START

Selected Topics in Assurance Related Technologies

Quality Control Charts

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Introduction

Methods of statistical process control (SPC) have been in existence for over eighty years now in industrial statistics (Shewhart, Romig, Wald, Deming, etc.). SPC methods are used, among other things, to detect when a stable process, defined as one with a fixed mean level and a fixed variation, departs from stability. SPC is also used to assess the quality of a product that we are either producing ourselves or trying to acquire from a supplier. The first objective falls within "quality control" (QC) procedures while the second falls within "acceptance sampling" methods.

QC methods are based on the assumption that performance measures (PM) from "stable" processes follow some statistical distribution with fixed mean and variance. Hence, we periodically draw independent and random samples from these PMs to verify they remain stable. An example of PM of central tendency is the sample mean ($\overline{x}$). Examples of PM of variation or dispersion include the sample standard deviation (s) or the sample range (r). Under stable and Normally distributed processes, PMs fall within well-specified regions of the QC charts. The systematic plot and analysis of such PM, within the context of such QC charts, is the essence of QC. This START sheet provides an overview of some of these QC methods. A forthcoming one will do likewise with acceptance sampling.

Some Essential Concepts

We first review the main concepts involved in quality control. These are not definitions, but rather practical interpretations, to be enhanced with the referenced bibliography.

The understanding of these key concepts is basic for the correct implementation of SPC.

<u>Confidence</u>: statistical assessment of the validity of a specific statement, given the data under consideration (References 5, 7). For example, "with 99% confidence" the reliability of an item to complete its mission is at least 90%.

<u>Null Hypothesis</u> (H_0): assumed status (e.g., that the process is under control; that the product is of good quality; (References 4, 6)).

<u>Alternative Hypothesis</u> (H_1): negation of the null; alternative situation (e.g., that the process is out-of-control; that the product is defective; (References 4, 6)).

<u>Type I Error</u>: to decide that the alternative hypothesis (H_1) is true, when in fact the null (H_0) is true (e.g., assume that the process is out-of-control, when in fact it is running correctly; reject the product as defective, when in fact it is of good quality; (References 4, 6)).

<u>Type II Error</u>: to decide that the null hypothesis (H_0) is true, when in fact the alternative (H_1) is true (e.g., assume that the process is running correctly, when in fact it is out-of-control; accept the product as having good quality, when in fact it is defective; (References 4, 6)).

<u>α probability (also called producer's risk)</u>: the probability of Type I error (e.g., the risk of rejecting a good product, or of shutting down a process that runs in control; (References 4, 6)).

<u>β probability (also called consumer's risk)</u>: the probability of Type II error (e.g., the risk of accepting a defective product, or of continuing to run an out-of-control process; (References 4, 6)).

<u>ARL (average run length)</u>: is the "average" number of time periods required for a PM to fall outside the QC Chart bounds, under a specific assumption (References 1, 2, 3).

Such assumptions include that the process is under control (e.g., target mean is the assumed "μ") or that it has gone out-of-control (e.g., due to a shift in the mean μ, of size "δ"; to a new mean $\mu' = \mu + \delta$).

OC (Operating Characteristic) Curve: probabilistic statistical function or PM that assesses charts and sampling plans. For example, OC is the probability of accepting a product, given the desired product conditions (e.g., quality). The OC function depends both, on the true parameters (e.g., quality) as well as on the required sample size "n" (References 1, 2, 3, and 4).

OC and ARL are two important procedures that yield results used in characterizing the performance of, or in deriving the parameters for, QC charts and methods. The sample sizes of QC charts, for example, are determined by considering the OC and ARL values, defined via the required probabilities α and β.

Some QC Charts

There are two types of outputs obtained from random processes. Hence, there are two types of QC charts to analyze them. One type of PM is qualitative (e.g., pass or fail, good or bad) and the QC charts to analyze them are known as "attribute." The other type of PM is quantitative (e.g., speed, temperature, weight) and the QC charts that analyze them are known as "variable." These two types of charts address different types of situations, are based on different assumptions and should not be confused (i.e., don't try to use a "variables" chart when you have a qualitative PM or vice-versa).

