

Using Statistical Process Control in the Call Center

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The goal of statistical process control is to measure process stability and make a process stable over time, and then keep it stable unless planned changes are made. In the contact center are many processes to which statistical process control may be applied. Important, however, is to understand that stable does not mean constant. All processes have variation. The aim of statistical process control is to manage or reduce the variation. In order to manage, one must measure. Statistical process control charts give you the ability to measure and understand the variability in your process, whether that is your call handling process, forecasting process, quality process or training process.

The call center or contact center is largely a human endeavor. People are an integral part of the processes in a center, and no two people have exactly the same skills, the same attitude and the same behavior. Plus, no two interactions between the person making a contact and the agent receiving the contact are exactly the same. The makeup of the contacts coming into the center varies minute-by-minute, hour-by-hour, day-by-day.

But, why is it important to measure and reduce variability? Well, I am 6 feet tall and when considering crossing a river, knowing the *average* depth is 5 feet is really not very helpful. I could have one foot in a bucket of water at 200F degrees and my other foot in a bucket of water at 0F degrees. On average, I feel pretty good. Hence, averages do not tell a very good story. If I call into my favorite call center and get my call answered in 10 seconds one time and 4 minutes the next, my level of satisfaction with my answer speed is going to be 50%. But, what actions do I take to increase the 50% satisfaction? Good question! Both the 10 second pickup and the 4 minute pickup are very likely anomalies, but how do I know? If my call is consistently answered in 60 seconds, I can express my satisfaction or dissatisfaction with 60 seconds. Now, management can make a decision on whether 60 seconds is the right target, or not. If I have a 60 second target, because I have found that the level of satisfaction with wait time is acceptable there, but I have a wide degree of variability, it means that I really don't know what the caller is reacting to when indicating satisfaction.

Call centers rely on averages too often, such as Average Handle Time and Average Speed of Answer. Often we take averages of averages, as in a monthly average of daily average speed of answer measurements. However, *a key determiner of customer satisfaction is in the meeting of expectations.* If a company's Contact Us web site page has me fill out an eMail, informing me that I will receive a response within 1 business day, my expectations are set. The expectations are positive assuming they

are reasonable. I went into my cell phone provider store two weeks ago to upgrade my phone. I chose the model that cost me \$0 to upgrade. When checking out, the counterperson explained that the \$0 means I need to pay \$50 now and I will get a rebate check; in 6-8 weeks. My expectation was set, but it was not positive. Even if my expectations were exceeded and the check arrived in 5 weeks, I would still not be satisfied, as I believe in these days of advanced technology, 5 weeks is much too long. Back to my eMail Contact Us example. A 1 business day turnaround is fairly standard within the industry, and I have positive expectations. If one time I eMail the company and receive a response in 8 hours, the next time I receive a response in 3 days, and the next time I receive a response in two and a half days, my expectations are clearly not being met. Worse yet, when I received my first response in 8 hours, that is likely where my expectations will now be set, meaning I am even unhappier with a 3 business day response.

Averages will simply not tell me how much variability I have, or conversely, how consistently my service is being delivered. Again, given that the call center is a human endeavor on both ends of the interaction, variability is always present. Because variation is always present, we can't expect to hold a measurement exactly constant over time. The statistical description of stability over time requires that the pattern of variation remain stable, not that there be no variation in the measurement. In the language of statistical process control, a process that is in control has only common cause variation. Common cause variation is the inherent variability of the process, due to many small causes that are always present. When the normal functioning of the process is disturbed by some unpredictable event, special cause variation is added to the common cause variation. The aim of statistical process control is to discover what lies behind special cause variation and eliminate that cause to restore the stable functioning of the process.

An example of a common cause variation is a customer service agent that comes to work sick one day. Their numbers will vary from days when they are functioning at 100%, and will vary from what other customer service agents in their group are doing that day. A special cause variation could be that a new company program was introduced and the customer service agents do not have the proper scripts or knowledge articles to respond to questions. Or, the customer service agents struggle through a poorly written procedure or knowledge article for a given situation and talk time increases.

The goal of management is to reduce the common cause variation and eliminate the special cause variation. How each of these is addressed is different. As we will see, common cause variation is reduced with process improvements. Reducing complexity is a key approach to reducing variation. I still see too many call centers with two screens on the desk of every customer service agent. I always ask why, and always get the same answer; the agent needs to use 5 or 10 applications to service the caller. The agent needs to know when and under what circumstances to use each of the applications, needs to know how to interact with each of the applications (oh, you mean the customer number in these two apps needs a hyphen, and in these three apps it doesn't?), and what to do for each app if an error or some exceptional condition occurs. *In short, to reduce common cause variation, reduce complexity.* Special cause variation is typically due to a flow of work that should be described and documented as a process, but isn't, or is a flow of work that needs a process to manage it. A good example is a new marketing program or a major change to an existing program that is introduced by a company, with

inadequate training for the call center. What is needed is a management process to ensure that the call center receives all of the material and training it needs to successfully support the new program.

