THE USE OF STATISTICAL QUALITY CONTROL CHARTS IN MONITORING INTERVIEWERS

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1. Introduction

Quality is important to any organization which produces a product or service for consumption by its customers. An effective quality control process identifies specifications to which the product or service must conform in order to be of value to the consumer. Once the standards are established, then a system must be designed to ensure that the product or service conforms to these standards.

For years, the manufacturing industry has utilized the concept of statistical process control charts. In fact, control charts helped the Japanese become the world leader in quality in the late 70's early 80's. These charts are based upon quality which is defined as "conformance to specifications". Before a product can conform to its specifications, the production process of that product must be "in control". In other words, the units resulting from the process must contain measurements which are in conformance to specifications or within the bounds of reasonable variation. This can also be related to interviewers. Before interviewers can be expected to conform to certain standards, their interviewing process must be in control. Control charts provide the data necessary for management to make and implement the decisions which will bring the process into control. This paper discusses how control charts can be used in the field of survey research to assist in improving data quality and interviewer productivity.

2. The Importance of Quality in Survey Research

Surveys are made up of three components. These components are the sample, the questionnaire, and data collection. Each has its own specifications. Examples of survey components and some conformance standards might be as follows:

Component	Standards
Sample	•Representative •Unbiased
Questionnaire	•Obtains information needed •Understandable by respondent
Data Collection	•Proper administration of questionnaire •Proper data entry

The focus of this paper is on the application of control charts to monitor quality and productivity in survey data collection. The basic steps for performing statistical process control (SPC) to monitor quality and productivity are:

1) Establish quantifiable quality standards.
2) Collect data.
3) Make comparisons between data and quality standards.
4) Make decisions as to the type and amount of corrections required (if any).
5) Take corrective action.

The value of SPC can be illustrated by examining the manufacturing process which produces bolts. It is assumed that the critical factor in determining the quality of a bolt is the diameter of its stem. As a result, the mean, $\bar{X}$ charts, and range, R charts, are constructed to demonstrate how the charts can be used to monitor quality.

To establish quantifiable quality standards, the units of measure and measuring techniques must be determined. Once this is done standards can be established. For the production of a bolt, the unit of measure is the inch and the measuring tool is the calipers. In order for the bolt to be useful it is determined that the bolt stem must be $.5 \pm .005$ inches in diameter. Thus the quality standard becomes the diameter of the bolt stem or $.5 \pm .005$ inches.

After the quality standard is established, data must be collected to determine if the product conforms to the standard. In collecting data, n samples of the product are taken over a period of time. The size (k) of the sample (i) must be large enough to adequately represent the product. Once these samples are drawn, sample means ($\overline{X_i}$) and ranges (R_i) are calculated. This data is then plotted on control charts. In constructing these control charts, the mean of the sample means ($\overline{\overline{X}}$) and the mean of the ranges ($\overline{R}$) are calculated. From this data, upper (UCL) and lower control limits (LCL) are established. In this example, the UCL and LCL are set at three standard deviations above and below the mean respectively. The formulas for calculating the means and control limits are listed in Table 1 where three standard deviations is easily estimated by the range and constant factors based upon the sample size. In addition, a partial factor chart is shown in Table 2. Full factor charts can be found in any quality book.

Table 1: Means and Control Limit Formulas.

$\overline{X}$ - Chart:	R- Chart:
$\overline{\overline{X}} = \sum_{i=1}^{n} \overline{X_i} / n$	$\overline{R} = \sum_{i=1}^{n} R_i / n$
$UCL_{\overline{x}} = \overline{\overline{X}} + A_2\overline{R}$	$UCL_R = D_4\overline{R}$
$LCL_{\overline{x}} = \overline{\overline{X}} - A_2\overline{R}$	$LCL_R = D_3\overline{R}$

Table 2: Factors for $\overline{X}$ and R Charts.

Sample Size	A_2	D_3	D_4
2	1.880	0	3.267
3	1.023	0	2.575
4	0.729	0	2.282
5	0.577	0	2.115
6	0.483	0	2.004
7	0.419	0.076	1.924

The example assumes that the manufacturer produces bolts seven days a week twenty four hours a day. It is decided that the process will be observed over a course of a full day with samples of bolts being drawn every hour. Three bolts are pulled from the production process at each drawing. Thus, twenty four samples of size three are drawn. In the first sample, the measurements of the diameters of the bolts are .500, .498, and .505 inches. As a result, a sample mean of .501 inches and a sample range of .007 inches are calculated. Figure 1 shows these calculations.