For a better understanding of the implementation and the philosophy behind QC charts, we will overview several of each type. We start with QC charts for variables (continuous measurements) and overview charts for the mean and range. Then, we discuss ways of speeding up decisions by including "warning limits" in the traditional (or Shewhart) charts or by using CUSUM charts instead. Finally, we discuss charts for attributes and overview QC charts for proportions (percent defective) and for the number of defects.

Variable Control Charts

When the measurements taken are continuous (e.g., times to failure, weights, lengths, etc.) as are their means, variances, ranges etc., we deal with "variable" measurements. Thus we use the "variable" control charts. We discuss next two of the most frequently used charts.

Charts for the Mean and Range

Stable production process outputs are randomly distributed, with a mean μ and a variance σ^2 (or standard deviation σ). If the outputs are Normally distributed, it is a well-known statistical result that 99.74% of these outputs are within three standard deviations of the mean. It also follows that 99.74% of the averages ($\overline{x}$) of "n" independent sample outputs, are within three standard deviations of $\overline{x}$ from the process mean, where such "new" standard deviation is now defined as $\sigma/\sqrt{n}$.

This is the key rule used in these QC charts to assess whether a production process is under control or not. The chart for the mean consists of three parallel lines. In the center is the target line for the Process Mean. Above and below this line, we find two other lines: the Upper Control Limit (UCL) and Lower Control Limit (LCL), respectively. They are three standard deviations above and below the line of the Mean. In-between the Control Limits and the target line there may be "Warning Limit" lines, which are situated one and two standard deviations above and below the target line. We discuss them in the next section.

If the process is under control, averages from independent samples, taken at regular times and plotted in the QC chart, fall randomly, with probability 0.9974, within the LCL and UCL limits. The process may go out of control, say by a shift "δ" in the mean. Then, the process sample averages will soon also fall outside these two LCL and UCL lines.

Usually, before a QC chart signals that a process is out-of-control, there are some warning symptoms that we can take advantage of. For example, the charts show slight trends up or down, longer-than-usual runs above or below the Mean line, etc. All these symptoms point toward the non-randomness in the process output, but still within the LCL and UCL lines. To take advantage of this additional information, the "warning" limits have been devised.

All of this is better explained through an example. Let a packaging machine fill bags with (mean) $\mu = 16$ oz. of coffee. The natural variation in the packaging process has a (standard deviation) $\sigma = 1$ oz. Assume that bag weights are Normally distributed and that in the first three periods, the machine is functioning correctly. After that, the machine goes out of adjustment and starts overfilling the bags at a rate of 0.1 oz per hour, every hour.

We want to construct a QC chart for the Mean and the Range, to assess whether this machine is working on target or is out of

adjustment. We take random samples of n = 2 bags of coffee (denoted first and second) at hourly intervals and we weigh them and then find their average.

The choice of the sample size (here, n = 2) depends on the trade-off between the costs of a higher detection capability of the QC chart and the cost of drawing a larger sample size for supporting such QC operation.

The weights of the ten samples of two bags each, taken every hour, are shown in Table 1. The range is a measure of (population) variability, related to the standard deviation. Sample range is the difference between the largest and the smallest values in the sample.

Table 1. Sample of Bag Weights

Row	First	Second	Average	Range
1	16.2455	16.2475	16.2465	0.00203
2	15.9588	14.4558	15.2073	1.50302
3	16.9662	15.6244	16.2953	1.34183
4	16.8577	17.5097	17.1837	0.65204
5	16.8843	15.4213	16.1528	1.46301
6	15.9770	16.4575	16.2172	0.48046
7	17.0658	17.4635	17.2647	0.39773
8	16.5118	17.5911	17.0514	1.07927
9	17.4778	18.0616	17.7697	0.58384
10	17.2812	17.7638	17.5225	0.48260