Another example is a change to the CRM app the service agents use on each and every call. The call center is clearly missing a seat at the table of the I/T change management process. Another key reason to reduce variation or variability is for predictive purposes. The smaller the variation in a process output or metric, the more accurate we can predict what will happen to that metric in the future. If Average Handle Time is a key input to the staff forecasting model, then large variability means I not only have less predictive insight into Handle Time, but less predictive insight into a forecast, which will drive further instability and variability.

The statistical process control tool that is described in this paper is the Control chart. In a graphical and very visual way, Control charts distinguish the ever-present common cause variation in a process from the additional variation that suggests that the process has been disturbed by a special cause.

There are two basic Control charts discussed in the paper, \bar{x} and s . For those that do not have a background in statistics, there are some rather simple concepts that will be introduced; mean and standard deviation. For the explanation of Control charts, x will represent the variable or metric we wish to study. It could be Handle Time, Answer Speed, Schedule Adherence, Forecast Accuracy, or any other metric of interest.

First, the notion of groups needs to be introduced. A group has common characteristics. It could represent a group of like-skilled service agents, or a day such as Monday. You are trying to find as homogeneous a collection as possible for a given group. The reason should be clear. First, try to understand and address variability within a group having like characteristics. For most support centers, Monday is by far the highest call day of the week. And, there are intervals during the day that are higher than other intervals, typically 9am-11am and 1:30pm-3pm. If this is the case, limit your group to these intervals. Once variation is understood within a group, then we look for variation across groups. How you choose your groups will be somewhat unique to your particular organization. One important note; you will not be able to manage the variation of a single metric with a single Control chart. Properly managing the variation of services across your call center may take dozens of Control charts. So, start with one metric and increase as your staff becomes accustomed to the practice. For the example in this paper, the *Resolved On Call* metric is chosen. In this case I will have a group, for example all calls for the ordering of a widget, and I'll name that group Order. I will also have subgroups based on agent skill level, which can be measured any number of ways, but I will simply use tenure for the example. Don't go crazy at this point and add sub-subgroups and sub-sub-subgroups. You will quickly get lost and not be able to determine what question you were trying to answer.

Once you have your groups defined or at least your grouping approach in place, it is time to select data samples to understand where your process currently is with respect to variation. You want to select your data samples from timeframes when your process was, as far as you know, stable. So, don't choose data for a sample for service agents that have just completed training, or for a month when a major product or service was rolled out. Use data as recent as possible so that you understand what your process is doing *now*, not six months ago.

A couple of additional definitions before we get started. The distribution of a variable or metric x for a process represents a probability of occurrence of each measurement. If the process is in control, this is a *normal* distribution or bell curve. The process mean, μ represents the center point of the bell curve, and the process standard deviation, δ represents the 'spread' of the bell curve. \bar{x} represents the average of the values in a given sample, and s represents the standard deviation of a given sample. This should all become clear as we progress through the example.

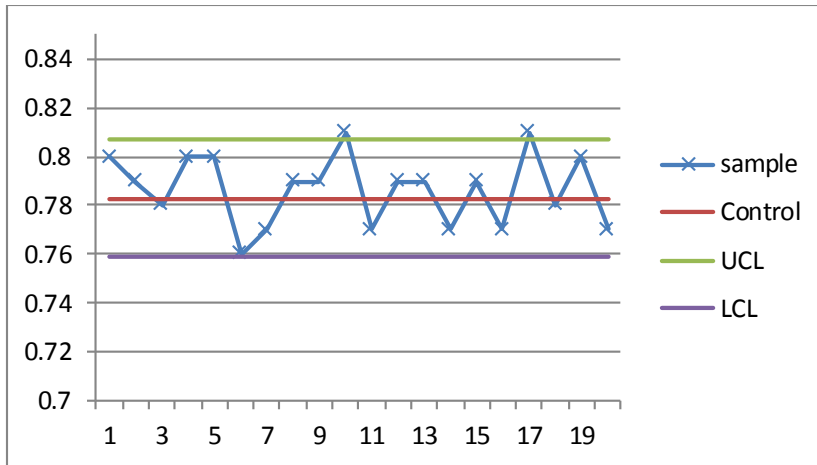
The table below contains Resolved On Call measurements for the Order calls for service agents with tenure exceeding 1 year. Each sample represents 25 calls, typical for a day in the call center.