Figure 1: Calculations of the First Sample Example:

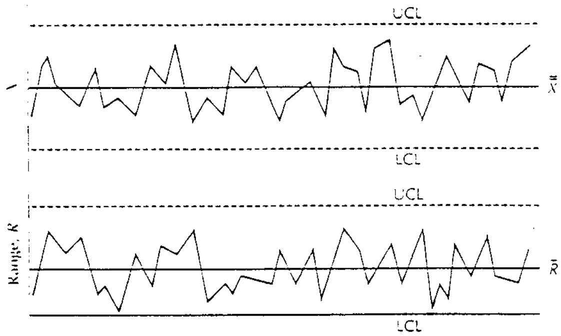
Bolt 1 = .500 Bolt 2 = .498 Bolt 3 = .505

$$\overline{X} = (.500 + .498 + .505) / 3 = .501$$

$$R_1 = .505 - .498 = .007$$

Samples are continued to be drawn for each hour of every shift during the week. Similar computations are then performed on each of the samples taken. Once all the samples are drawn, the means and ranges are then plotted on $\overline{X}$ and R charts. In these charts, the horizontal axis represents the period over which samples are taken, and the vertical axis represents the measurement of concern. In addition, the dotted lines above and below the means represent the control limits. As a result in the example of the bolt, we could have $\overline{X}$ and R charts similar to figure 2.

Figure 2: Example $\overline{X}$ and R Charts.

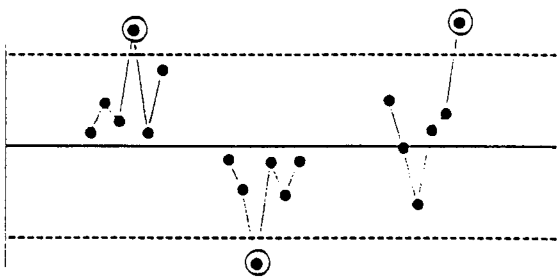


3. Interpretation of the Charts

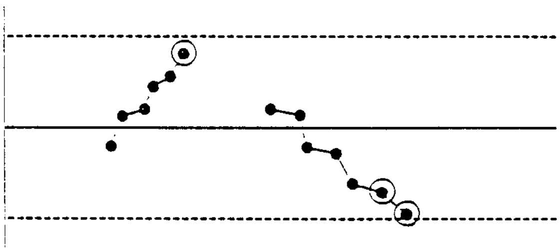
Statistical process control assumes that variation in a product or service comes from either a combination of natural (random) causes or assignable causes. Natural or random causes are uncontrollable. However, assignable causes can be related to a specific event and hence can be controllable. The problem that arises is the need to determine whether variation that is occurring is natural (uncontrollable) or assignable (controllable). Some examples of assignable causes in control charts are shown in Figure 3. These include points that are outside the control limits, trends, sudden shifts, and cyclic behavior of points.

$\overline{X}$ and R charts, in conjunction with the central limit theorem, establish behavior such that variations exceeding these behaviors above can be classified as assignable and hence are controllable. As a result for a process to be in control, all points on the control charts must be within specified control limits and exhibit random behavior. Plots outside the limits indicate points where control must be exercised.