The X-Bar chart, when mean μ and variance σ² are known, is obtained by placing the upper and lower control limits (UCL, LCL) at a distance $3 \times \sigma / \sqrt{n}$ units above and below the line of the historical Mean. For the numerical example given, the Target is μ =16 and the distance is $3 \times \sigma / \sqrt{n} = 3 \times 1 / \sqrt{2} = 2.121$ (Figure 1).
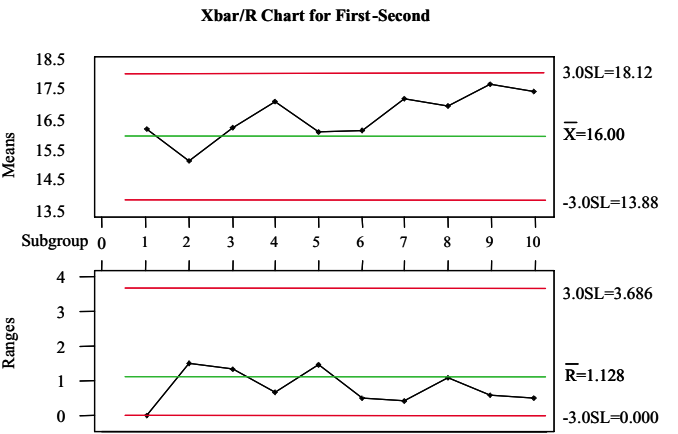

Xbar/R Chart for First-Second

Figure 1. QC Chart for Mean and Range, When Parameters are Known

Notice how, in Figure 1, all weight measurements from the third hour on are above the Mean. However, all measurements are still within the X-Bar chart's control limits and we cannot, directly from observing the QC chart, diagnose a problem. We will see in the next section what other things can be done to improve on this.

In many occasions, we do not have the "historical" mean and variance to build the chart and must estimate them from the data. It is strongly recommended that data from at least 20 time periods are set aside and used solely for estimating the stable mean and variance.

For illustrating such calculations only (and to provide a counter example of what can go wrong if the above rule is violated) we use the same ten data for both, developing the chart parameters, as well as for charting. The statistical "description" of the coffee sample data is shown in Table 2.

Table 2. Statistical "Description" of the Coffee Sample Data

Variable	N	Mean	Median*	StDev	SE Mean
First	10	16.723	16.871	0.529	0.167
Second	10	16.660	16.960	1.206	0.381
Range	10	0.799	0.618	0.810	0.514

*Median is the data value in the middle of the sorted sample The General Sample Mean $\overline{x}$ is 16.691 and the Average Range $\overline{R}$ is 0.7986. Then, from a well-known relation between range and standard deviation (3) we obtain the estimation of the standard deviation of the process of filling the coffee bags (denoted here as S):

$$S = \text{Avg. Range} / k = \overline{R}/ k = 0.70796$$

In our example, tabulated value k = 1.128 (4), which depends on the sample size, is used for obtaining the standard deviation S from the range. The standard deviation of the sample average is then the estimated standard deviation (S) divided by $\sqrt{n} = \sqrt{2}$ ($S/\sqrt{n} = 0.501$). Finally, the 3-Sigma distance for establishing the LCL and UCL values is obtained by multiplying $3*S / \sqrt{2}$ (= 1.502). All mentioned chart values are tabulated and their tables can be found in [References 1, 2, 3, and 4]. The resulting Chart lines, for the X-Bar chart (Figure 2) are: Target (Mean = 16.19), LCL (15.188) and UCL (18.192).
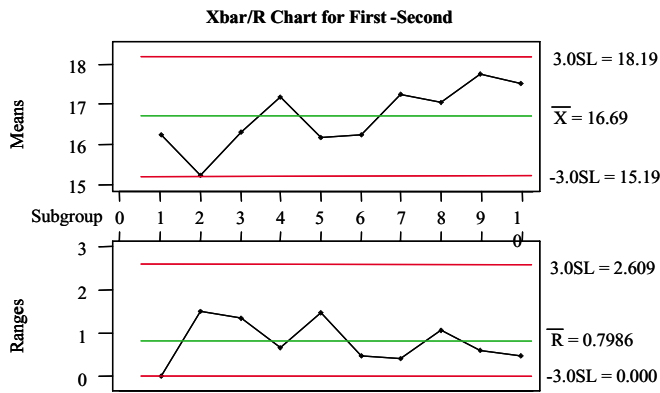
Xbar/R Chart for First -Second

Figure 2. Mean and Range QC Charts, When Parameters are Estimated

Notice how, <u>by using the same data values both, for establishing the QC chart limits and for the charting</u> itself, the "Target" line <u>has moved up to 16.69</u>, from the original Mean = 16. This occurs because <u>data used for both objectives</u> (charting and establishing the chart limits) <u>reflect the actual drift</u> occurring in the process mean. This, in turn, modifies the chart control limits which, as <u>reference values, should be fixed and not move with the data</u>. To avoid this problem it is <u>strongly recommended that 20 or more periods under stable process are used</u> **solely** for <u>obtaining the QC chart limits, before starting to chart any data values</u>.