Sample	\bar{x}	s	Sample	\bar{x}	s
1	0.80	0.0449	11	0.77	0.0464
2	0.79	0.0441	12	0.79	0.0385
3	0.78	0.0336	13	0.79	0.0410
4	0.80	0.0369	14	0.77	0.0324
5	0.80	0.0441	15	0.79	0.0471
6	0.76	0.0422	16	0.77	0.0408
7	0.77	0.0396	17	0.81	0.0366
8	0.79	0.0369	18	0.78	0.0446
9	0.79	0.0489	19	0.8	0.0444
10	0.81	0.0354	20	0.77	0.0337

From the data in the table, we can now construct an \bar{x} chart as follows:

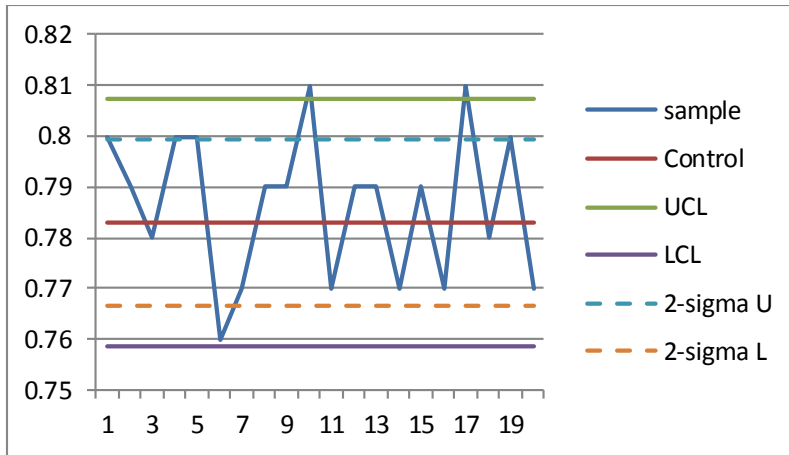
1. We will need to choose a μ or process mean, sometimes referred to as the *Control Line*. We could use our target for the Resolved On Call metric, which is 79%. Or, if we want a better understand of how our process is really working, we can calculate the average of all \bar{x} values (called $\bar{\bar{x}}$), which is 78%.
2. We need to calculate s for each sample. With 25 values per sample, you will want to use a spreadsheet program that can calculate the standard deviation (STDEV.P in Excel for example).
3. Next, we calculate δ by taking the average of the s values. We are allowed to do this as long as our sample sizes (in our example 25) are relatively large. If we take sample sizes < 20 , we need an adjustment constant. Therefore, δ is equal to 0.0406.
4. Now, our control limits, upper and lower are equal to 3 standard deviations from the Control Line, and are calculated as:
 - a. $UCL = \mu + 3 * \delta / \sqrt{N}$, where N is 25, our sample size; therefore $UCL = .8074$
 - b. $LCL = \mu - 3 * \delta / \sqrt{N}$, where N is 25, our sample size; therefore $LCL = .7586$

Our graph looks like:



Note that the sample (\bar{x}) is outside of the control limits for samples 10, and 18. The variation from the Control at all other points is common cause variation and the points outside of the control limits are points showing special cause variation. What else can we glean from the \bar{x} Control chart? Out of control limit conditions are special cause variations that need to be addressed, but is there anything to look for in the common cause variation that should capture our attention? The short answer is, yes. Patterns are important as signals. For example, a certain number of successive points above or below the mean or control line should drive interest, as should a certain number of successive points that are moving in the same direction, either upward or downward. The number of successive points depends on the number of samples in your Control chart. A good rule of thumb is 20%. In other words, in our example, 4 successive points above or below the control line, or 4 successive points moving upward or downward should garner particular notice. In our example, sample 6-10 would have produced a signal after sample 9 and caused investigation into what may have changed that is causing a steady uptrend in the Resolved On Call metric for this agent population. If there was a change, whether a better knowledge article, more training or whatever, it is time to go back to sample 6 and redraw or recreate the Control chart. More on when and under what circumstances you should redraw your Control chart a bit later.

In the diagram, the Upper Control and Lower Control Limits are at ± 3 -sigma (3 standard deviations from the control line). One approach to refine your investigation, especially for processes that have low variation, is to calculate and draw the 2-sigma lines as shown in the diagram below.



