < T + \delta_2) = 0.9973$. With the μ and σ found, compute $E_o(loss)$.
4. Compute PQI and SQI: PQI = $E_a(loss)/E_o(loss)$, SQI = $E_s(loss)/E_o(loss)$.

4. Comparison of Process Capability Indices

In this section, we explore the difference between the proposed quality index and the traditional process capability indices (PCIs). Among the PCIs, C_p, C_{pk}, and C_{pm} are chosen because they are the most widely used process capability indices. We compare the indices using the examples in Taguchi's (1987) book. Taguchi (1987) addressed many different types of loss functions as described before. In this study, we adopted N type loss function. He also mentioned that loss function is not always symmetric, but can be asymmetric (Taguchi, 1987). Thus, we compare the newly proposed quality index against three traditional process capability indices under symmetric and asymmetric loss functions respectively.

5. Comparison of Process Capability Indices under a Symmetric Loss Function

Consider a manufacturer of ball bearing defines its quality by hardness. Brinell hardness number (BHN) is used to measure the quality of ball bearing. The specification of hardness is given such as 250 ± 5. The loss caused by unacceptable BHN is \$40. The quality loss function is

$$L(y_i) = \begin{cases} 40 & y_i < 245 \\ 1.6(y_i - 250)^2 & 245 \le y_i < 250 \\ 1.6(y_i - 250)^2 & 250 \le y_i < 250 \\ 40 & 255 \le y_i \end{cases}$$

Suppose the process distribution is normal. The mean and the standard deviation of the distribution of bearing hardness are computed to be 252 BHN and 1.46 BHN. The expected quality loss is

$$E(L(y_i)) = \int L(y_i)dF(y),$$

where F is normal distribution with the mean μ and the standard deviation σ.

The expected quality loss for the actual process of ball bearing $E_a(loss)$ is \$10.53 with μ = 252 and σ = 1.46. The expected quality loss after adjusting the mean, $E_s(loss)$ is \$3.41 for μ = 250 and σ = 1.46. In order to compute the $E_o(loss)$, we first find the standard deviation of the distribution of bearing hardness so that at least 99.73% of the distribution falls within the tolerance limits, i.e. $P(T - \delta_l < T + \delta_2) = 0.9973$ by setting the mean of the distribution in the target value (250 BHN). For this problem, the standard deviation σ_o is obtained to be 1.6835 and Eo (loss) is \$4.42 for μ = 250. Therefore, we obtain PQI = 2.382, and SQI = 0.771. This means that the process does not seem to be capable because the PQI is greater than 1. However, SQI shows that the process has potential to become capable if the manufacture can adjust the mean of distribution of the ball bearing's hardness to the target value because its value is less than 1.

Mean	Sigma	Cp	Cpk	Cpm	QI		Ea(L)	Es(L)
					PQI	SQI		
246	1.00	1.667	0.333	0.404	7.072	0.354	31.94	1.60
248	1.00	1.667	1.000	0.745	1.782	0.354	8.05	1.60
250	1.00	1.667	1.667	1.667	0.354	0.354	1.60	1.60

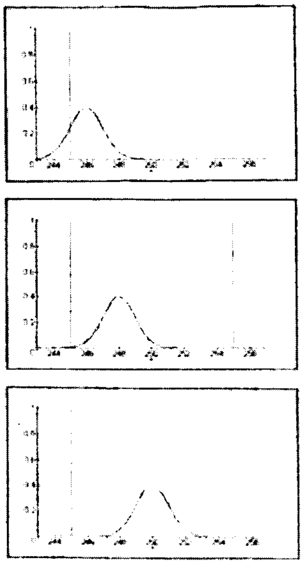

Figure 1. Comparison of QI with PCI's under N type Loss Function

Figure 1 illustrates the superiority of the quality index proposed in this study against C_p and C_{pk} under the N type loss function when the process distribution is normal. The farther the process mean deviates from the target value, the larger the PQI value is while the C_p remains constant. Therefore, PQI seems to reflect the process capability better than C_p. In addition, even though C_{pk} reacts to the changes in the process in the same way as C_{pm} and PQI, the C_{pk} often fails to indicate whether the process mean is off the target or not. For the second process in Figure 1, the mean of the process is 248 and C_{pk} indicates 1, which means that the process is barely capable. However, the process distribution indicates its mean deviates from the target and its left tail is out of the lower tolerance limit. In contrast to C_{pk}, the PQI successfully reflects the departure of the process mean from the target value. The difference between the PQI and the C_{pm} becomes apparent when the loss function is asymmetric around the target value.

