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Estimating Potential Capability of an Unstable Process

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ESTIMATING POTENTIAL CAPABILITY OF AN UNSTABLE PROCESS

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ABSTRACT

In this paper we describe several methods for providing a benchmark estimate of the potential width capability of a process when the process becomes stable in the statistical process control (SPC) sense of the word. We define "process capability" as the ability of the process to continually meet customer requirements which are expressed in terms of product specifications. Product specifications are generally concerned with both the center and the width of the various characteristics of the process output. The term "capability" is appropriate for process variables which are judged to be "in control" in the SPC sense. Should the process not be in control, the term "process capability" (C_p) should be replaced by "process performance" (P_p); and the ratio calculations should be based on the capability standard deviation and the performance standard deviation respectively. This point is often overlooked in reporting of quality indices. This paper describes several methods for evaluating the capability standard deviation which do not require the use of control charts. A numerical example is given.

DISCUSSION

SPC is a key component of the total quality philosophy in the sense that it is process-oriented, preventive, and helps identify types of variation in a process. SPC, itself, has several components, such as describing the current process performance (e.g., using some descriptive statistics); monitoring the process over time (e.g., using proper control charts); and assessing the capability of the process (e.g., using capability estimates such as capability indices). For more detail on SPC, see, for example, Montgomery [5], Duncan [1] and Grant and Leavenworth [2].

In this paper we will deal with the third component of SPC mentioned above, i.e., estimating the capability of a process. A capable process is one that is narrow enough to allow the production of all parts (i.e., process output) within the specification limits and is centered on the process nominal (target). The process may be narrow enough (i.e., small variation) but may not be centered properly which might cause some outputs to fall outside the specification limits. This paper deals with the first issue: the width of the distribution. We propose several methods for determining the potential capability of a process should the state of statistical control be accomplished. The smaller of these

two estimates could then be used as a benchmark for process improvements that may be achieved by reducing the process variation.

The method that we propose involves calculating two additional process variance estimates in addition to the regular variance estimate. The two additional (capability) estimates are:

1. Variance estimate using the mean square successive differences (MSSD)
2. Variance estimate using the occurrence of "runs" in the data.

The smaller of the two estimates, as mentioned above, would be picked as the variance that the process could have if some of the non-random patterns that exist in the process were eliminated. Therefore this variance estimate can be used to determine the potential width capability of the process. The smaller variance becomes a benchmark for the process and then management can take the proper measures to achieve it. It should be noted that an F test of the significance of the ratios of the regular variance estimate and the ones mentioned above would also signal whether or not the process is in fact stable with respect to the center.

The usual process variance estimator for σ^2 (performance) is given as

$$s^2 = \frac{\sum_{i=1}^n (X_i - \bar{X})^2}{n-1} \quad (1)$$

where X_i are the individual observations from the process, \bar{X} is the estimate for the process average and n is the number of observations.

As one can see, the usual variance estimator does not take into account the time order of the data. Therefore, if there are movements in the process average over time, such as trends, cycles, etc., those are reflected in this estimate and in return the variance becomes large. In other words, this estimate represents the total variation that exists in the process.

1. Variance estimate through mean square successive differences (MSSD):

The MSSD is defined as

$$\text{MSSD} = \frac{1}{(n-1)} \sum_{i=1}^{n-1} (X_{i+1} - X_i)^2 \quad (2)$$

(See, for example, Neumann, et al. [6], Hald [3] and Holmes and Mergen [4]). Using these differences an unbiased estimate for the process variance is given by Hald [3] as

$$q^2 = \frac{1}{2(n-1)} \sum_{i=1}^{n-1} (X_{i+1} - X_i)^2 \quad (3)$$

The variance estimated through MSSD, q^2 , as defined above, looks only at the successive differences (by taking into account the time order of the data) and represents the variation that a process could display if some of the non-random elements, such as trends, cycles, etc., were eliminated. The q^2 and the usual variance estimator would be different if there are such non-random patterns in the process; otherwise they will be very close to each other, implying that the process displays only random (i.e., common) causes of variation.

2. Variance estimate by looking at the "runs" in the process:

Another method to estimate the process variance is to take into account the "runs" that may exist in some processes. The run is defined as successive points above or below the median. For example, assume that the median is 5 and we have the following time ordered sample data from the process:

5.5 3.5 4.6 4.3 5.7 6.1

In this sample there are three runs; which are (5.5), (3.5, 4.6, 4.3) and (5.7, 6.1).

For the purposes of this paper, we define "significant" runs as those with nine or more successive points on the same side of the median. We then calculate a variance estimate in each run and get a pooled estimate of the process variance as given below.

$$s_{\text{run}}^2 = \frac{(n_1 - 1)s_1^2 + (n_2 - 1)s_2^2 + \dots + (n_k - 1)s_k^2}{(n_1 - 1) + (n_2 - 1) + \dots + (n_k - 1)} \quad (4)$$

where s_i^2 's are the variance in each run as defined above and n_i are the size of each run (i.e., nine or more) and k is the number of runs.

This s_{run}^2 is another variance estimator which takes into account the time order of the process data. It represents what the process variation would be if the runs, as defined above, were eliminated. This estimator could also be compared

with the usual variance estimator and tested for significant difference.

To determine the potential capability of an unstable process the smaller of these two variance estimators is picked and standard deviation is determined by taking the square root of the corresponding variance. (Roes, et al. [7] suggested a minor correction factor in estimating the standard deviation when MSSD approach is used. This factor disappears as the sample size gets bigger.) The smallest standard deviation estimate could then be used in, for example, the C_p calculation to see what the potential capability of the process is. The C_p index is defined as

$$C_p = \frac{\text{USL} - \text{LSL}}{6\sigma} \quad (5)$$

where USL and LSL are the upper specification limit and lower specification limit, respectively, and σ is the process standard deviation estimated by using the variance estimator described in either equation 3 or 4.

This potential capability estimate of the process can be compared to the current capability estimate (which uses the regular variance estimator defined in equation 1), and the proper projects can then be designed by the management to achieve the potential capability.

EXAMPLE

The example time series data is from a glue factory on the viscosity for the glue. There are 310 data points (the data set is available from the authors upon request). The specifications for glue viscosity are set as 9.4 ± 1 centipoise (centipoise is the unit of measure for viscosity). Control charts (X-bar and R) for the data indicated that the process average is not stable. The descriptive statistics for the data is given below.

Mean:	9.1348
Std. dev. (regular):	0.6078
Std. dev. (MSSD):	0.2308
Std. dev. (run):	0.3251

As it is seen, MSSD standard deviation is the smallest, which indicates the potential capability variance of the process, if non-random variations are eliminated.

When the C_p index is calculated using the regular and MSSD standard deviations, respectfully, we get the following results:

$$C_p = \frac{10.4 - 8.4}{6(0.6078)} = 0.5484$$

and

$$C_p = \frac{10.4 - 8.4}{6(0.2308)} = 1.4443$$

The current capability, i.e., the performance, of the process is only 0.5484, which indicates that the process is not fully satisfying the specification limits. However, C_p value of 1.4443 indicates that the capability of this process could be raised up to 1.4443, if the non-random elements which make the process average unstable, were eliminated.

CONCLUSION

In this paper we proposed a method to estimate the potential capability of an unstable process. This estimate can be a valuable benchmark for the management in order to select the right process improvement projects and set more rational goals for these projects.

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