Chapter 7
Conclusions

Process capability indices, which establishing the relationship between the actual process performance and the manufacturing specifications, have been the focus of recent research in quality assurance and capability analysis. The quality yield has been proposed to calculate the process capability by taking customer loss into consideration. It penalizes yield for variation of the product characteristics from its target, combining the proportion of conformities and the average process loss.

In Chapter 2, we develop a reliable approach to obtain a lower confidence bound of Y_q, which can be applied to production processes with very low fraction defective where existing method cannot be applied. The results obtained in this chapter allow one to perform capability testing based on yield and customer satisfactions. A real-world application to the amplified pressure sensor manufacturing process is also presented for illustrative purpose. Quality yield is a flexible index because it compares the quality of different characteristics of a product on a single percentage scale, and indicates how close a product comes to meeting 100% customer satisfaction. Furthermore, comparing with the existing capability indices, they rely on the underlying assumption of normality. Although new capability indices have been developed for non-normal distributions, those indices are harder to compute and interpret, and are sensitive to data peculiarities such as bimodality or truncation. If a process is clearly non-normal, there is some question as to whether any process index is valid or should even be calculated. No the other hand, these indices do not explicitly account for the manufacturing cost or customer's loss.

In Chapter 3, the nonparametric, computational intensive but effective estimation bootstrap method is applied to the Q-yield measure $\hat{Y}_q$ to obtain the lower confidence bounds. The lower confidence bound provides information regarding actual process performance for both the fractions of defectives units and customer quality loss. The proposed approach makes it feasible for the engineers to perform approximate process quality testing using the calculated Y_q.

In Chapter 4, we used the worth function to generalize the concept of the Q-yield Y_q for processes with asymmetric tolerances. The analysis and comparisons showed that the new generalization Y_q incorporates the asymmetry of the manufacturing tolerance (with asymmetric loss function), which reflects process performance more accurately. We also proposed the unbiased estimator of Y_q to access the ability of the considered process, which does not require the assumption of normal variability. Some Monte Carlo simulations are conducted to investigate the behavior of the sampling distribution of the estimated Y_q. The result showed that for moderate sample size n of no greater than 300 the distributions of the estimated Q-yield all appear to be normal. Therefore, normal approximation approach may be used to perform the capability testing.

Johnson (1992) introduced the relative expected loss $L_e = L_{pe} + L_{ot}$, which provides an uncontaminated separation between information concerning the relative inconsistency loss (L_{pe}) and the relative off-target loss (L_{ot}). The definition of L_{ot} and L_{pe} are the square of the ratio of the deviation of mean from the target and the half specification width, and the ratio of the process variance and the square of the half specification width, respectively. Both of them have clear interpretation on process loss.

In Chapter 5, we considered the three indices, and investigate the statistical properties of their natural estimators. For the three indices, we obtained their UMVUEs and MLEs. For each index, we compare the reliability of the two estimators based on their relative errors (square root of the relative mean squared error). We summarize the definitions of the process losses indices L_{pe}, L_{ot} and L_e, accompanied with different estimators corresponding to these indices (see Table 30). Which estimator should be preferred for what sample sizes is also suggested. In addition, we constructed 90%, 95%, and 99% upper confidence limits, and the maximum values of $\hat{L}_e$ for which the process is capable. The results obtained in this chapter are useful for the practitioners in choosing good estimators and making reliable decisions on judging process capability.

Table 30. Recommended estimator of the loss indices for different sample size.

Loss Indices	Definition	UMVUE	MLE	Estimator Recommended
L_{pe}	$\left(\frac{\sigma}{d}\right)^2$	$\frac{S_{n-1}^2}{d^2}$	$\frac{S_n^2}{d^2}$	$n \le 35$: MLE $n > 35$: Difference is negligible ($<0.52\%$)
L_{ot}	$\left(\frac{\mu - T}{d}\right)^2$	$\frac{(\bar{X}-T)^2}{d^2} - \frac{S_{n-1}^2}{nd^2}$	$\frac{(\bar{X}-T)^2}{d^2}$	$n \le 30$:UMVUE $n > 30$:Difference is negligible ($<0.04\%$)
L_e	$\frac{\sigma^2 + (\mu - T)^2}{d^2}$	$\frac{S_n^2 + (\bar{X}-T)^2}{d^2}$	$\frac{S_n^2 + (\bar{X}-T)^2}{d^2}$	---

In Chapter 6, we considered a new generalization L_e'', a modification of the process loss index L_e, to handle processes with asymmetric tolerances. The new generalization L_e'' not only takes the proximity of the target value into consideration, but also takes into account the asymmetry of the specification limits. We also investigated the statistical properties of the natural estimator of process loss indices L_e'', L_{ot}'', and L_{pe}'' assuming that the process is normally distributed. We obtained the rth moment, expected value, and the variance of the natural estimator $\hat{L}_e''$, $\hat{L}_{ot}''$, and $\hat{L}_{pe}''$, respectively. We also analyzed the bias and the MSE. The new generalization L_e'' measures process loss more accurately than the original index L_e. Therefore, the new generalization L_e'' should be recommended for in-plant applications.