We now obtain the QC chart for the Range (R) a measure of variability. For, the process can also go out-of-control by changing its variability, while still averaging the target mean value. We obtain the parameters for the R-Chart as follows.

The Range (Target) line is the Range sample average $\overline{R}$ = 0.799. The UCL and LCL of the QC chart for the Range are obtained by using two other tabulated values: D1 = 0 and D2 = 3.267 that, as the above-mentioned constant k, also depend on the sample size used for constructing Range charts. More information about both of these QC charts, and about the tables they use, can be found in [References 1, 2, 3, and 4].

LCL = 0 (LCL cannot be < 0) and UCL = $\overline{R}$* D2 = 2.61

Verify how all the hand-calculated numerical results obtained above coincide with those in the Minitab charts. The data were drawn from a process that started shifting upwards after the third time period, at a rate of 0.1 oz. per time period. However, all chart points are within their Control Limits, suggesting (erroneously) that the process is still in control. We will see, in the next two sections, how "warning limits" and CUSUM charts, that use additional rules and past information, improve our chances of detecting such shifts in the processes.

Warning Limits: Uses and Rules

The QC chart in Figure 1 (X-Bar Chart) shows a clear trend upward after the fourth or fifth time period. If such upward trend continues, the sample mean will eventually fall outside the UCL in a few time periods more. However, the X-Bar Chart, as defined so far, is unable to signal a change in the process with the data charted. This occurs because, in standard Shewhart charts, only individual time period samples are compared with the target value, and with the control limits of such target value, to verify that they are still within valid bounds. If an individual sample point falls outside the limits, then the process is declared out-of-control. The problem with this approach is that it may take a long time, for one individual sample value of an out-of-control process, to be 3 standard deviations away from its target, especially when shifts δ are small. To improve on this, the "Warning Limits" and companion rules that alert about possible deviations of the process, were defined.

The Warning Limits are lines parallel to the Target line, between such line and the UC/LC Limits, at one and two standard deviations above/below the Target. The Warning Limits included in the QC charts come along with some rules for their interpretation vis-à-vis the behavior of past data. For we use, in addition to the current time period value, several previous ones in the QC chart. This additional information, in conjunction with Warning Limits, serves to "warn" QC chart analysts that a trend, that will likely result in a process being out-of-control, has appeared. Therefore, it may be time to either stop the process, or at least to take a very close look at it, because it is sending us a signal about its status.

There are several empirically derived rules that accompany these Warning Limits. As such, there is not an absolute agreement about their exact numerical values (readers may find other sources with slight variations). We will use the rules defined in Reference 2, which state that a process is out-of-control if any one or more of the following criteria, regarding the QC Chart parameters, the Warning Limits and the past time period data, are met:

1. One or more chart points fall outside the two (Upper or Lower) Control Limits.
2. A run (sequence of similar observations) of at least eight chart points, upwards or downwards occur above or below the median, mean, or target line used.

3. Two of three consecutive chart points fall outside the 2σ warning limits (but still within the Control Limits).
4. Four of five consecutive chart points fall beyond the 1σ limit.
5. There occurs and unusual or nonrandom pattern in the chart points.
6. One or more chart points fall very near a Control Limit.

If any of the above situations occur, it is no longer necessary to wait until a charted value eventually falls outside of the three standard deviation (UCL/LCL) chart limits. We stop the process, or at least take a very close look at it, to assess whether it has deviated from its stable state. Experience suggests that a graduated response is adequate.

