The Secret of Process Adjustment

Unneeded adjustments always make things worse

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When your process outcomes are not what you expect them to be it is common to adjust the process. This is not always appropriate. To understand when adjustments are appropriate, and when they are inappropriate, we will need to learn how to distinguish between the noise contained within the data and a signal that an adjustment is needed. Both the problem and the solution will be illustrated by an example from my own experience.

PLANT A

Plant A was operated using the values delivered by the in-house lab. The lab director wanted to deliver good values, so he faithfully followed the recommendation of the manufacturer of one of his key analytical instruments and checked the calibration that instrument every day. This calibration check used a known industrial standard. If the value he obtained did not match the accepted value for the standard, he would adjust the instrument by an amount equal to the difference between the accepted value and the observed value. Since he ended up making adjustment over 80 percent of the time, the lab director was convinced that his adjustments were both necessary and correct. Figure 1 shows the observed values for 100 consecutive tests of the known standard for Plant A.

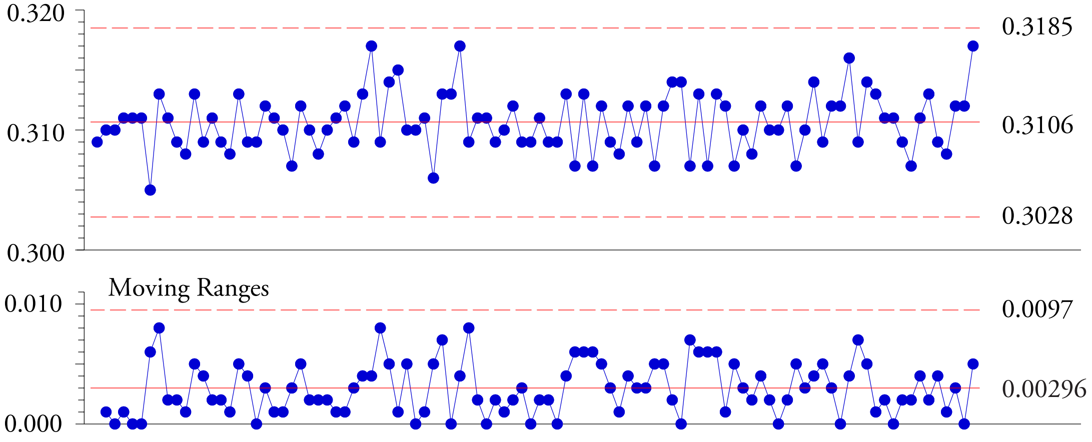

Figure 1: *XmR* Chart for 100 Measurements of a Known Standard at Plant A

This *XmR* chart shows a reasonably consistent and predictable process. During this 100 day period the process was adjusted 82 times and was manually recalibrated 6 times. Since the accepted value for the known standard was 0.310 the lab director felt quite content that his lab was delivering unbiased, high-quality measurements to the plant.

And just how good are his observations? Since the chart in Figure 1 shows repeated measurements of the same standard, the moving ranges may be used to characterize the uncertainties in these measurements. The Average Moving range is 0.00296 units, so when we divide by the appropriate d_2 bias correction factor of 1.128 we obtain an estimate of the standard deviation of the measurement system:

$$\text{Estimated Standard Deviation of Measurements} = \frac{0.00296}{1.128} = 0.00262 \text{ units}$$

$$\text{Probable Error of Measurements for Plant A} = 0.675\,(\;0.00262\;) = 0.00177 \text{ units}$$

This latter value means that a single measurement will err by 0.0018 units or more at least half the time. So while these measurements are being recorded to 0.001 unit, they are essentially good to the nearest 0.002 units, which means that they are almost, but not quite as good as they look.

PLANT B

Plant B is a competitor of Plant A. The in-house lab at Plant B has an analytical instrument that was exactly the same make and model as that used at Plant A. They also tested the same industrial standard every day like Plant A. However, this was where the similarities ended. Rather than adjusting the instrument based upon each reading, the lab director at Plant B placed each observed value for the standard on a Consistency Chart. A Consistency Chart for a known standard is an *XmR* chart where the central line for *X* is set at the accepted value for the known standard. As long as this chart shows no evidence that the analytical instrument is off-target, no adjustments are needed, and so none are made. On those rare occasions when an observed value fell outside the limits on this *X* chart, an appropriate adjustment was made.

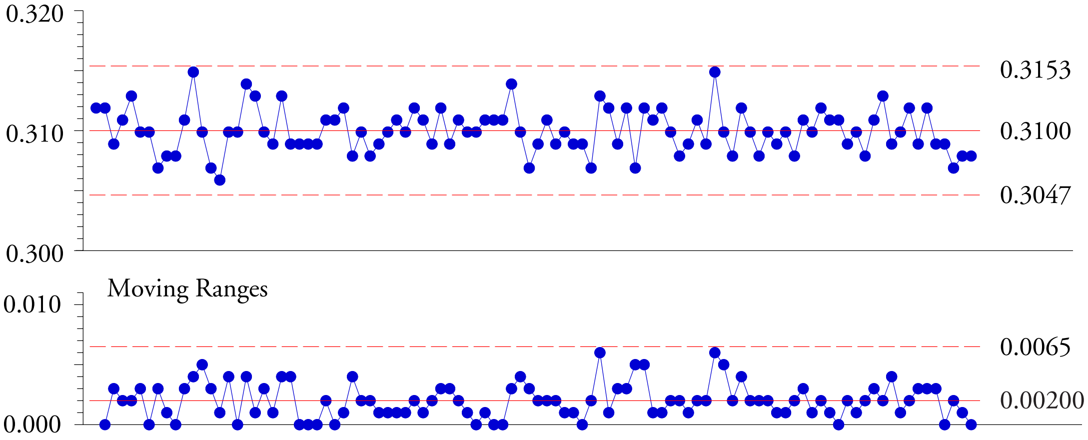

Figure 2: *XmR* Chart for 100 Measurements of a Known Standard at Plant B

Figure 2 shows 100 successive tests of the known standard at Plant B. No adjustments were required during this period. The Average of 0.3101 units is essentially the same as the accepted value of 0.3100. The Average Moving Range of 0.00200 units results in an estimate of the standard deviation of the measurement system of:

$$\text{Estimated Standard Deviation of Measurements} = \frac{0.00200}{1.128} = 0.00177 \text{ units}$$