6. Comparison of Process Capability Indices under an Asymmetric Loss Function

Consider an automobile manufacturer expects that the clearance between the cylinder and the piston of a four-cylinder engine be 1μm and 6μm with the 3μm. The loss due to a not-acceptable clearance is \$250. The loss function asymmetric around the target value:

$$L(y_i) = \begin{cases} 250 & y_i < 1 \\ 62.5(y_i - 3)^2 & 1 \le y_i < 3 \\ 27.78(y_i - 3)^2 & 3 \le y_i < 6 \\ 250 & 6 \le y_i \end{cases}$$

Suppose the clearance is normally distributed with the mean 4 and the standard deviation 0.5. With the same procedure, we compute $E_o(loss)$ = \$23.14 with μ = 3 and σ = 0.7184, $E_a(loss)$ = \$38.53 with μ = 4 and σ = 0.5, and $E_s(loss)$ = \$11.28 with μ = 3 and σ = 5. This follows PQI = 1.665 and SQI = 0.488. The current process is not capable because its mean is off the target. But, the SQI indicates that the process is highly potential if the process mean can be adjusted to the target value.

The Figure 2 obviously illustrates the superiority of the proposed quality index, PQI against C_p, C_{pk}, and C_{pm}. All three traditional indices, C_p, C_{pk}, and C_{pm} do not accurately reflect the changes in the process distribution. For instance, let us compare C_{pm} values for the first process (the process with μ = 2 and σ = 0.50) and the third process (the process with μ = 4 and σ = 0.5) in Figure 2. The C_{pm} values for two process distributions are the same, which demonstrates the capability of both processes is at the same level. However, in terms of the graphs in Figure 2, the third process appears to be better than the first process. About 2% of the process distribution of the first process is out of the lower tolerance limit and almost all area of the third process falls within the tolerance limits. This implies the third process is performing better than the first process, but the same value of C_{pm} for the two processes gives false information about capability of the processes. On the other hand, PQI successfully reflects the process capability. The PQI value of the first process is greater than that of the third process, which indicates the capability of the third process is better than that of the first process. Similar argument can be made for the lognormal process distribution.

Mean	Sigma	Cp	Cpk	Cpm	QI		Ea(L)	Es(L)
					PQI	SQI		
2	0.50	1.667	0.667	0.745	3.373	0.476	79.92	11.28
3	0.5	1.667	1.333	1.667	0.476	0.476	11.28	11.28
4	0.5	1.667	1.333	0.745	1.626	0.476	38.53	11.28
5	0.5	1.667	0.667	0.404	5.204	0.476	123.23	11.28

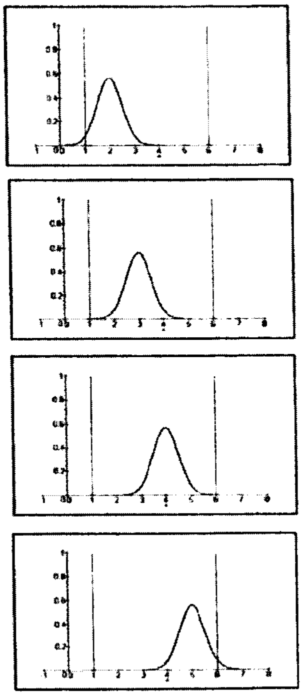

Figure 2. Comparison of QI with PCI's under N type Loss Function

7. Conclusion

The objective of this study is to propose a new process capability index which can work better than the traditional process capability indices. One advantage of the newly proposed index is that it can be applied to any shape of process distribution. More importantly, this index will be more useful to managers because it incorporates monetary loss by defects into the index. Because it is complicated to derive an optimal algorithm to find the minimum expected loss when some of the parameters for a process distribution are unknown, the researcher suggested a heuristic approach to compute the expected dollar loss using Taguchi's loss function. Also numerical examples demonstrated superiority of the proposed process capability index against the existing process capability indices, C_p, C_{pk}, and C_{pm}. Further analysis is needed to understand the superiority of the proposed process capability index under various types of process distributions.

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