Let's illustrate the use of such rules with an example. Applying Rule 2, we would stop (or at least closely monitor) the process chartered in Figure 2. For all points in X-Bar Chart, from time period 3 onward, are above the Mean. We do not need to wait until any chart points actually fall outside the UCL to start worrying. The Warning Limits save us time as well as having to scrap or rework the products manufactured. For, we save the extra time periods we would have to go through, until a chart value falls outside the QC Chart limits.

CUSUM Charts

Cumulative Sum (CUSUM) charts are statistical QC procedures for the Mean. But, just as the "warning" rules discussed above, CUSUM uses past information to help detect small (δ) process departures from its stable state, faster than standard Shewhart charts. CUSUM Charts have upper and lower control limits, inside which a stable process should evolve. However, in addition to just looking at the present (j^{th}) time period values, the CUSUM statistic uses past data values information ($1 \leq i < j$) in the form of "accumulated differences" from the target of interest (e.g., the process mean μ).

CUSUM assesses whether such cumulative deviations from the Target (instead of just the current sample average) remain within some bounds. Because deviations are cumulative, they pile up, allowing CUSUM to detect even very small deviations δ, much faster. To illustrate this, we reanalyze the data used in Figure 2, via CUSUM. We calculate the cumulative differences (S_j) of each (j^{th}) period sample mean ($\bar{x}_j$) to process target (μ):

$$S_j = \sum_{i=1,j} \left(\bar{x}_i - \mu\right) = S_{j-1} + \left(\bar{x}_j - \mu\right)$$

Then, we plot the successive cumulative differences S_j vs. its sample number j: $1 \leq j \leq n$ (Figure 3) and assess whether these S_j fall within the CUSUM control limits or not:

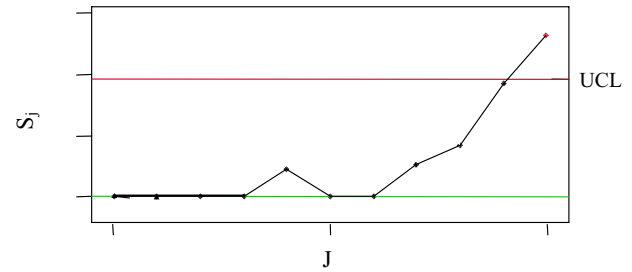*Figure 3. CUSUM Chart*

Notice how the Sj values start increasing until they cross beyond the UCL = 1.9184. Based on the CUSUM result, the said process is out of control.

The upper (lower) CUSUM limits are given by the reference value "h". These are either taken from "nomograms" or by convoluted formulas, found in References 1, 2, 3, and 4. This "h" is a function of the sample size "n" taken at every time period, of the variance σ^2 of the process and of the process shift δ that we want to detect. In addition, the desired ARL (average number of time periods before a "false alarm" occurs) and the probabilities α and β of "false alarms" and "failure to detect" a shift, result from the value "h".

Parameter derivations for the CUSUM chart are beyond the scope of this introductory START. The interested reader can find them in References 2, 3 and write a program or macro to calculate them. However, several statistical packages, such as Minitab, have automated procedures that calculate and plot the CUSUM limits (Figure 3). This makes the CUSUM chart, with its main advantage of early detection of very small shifts in the process mean, also available to the practicing engineer who is able to understand its logic and operation.

Attributes Control Charts

When the PM for QC analysis are "attributes" (say, defective or not, in a production process) then we cannot use "variables" charts. Instead, we use "attribute" QC Charts. We follow, however, the same philosophy described before, with the pertinent modifications. We still need to define a "Target" line (say, the percent defectives) and its corresponding UCL and LCL lines at 3σ distance from the target. We can also use "warning" limits,

as described earlier. But now, the parameters are obtained based on different statistical assumptions and even distributions.

Chart for the Percent Defective (Attribute Chart)

The modifications come about from the fact that, now, the distribution of the data is not assumed Normal, but Binomial, with parameters "n" (sample size) and "p" (the percent or fraction defective). Let ND be the number of defective items in a sample of size n. Then, PD = ND/n is the percent defectives in the sample (an estimator of parameter "p"). Since the distribution of ND is Binomial (n, p), that of PD (for n > 20) approximates the Normal, with mean p and variance = p(1 - p)/n. Then, the QC Chart parameters for PD are obtained as:

$$UCL = p + 3\sqrt{p(1-p)/n} \text{ (if UCL} < 1; \text{otherwise UCL} = 1)$$

$$Mean \text{ (Target)} = p$$

$$LCL = p - 3\sqrt{p(1-p)/n} \text{ (if UCL} > 0; \text{else UCL} = 0)$$

As before we draw, at regular time intervals, independent samples of size n, obtain the ND, calculate from them the PD and finally plot these in the QC Chart. As long as PD remains within its LCL and UCL lines, the process is assumed in control. As before, the probability of PD being outside the control limits, while the process is still in control, is less than 0.0026. Let's illustrate this via a numerical example.