Probable Error of Measurements for Plant B = 0.675 (0.00177) = 0.00120 units

This Probable Error value means that the observed values were essentially good to the nearest 0.001 unit. Since they were recorded to the nearest 0.001 unit they were as good as they looked. By filtering out the noise in the data rather than treating each value as a signal, the lab director at Plant B reduced the work load in his lab by avoiding all the adjustments and recalibrations. At the same time he delivered higher quality data using the same instrument.

But the real pay-off for the Consistency Chart was not in the lab. In the words of the lab director for Plant B, “You don’t know how much grief you’ve saved us! When we started using the Consistency Chart for the standard, suddenly the whole plant started running better!”

THE DIFFERENCE

The adjustment methodology used by Plant A is known as a proportional controller, or P-controller, with no dead band. It makes an implicit assumption that the data contain no noise. This is equivalent to assuming that two numbers that are not the same are different. Unfortunately, this is rarely true. In this world, numbers that are not the same are not necessarily different. As a result of interpreting each value as a signal, Plant A made many needless adjustments. These needless adjustments merely added to the variation in the measurements and degraded the quality of the reported values. This may be seen in Figure 3 which shows the two charts above side-by-side.

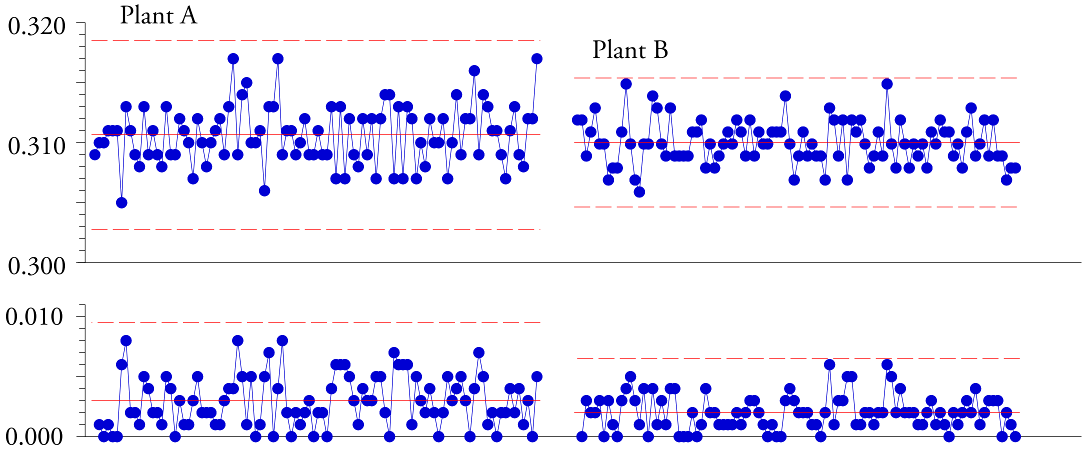

Figure 3: Charts for Plant A and Plant B

In addition, the almost daily changes in the measurement process represented by Plant A’s adjustments created chaos in production. Following each adjustment made in the lab, who knows how many adjustments were made in production. When they stopped using a rubber ruler in Plant B the production department found that everything went more smoothly. Variation always creates costs. Excess variation creates unnecessary costs.

As seen by the example of Plant B, this degradation in the quality of the measurements was avoidable. The secret of how to avoid unnecessary adjustments is the central secret of all of data analysis. Since all data contain noise, it is imperative that you learn how to filter out the probable noise before you react as if you have found a potential signal. And the simplest, most robust noise filter is a process behavior chart. Any attempt to start interpreting your values before you have filtered out the noise will result in your being misled by the noise.

But why didn't Plant A's chart show the adjustments as signals? As shown in last month's column, "But the Limits Are Too Wide!" when the signals become ubiquitous, they look like routine variation to the computations and end up inflating the limits.

As I showed in my March 2011 column "Three Questions for Success," a process behavior chart is an operational definition of how to get the most out of your process. It defines what a process is capable of doing when it is operated up to its full potential. It provides a way of moving a process towards its full potential. And it provides a way of judging how close to full potential your process is currently operating. When applied to repeated measurements of a standard, an XmR chart is known as a Consistency Chart because it can be used to assess the consistency of a measurement procedure. With a known standard, the central line for the X chart is placed at the accepted value for the known standard, and any signals are taken as evidence of a bias in the measurements or a change in the measurement process. In the case of an unknown standard, or with a biased measurement system, you may use the average value of the observed values as the central line for the X chart. Here signals will indicate a change in the measurement system.

Upon detecting a change it is appropriate to take action. Actions taken in the absence of such evidence are likely to be needless adjustments. And, as we have seen, needless adjustments are not benign. They inevitably increase costs, waste effort, and create grief.