The Dos and Don’ts of Control Charting—Part II

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"Analysis and Control of Variation" is dedicated to revealing weaknesses in existing approaches to understanding, reducing, and controlling variation and to recommend alternatives that are not only based on sound science, but also that demonstrably work. Case studies will be used to illustrate both problems and successful methodologies. The objective of the column is to combine sound science with proven practical advice.

Reader comments, questions, and suggestions will help us fulfill our objective for this column. Case studies illustrating the successful reduction or control of variation submitted by readers are most welcome. Please send your comments and suggestions to column coordinator John McConnell at john@wysowl.com.au or journal coordinating editor Susan Haigney at shaigney@advanstar.com.

KEY POINTS DISCUSSED
The following key points are discussed:
• There is a right way and a wrong way to control chart.
• Do not use aggregated data when constructing a control chart.
• Do not control chart a measure simply because it is easy. Control chart the measure because it gives insight into the process.
• Do make sure that the control chart limits are calculated correctly.

EXAMPLE FOUR
Sometimes we monitor a measure at a lower frequency than is possible. This reduces the usefulness of the measure. The motivation for this is usually that we already have weekly or monthly meetings that review measures and we simply organize the data around this frequency. So we control chart data that are aggregated from a more granular set of data. Also, we reason that the people who are looking at the data will not be interested in the data on a more frequent basis. However, when we do this, we may lose significant information about the current

INTRODUCTION
A previous article (1) in this series discusses the following dos and don’ts associated with the use of control charting:
• Do always start by looking at the trend of data over time
• Do not use a metric that is not the best way available to represent the direct variation of the system
• Data are gold—do make sure you use all the available data before reaching a conclusion
• Example case studies illustrating the above are provided.

Part one of this article illustrates three examples addressing the dos and don’ts of control charting. Part two continues to illustrate the concepts presented in part one in the following examples (1).
and past behavior of the measure being evaluated. This can lead to incorrect conclusions about what we should be doing with respect to this measure. In the past we may have been able to rationalize this approach when the construction of control charts was more labor intensive. With modern computer systems, however, this is no longer the case.

As an example, we look at a set of data representing the conversion time (cycle time) for a lot of a certain product. The data are averaged over a monthly time period and are reviewed in a monthly meeting. The control chart for the data over a 13-month time period is shown in Figure 1. Figure 1 suggests that there might be an upward trend, but the data are inconclusive. The data do not break any statistical trend rule, which is not surprising because we only have 13 data points. Approximately three to four lots of the product are made per month, so if we were to look at the data on a per lot basis, we would immediately get much more data. The lot-by-lot control chart is shown in Figure 2.

We now have 40 data points instead of 13. The behavior of the conversion time is now much clearer. We have had basically three regions of behavior over the last year. These are as follows:

Figure 1: Conversion time monthly average.

![X Chart for Conversion Time Monthly Average](chart1)

![mR Chart for Conversion Time Monthly Average](chart2)
• Region 1—from lot 1 to lot 18. This has two special cause points at lot 11 and lot 14. The common cause average and sigma for this region are 35.1 and 4.6 days, respectively.
• Region 2—from lot 19 to lot 30. There are no special cause signals. The common cause average and sigma for this region are 55.6 and 8.1 days, respectively.
• Region 3—from lot 31 to lot 40. It appears that the last three to four lots of these data are trending sharply upward.

We can see from Figure 2 that the trend we suspected in Figure 1 looks more like a step change at lot 19. Therefore, we should be asking what changed in the process between lots 18 and 19. Similarly, we should be asking what changed between lots 30 and 31 and what is causing the trend upward from lots 37 and 38. None of these questions would be asked if we only look at Figure 1. Thus we are missing a large amount of process behavior by only looking at monthly average data.

The lesson learned from example four is that aggregated data should not be used when constructing a control chart. The most granular data available should be used.

EXAMPLE FIVE
Sometimes we control chart measures that do not really measure the intended process performance. The rational for this is typically a lack of understanding of the true
purpose of the process or a realization that a measure that truly represents what we want will be difficult to measure. We then use a simpler measure. Some examples demonstrating this are as follows:

- **Percent completed training.** The only measure we have around people performance is %ITP. %ITP is the percent of their training plan that individuals (ITP) have completed. This measure only reflects whether a person has obtained all their required training courses. However, the purpose of a “people performance” process is to ensure that the people impact on a process or people performance is optimal. We should look to see what the true impact of people might be on the process. One way to approach this is to look for measures that more directly show the impact of people variability on the process. It would be far preferable to observe the number of deviations whose root causes are due to gaps in the “people performance” process. Some of these may be due to lack of training, misunderstanding of instructions, and other reasons.

- **Percent analytical variation.** In a quality control laboratory, we may fail to measure one of the most important measures from a customer’s perspective, that is, the % of total variation in an assay that is due to measurement error or uncertainty. This is an important measure because, for example, too much measurement error degrades the performance of a production control chart that is trying to detect changes in the production process. Performing assays speedily and efficiently may not be enough if the error of the measurement process is large. In general, a standard for the measurement error is the following equation:

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\frac{\sigma_M^2}{\sigma_M^2 + \sigma_P^2} \leq 0.1
\]

where \(\sigma_M\) is the variation due to measurement and \(\sigma_P\) is the variation due to the process. This is why control charting laboratory assay controls are so important. If the controls begin to display a lack of statistical control on the control chart, it may indicate that assumed measurement uncertainty of the assay is suspect.