In the previous coffee-packaging example we now assume that samples of n = 50 bags are taken and weighted every day. Assume that, if the number of coffee-bags reported out-of-spec is 5 or less, then the process is in control (acceptable process PD is less than 10% i.e., $p \leq 0.1$).

Hence:

$$3\sqrt{p(1-p)/n} = 3\sqrt{((0.1)(0.9))/50} = 3\sqrt{0.0018}$$

$$= 3 * 0.04242 = 0.12727$$

and

$$LCL = p - 3\sqrt{p(1-p)/n} = -0.0272 \Rightarrow LCL = 0$$

$$\text{and } UCL = p + 3\sqrt{p(1-p)/n} = 0.2272$$

Assume the process goes out of control after 10 days (p becomes 15%). Table 3 shows the ND data for such defined 20 days. In Figure 4, we show the corresponding PD Chart.

Table 3. StackNum: Number of Defectives (ND) in Samples of n = 50

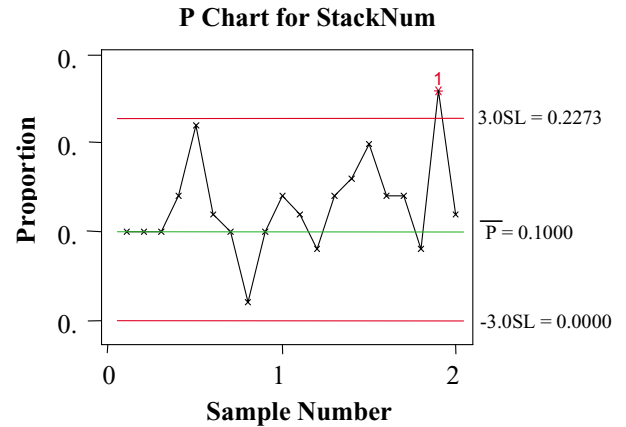|				
5	5	5	7	11
6	5	1	6	4
5	7	7	8	10
7	7	4	13	6

Figure 4. Control Chart for Percent Defectives
Notice that after the 10th time period, there is a clear trend up and in the 19th time period, there is a point above the UCL. If Warning Limits had been used, a problem could have been detected earlier.

From the chart in Figure 4, we can state that the process has fallen out-of-control. Again, often the process parameters are not known and must be estimated from the data. It is strongly recommended that at least 20 time periods are used solely for obtaining the QC Chart parameters.

Charts for Number of Defectives "C"

Other times, we look into the Number of Defectives (ND) per some unit (e.g., time, area). We can then assume that the distribution of ND is Poisson, with mean = λ and variance = λ. In such case, we can implement a control chart for ND using the same logic given earlier:

$$Mean \text{ (Target)} = \lambda; \ UCL = \lambda + 3\sqrt{\lambda}; \text{ and}$$
$$LCL = \lambda - 3\sqrt{\lambda} \text{ (if LCL is} > 0; \text{otherwise LCL} = 0)$$

Again in the coffee-packaging example, assume an acceptable daily production of 50 bags has an average of 5 defective bags. The Poisson mean is then $\lambda = 5$ and its variance is $\lambda = 5$. Chart parameters, see Figure 5, are obtained:

Mean (Target) = 5; UCL = 5 + 3*√5 = 5 + 3*2.236 = 11.71
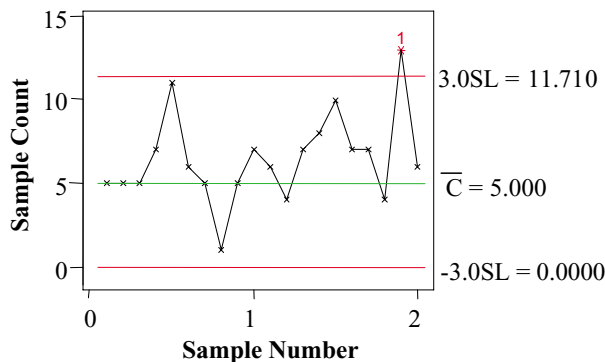LCL = 5 - 3√5 = 5 - 6.71 = -1.71 (therefore, LCL = 0)

Figure 5. QC Chart for Number of Defectives

Notice how Figures 4 and 5 are similar, differing in the target level and control limits because of their different distributions. In both, there is an upward trend followed by an out-of-control point, at the 19th value. The reasons for these similarities are discussed in the next section.

The Poisson Approximation

The PD Chart works well for cases where both percent defective "p" and the sample size "n" are such that $n \times p \geq 5$ (or $n \times (1 - p) \geq 5$). Whenever this requirement is not met, we use instead the Poisson approximation to the Binomial distribution, which is obtained by redefining the Poisson parameter $\lambda = n \times p$. Then, we construct a Chart for ND instead, as done previously.

Notice, in the two examples given above (for PD and ND), that $\lambda = n \times p = 50*0.1 = 5$ is precisely, the boundary value defined for using the Binomial or the Poisson distributions. For this reason, both numerical examples have yielded very similar results. In practice, when faced with creating a PD Chart, we first calculate $n \times p$. If $n \times p < 5$, the PD Chart is not efficient. We instead implement (assuming the Poisson distribution) a QC Chart for ND, as shown above. The results obtained will then be more efficient and valid.

Summary

In this introductory START Sheet we have overviewed several types of QC Charts (graphical methods) for assessing and tracking "variable" and "attribute" process data. We have also presented other, more advanced methods (Warning Limits and CUSUM Charts), that detect small upward or downward process shifts, δ, faster than traditional Shewhart Charts. We have provided several practical and numerical examples, implemented by hand and by software, that illustrate how to apply simple Charts in the industrial process control problems and context. Finally, we have included some technical bibliography for those interested in pursuing further the study of the more complex QC procedures discussed.

For Further Study

1. A.J. Duncan, Quality Control and Industrial Statistics, Fourth Edition, Irwin, Il, 1974, (Part IV: Control Charts).
2. Montgomery, D.C., Introduction to Statistical Quality Control, Wiley, 1991.
3. Kennet, R.S. and Sh. Zacks, Modern Industrial Statistics: Design and Control of Quality and Reliability, Duxbury Press, 1998.
4. Walpole, Myers and Myers Probability and Statistics for Engineers and Scientists, Prentice Hall, 1998, (Chapter 17: Statistical Quality Control).
5. Coppola, A., Quality Toolkit, RAC, 2001.
6. Romeu, J.L. and C. Grethlein, A Practical Guide to Statistical Analysis of Material Property Data, AMPTIAC, 2000.
7. Statistical Confidence, Romeu, J.L., RAC START: Volume 9, Number 4, October 2002, Available at <http://rac.alionscience.com/pdf/NLDIST.pdf>.

About the Author

Dr. Jorge Luis Romeu has over thirty years of statistical and operations research experience in consulting, research, and teaching. He was a consultant for the petrochemical, construction, and agricultural industries. Dr. Romeu has also worked in statistical and simulation modeling and in data analysis of software and hardware reliability, software engineering, and ecological problems.

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Romeu has received several international grants and awards, including a Fulbright Senior Lectureship and a Speaker Specialist Grant from the Department of State, in Mexico. He has extensive experience in international assignments in Spain and Latin America and is fluent in Spanish, English, and French.

Romeu is a senior technical advisor for reliability and advanced information technology research with Alion Science and Technology previously IIT Research Institute (IITRI). Since rejoining Alion in 1998, Romeu has provided consulting for several statistical and operations research projects. He has written a State of the Art Report on Statistical Analysis of Materials Data, designed and taught a three-day intensive statistics course for practicing engineers, and written a series of articles on sta-

tistics and data analysis for the AMPTIAC Newsletter and RAC Journal.

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