The areas between the 2-sigma and 3-sigma lines depict warning areas. In addition to investigating points outside of the control limits, points between the 2-sigma and 3-sigma lines should be examined. In our example, this would be samples 4, 5, 6 and 19. We would then review each sample and look for anomalies. Keep in mind how the group was chosen earlier, to answer the question “where is the variation in the Resolved On Call metric for Order calls across a group of service agents with at least one year of experience?” We could have instead set up our data collection to answer “what is the variability in the Resolved On Call metric for an individual agent?” in which case the group size would have been 1. Or, we could have asked the question, “how do all service agents in a group compare for the Resolved On Call metric?” in which case each sample would contain data for an individual service agent, and our graph would show those agents that should be on a ‘watch list’ for coaching and those that should be on perhaps a counseling list.

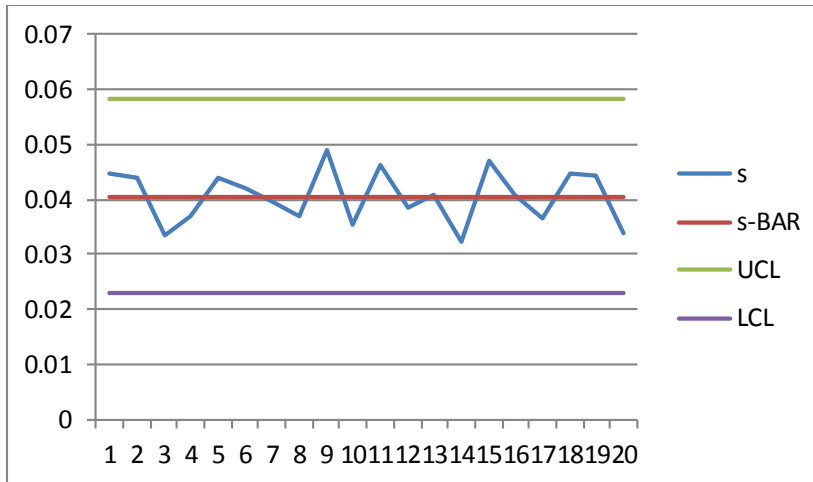
What about the amount of variation? Can we measure this? What will that tell us? The s chart will show us more. An \bar{x} chart focuses attention on the variation with respect to the control line or mean (μ) and is not good at detecting changes in variability (δ). This is precisely where an s chart is useful. Instead of graphing and examining the sample means (μ 's), we graph and examine the sample standard deviations (s 's).

If μ_s is the mean for the standard deviation of the samples (essentially \bar{s}), and δ_s is the standard deviation for the sample s 's, we can now plot the graph to understand the behavior of the variation. One simple correction we have to make here, because s will not represent a Normal distribution, we need a couple of constants (D_4 and D_3) to calculate δ_s . The explanation for why these are needed and the values of the constants is beyond the scope of this paper. Interested readers are urged to consult textbooks or other reference material on statistical analysis.

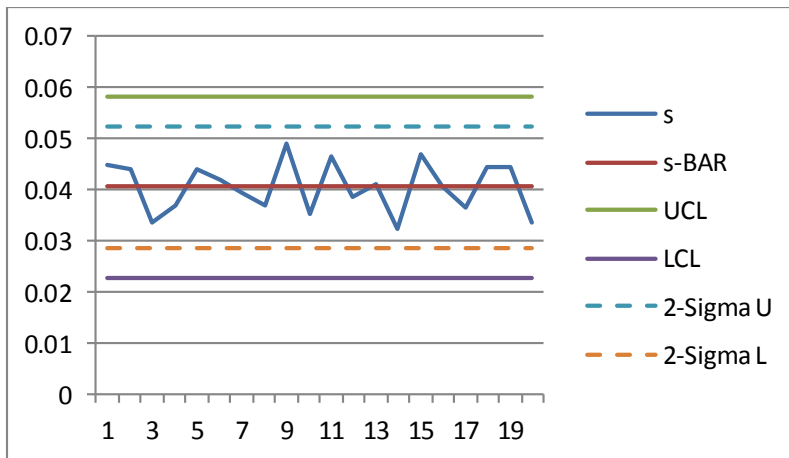
Calculating our needed values then:

1. $\mu_s = \bar{s} = .0406$
2. $UCL = D_4 * \mu_s = 1.435 * .0406 = .0583$
3. $LCL = D_3 * \mu_s = .565 * .0406 = .0229$

And our graph is shown below.