- **Raw materials management.** When monitoring the performance of a raw materials management process, we control such variables as quality, delivery, price, and other variables. Again the motivation for this is that these measures are easy to get and should be control charted. However, we may fail to measure the impact that the raw material has on the manufacturing process where it is used. This can lead to local optimization of the raw materials management process at the expense of the performance of the production process. It is also the reason why we may hear the following conversation during a root cause investigation:

  Investigator: “Have we looked at the raw materials as the source of the problem?”
  Technical support person: “No need.”
  Investigator: “Why?”
  Technical support person: “All the raw materials are in spec, so they cannot be having an impact on the process.”

Basically, because we have not fully characterized the impact of the raw material on the process—not an easy task—and all the raw material measures we do control chart are in statistical control, it is assumed that the raw material is not the issue. However, it may turn out that we were simply not looking at the right aspect of the raw material quality.

- **Asset management.** When monitoring the success of an asset management process, we can look at cost of maintaining assets, spares inventory levels, and other variables. However, we must also be sure that we measure the impact of the asset management system on the production process. This can be done by looking at the number of production incidents that were due to equipment issues such as unexpected equipment failure, wrong materials of construction, and other incidents.

The lesson learned from example five is that we should not control chart a measure simply because it is easy. Measures that give insight into the process should be selected for the control chart.

**EXAMPLE SIX**

Many years ago, one of the authors had a conversation with a new MBA graduate who had just joined their company. The graduate had been exposed to the use of control charts and was eager to use them in the process for which he was responsible. We discussed what we could do, and I suggested he send me some data so I could set up the charts and he could then...
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In the MBA classes, this illustrates a concern that Deming (3) warned about many years ago when he cautioned about statistical methods being taught by people who were not fully familiar with them. We end up with the photocopy effect where each time the methods and ideas are passed down, they get further and further from the original. Expertise in control charting and other statistical methods only comes from a significant investment in learning and application.

As a side note, the other issue with the MBA graduate’s approach is that he never constructed the moving range chart, which is a time series of the moving range values with an appropriate control limit. It is generally agreed (2) that there is value in looking at this chart, because it plots the same data in a different way and will give another view of what is happening in the process. It is easy to construct with modern computer software along with the individuals chart. Reference 2 shows how to construct the moving range chart.

In order to illustrate this point, a simulation was constructed where the base data consisted of a measure Y that varies randomly according to a normal distribution with a mean of 80 and a standard deviation of 2.0. A dataset consisting of 50 points was created using this distribution. A sine wave is introduced onto this base signal as shown in the upper left part of Figure 3. The lower left chart shows the control chart using the sample standard deviation and the right-hand side shows the proper individuals and moving range control charts.

It is clear from the charts that the method using the sample standard deviation tends to widen the control chart limits leading to a greater chance of missing an out-of-control signal. It simply does not account for the change in the data over time because there is nothing of the time sequence of the data in the calculation of the control limits. On the other hand, the individuals chart with the proper control limits is much more sensitive to the change. Note also that the moving range chart, shown on the lower right hand side of Figure 3, shows no out-of-control signals. That is useful information, because if we did not know what was going on, it tells us that the change in the process that led to the out of control signals in the individuals chart are not due to a change in the variability of the process, but more likely due to a trend in the average behavior of the data.

As a side note, if our objective in plotting data on a control chart is to justify the variability in our process, then there can be great advantages in plotting the control charts incorrectly. More often than not, plotting the charts using the incorrect methods desensitises the

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\text{Lower Control Chart Limit: } \text{LCL} = \mu_E - 3\sigma_E \\
\text{Upper Control Chart Limit: } \text{UCL} = \mu_E + 3\sigma_E
\]

where \( \mu_E \) is the estimated mean of the dataset and \( \sigma_E \) is the estimated standard deviation of the dataset.

The above is a correct approach to calculating control chart limits. The estimated mean is simply the mean of the dataset, formed by summing the data points in the dataset and dividing by the number of data points in the dataset. The estimated standard deviation was calculated by using the sample standard deviation. In Microsoft Excel this is obtained by using the stdev function and is easily calculated. This is not the correct approach. The problem with the use of the sample standard deviation is that it does not account for the time sequence of the data. No matter how you mix a set of data, it will still have the same sample standard deviation. So what is required is an estimate of the standard deviation that takes the time sequence of the data into account. In practice this is done by using the moving range of the data. For two consecutive data points, the moving range is the absolute difference between the two data points. So if the dataset had N data points, it will have N-1 moving range values. The standard deviation of the dataset can then be estimated as

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\sigma_E = \mu_{MR}/1.128
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where \( \mu_{MR} \) is the average of the N-1 moving range values (2). When the data were replotted on control charts with the proper control limits, out-of-control signals were clear. The MBA graduate who initially constructed the control chart limits using the Microsoft Excel stdev function had learned this approach

A dataset consisting of 50 points was created using this distribution. A sine wave is introduced onto this base signal as shown in the upper left part of Figure 3. The lower left chart shows the control chart using the sample standard deviation and the right-hand side shows the proper individuals and moving range control charts.
charts and makes out-of-control signals “fade into the background.” However, if our objective is to gain insight into the behavior of the process so we can improve the process, then it is clear that using the correct calculations is imperative.

The lesson learned from example six is that control charts must be calculated correctly.

CONCLUSIONS
In this article we have explored some more dos and don’ts of control charting. The important lessons are presented as follows:

• Do not use aggregated data when constructing a control chart
• Do not control chart a measure simply because it is easy; control chart the measure because it gives insight into the process
• Do make sure that the control chart limits are calculated correctly.

Again for control charting, as in all endeavours, there are the correct ways to do things and the incorrect ways. We will explore some further dos and don’ts of control charting in a future article in this series.

REFERENCES