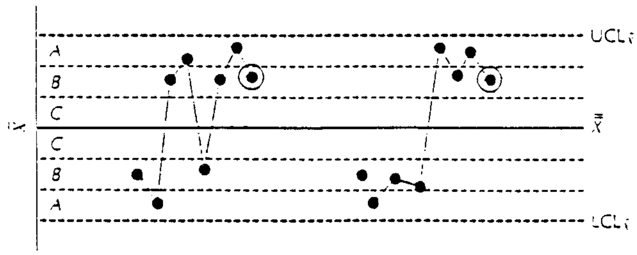
Figure 3: Examples of Assignable Causes



Extreme Points



Upward/Downward Trends



Sudden Shift in Points

4. Control Charts in Survey Research

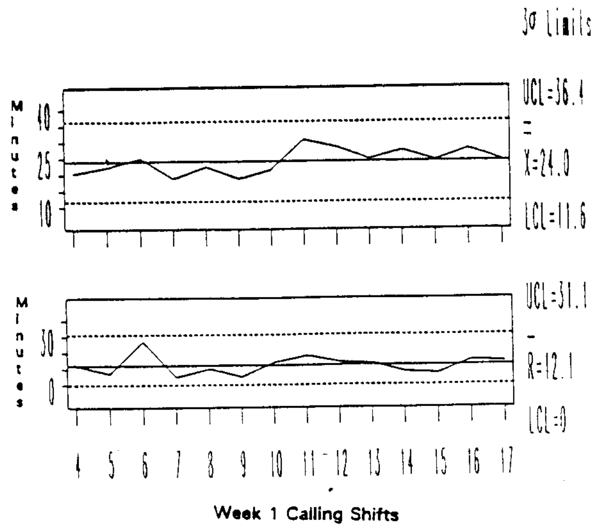
The preceding techniques can be applied to the field of survey research. For example in telephone surveys, data collection can be thought of as a production process in which the product is an interview. The data for the following two examples comes from the phone files of a statewide telephone survey. When collecting survey data, a large amount of calling information such as the outcome and time on the phone of every call, and the interviewer who made the specific call is obtained. This data can be used to measure the quality of data and efficiency of the interviewing process. The advantage of using this phone data is that the data is a by-product of interviewing. In other words, no personnel time is required to collect the data. In addition, the data is objective. As a result, there is no bias in the data.

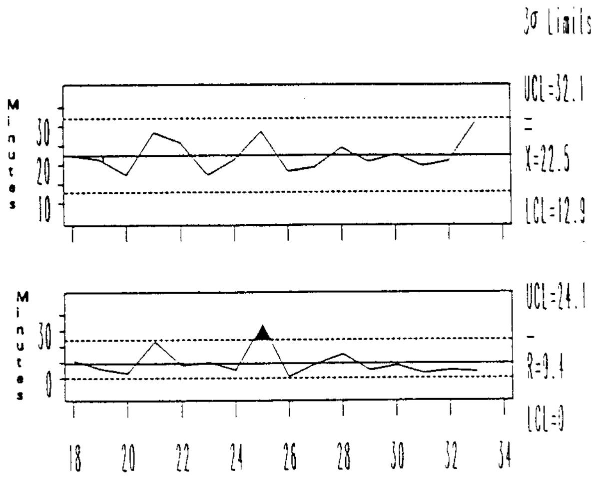
Several types of control charts can be constructed to quantify both the quality and productivity of the interview process. Two variables that may be useful in monitoring the process are the time it takes an interviewer to complete a telephone interview and the time to complete calls that result in no contact. From these variables, problems that may effect data quality can be analyzed. First, the quality of basic training and specific training can be interpreted. In addition, these times may pinpoint problems with the questionnaire which may effect the data quality. Identification of these problems is essential to finding acceptable solutions. The following illustrations demonstrate how these variables can be used in conjunction with SPC control charts to measure data quality and productivity.

The subjects for the statewide telephone survey were contacted over a two month period. The survey was conducted using three shifts: mornings, afternoons, and evenings, on Monday through Thursday, afternoons on Saturday, and afternoons and evenings on Sunday. As a result, the interviewing process was monitored over a period of a week where a sample was drawn each shift. The questionnaire was pretested at fifteen minutes.

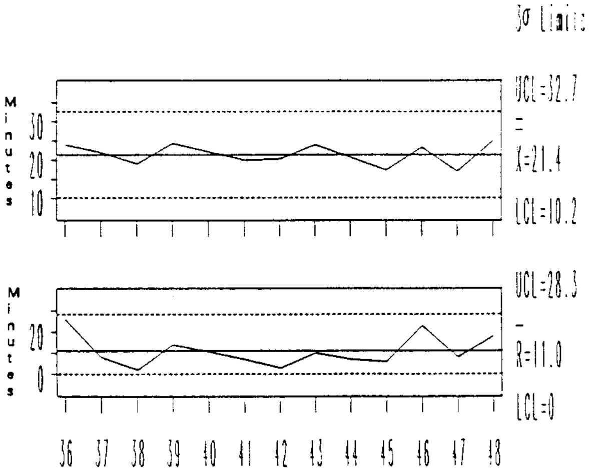
The first set of control charts were put together on a weekly basis. In addition, the process variable was the time to complete an interview. Figure 4 shows the control charts for the first three weeks.