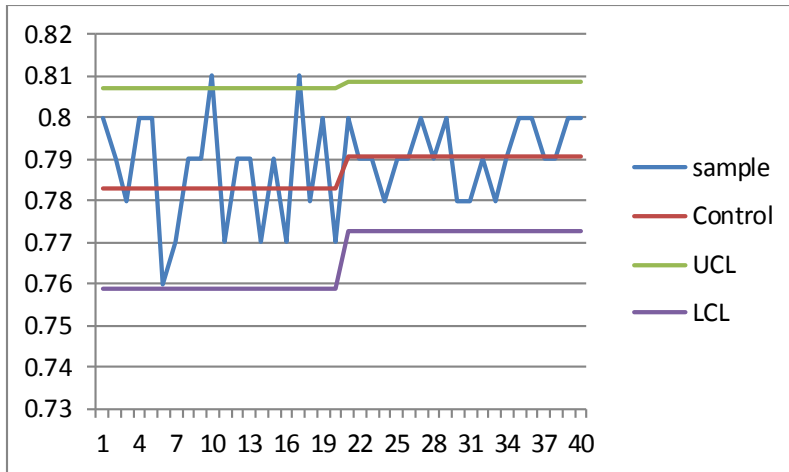


What the above graph shows is that, for our sample data, the variation is common cause and in control. Indeed, even looking at the 2-Sigma lines, the variation is still well behaved.



Again, any points lying outside of 2-Sigma would be a warning sign and should prompt an examination of the individual samples.

A question raised earlier is, “when do I redraw my Control chart(s)?” The short answer is when a change in the process is either detected and confirmed through Control chart analysis, or when a process change is made by the organization. I find it very instructive to ‘append’ the new Control chart on to the previous Control chart. This will show how your process characteristics are changing over time. The best condition is where the various process changes being made result in a Control chart that looks something like this:



As explained elsewhere in the in this paper, the role of management is to; (1) reduce special cause variation by challenging existing supporting processes or by developing new supporting processes, and (2) to reduce common cause variation through continuous improvement of the process under investigation. You can see from the composite Control chart above, that a process change or improvement was made in period 20 to improve the Control and reduce the common cause variation (narrowing of the difference between the UCL and LCL). Perhaps a change was made here to a supporting process as well to reduce special cause variation. An s chart would measure the change in variation we can see from a cursory look at the graph.

To this point, an example has been shown for a given group/sub-group, namely the Resolved On Call for Order calls for all service agents with a tenure exceeding one year. One can do the statistical analysis for each service agent subgroup and develop improvements for each subgroup based on that subgroup's characteristics. For example, for undue variation in a highly-tenured service agent population, perhaps a knowledge article for Order calls is insufficient or confusing and needs to be addressed. For relatively new service agents, the remediation may be to address training. Since the groups and subgroups are chosen to be largely homogenous, remediation efforts can be more targeted. There are cases, however, especially with customer-visible metrics such as Talk Time, and Resolved On Call that should be examined across the total service agent population to get an understanding of the customer experience. Such analysis may also point out improvements that can be made that would improve the metric as a whole, in other words increase Resolved On Call for all Order calls, or decrease Talk Time for all Order calls. In this case, your subgroup would be all service agents that handle Order calls. Some metrics do not depend on the service agent at all, such as Speed Of Answer, in which case you would simply sample according to skills grouping, or IVR option grouping.

Statistical analysis need not be confined to call metrics. Any process metric in the call center can be analyzed for variation. Examples are Forecast Accuracy, Shrinkage, Post-training supervisory-period scores, Quality scores, and Knowledge Accuracy. For large, multi-skilled, multi-channel, complex call centers, a statistical analyst is highly recommended. The statistical analyst can work with the management team to understand groupings and important metrics.

At some point, the management team may very well ask “when is enough, enough?” After all, as mentioned previously, the call center is a human-based business. There is only so much variation you can squeeze out of a human-based process or set of processes. I highly recommend the call center develop and implement a process improvement process for all processes across the center. All processes need periodic review for improvement opportunities, and your process improvement process should drive the statistical analysis.

Statistical analysis can provide leadership with much more information from which to manage the call center operations. Averages hide the variation in the processes and hence the variability of the service to customers. Customer satisfaction is highly dependent upon the meeting of expectations, which are set in one of two ways; either by the industry, or by previous interactions with the center. In the latter case, expectations are set by the best service received. If your customer-facing, customer-affecting metrics have a wide degree of variability, you will be setting unrealistic and unsustainable expectations by variance that appears to be for the good, but in the end is not. If my goal for Answer Speed is 60 seconds, and this is highly variable, the customer will remember a 5 second Answer Speed and that will set his or her expectations. This is specifically why seemingly exceeding a control limit ‘on the good side’ is actually not good at all. Consistency is the ally of the call center, variability is its enemy. Measuring and managing to averages leaves the call center leadership blind as to what is actually happening and how to fix it.