Figure 4: Time to Complete an Interview Control Charts





Week 2 Calling Shifts



Week 3 Calling Shifts

The first set of $\overline{X}$ and R charts exhibit random behavior. With respect to the random behavior, interviewers are performing well. However, it could be argued that there was a sudden shift in times on the $\overline{X}$ chart. In addition, the mean and range of these charts are fairly high. A factor that would support this activity would be that only experienced interviewers were trained and called on the project for the first half of the week. During the second half of the week, new interviewers started their live calls, thus an upward shift in time resulted. Because the mean and range is still fairly high the interviewers may be showing signs of learning. This is an aspect of the process that management will continue to monitor over the following weeks.

Week 2 charts exhibit random behavior; however, in shift 25, an outlier in the range chart occurs. Management needs to examine what happened at this point to determine why large variability occured during this shift and how it can be prevented in the future. Once the cause of the variation in the range is determined, management will establish controls to correct the problem. Analysis of the means of both charts shows that there is a reduction. However, it still is not close to the 15 minute pretest. On the other hand, it does indicate that interviewer learning is occurring. Management will continue to monitor and research the reasons for the large deviation.

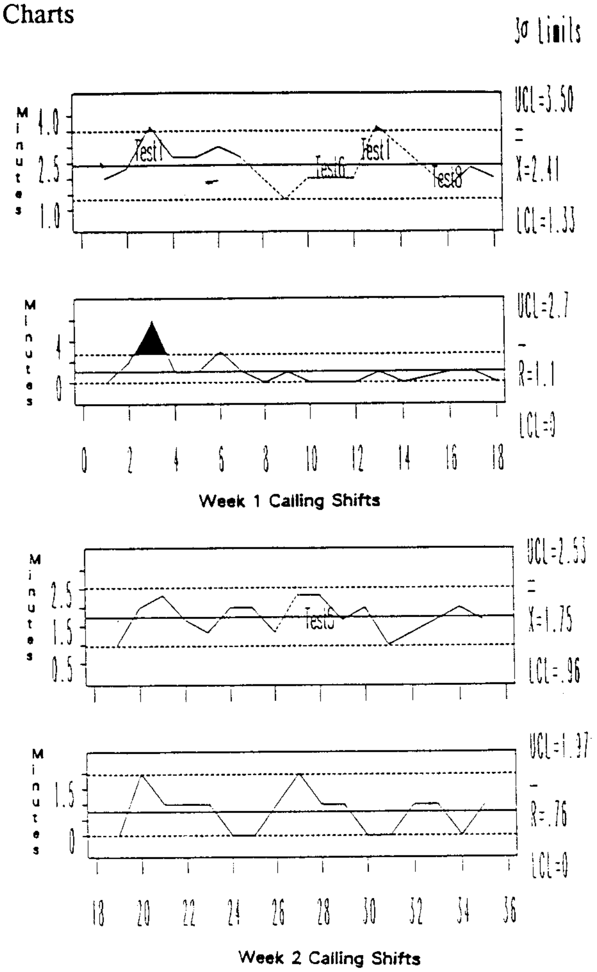
Week 3 charts again exhibit random behavior. Management has worked with the interviewers in understanding why the length of the interview is longer than 15 minutes. Inadequate pretesting of the questionnaire accounted for an underestimate in time to complete an interview. After another pretest, 20 minutes was identified as a more realistic time to complete the questionnaire. As a result, it can be concluded that the calling sessions are in conformance with the standards. The range chart does exhibit an increase in mean range. As a result, management must continue to watch this.

From this data, a learning curve factor has been identified. Calculation of this factor presents other implications of production of interviews. Is this learning curve factor too great? Can it be decreased by refining training, thus improving our data quality? These are all factors that can be identified to assist in improving data quality and interviewer productivity.

In the second example, the control charts were also put together on a weekly basis. The process variable of concern was the time of non-contact dispositions such as no answer and answering machine. Interviewers are trained to let the telephone ring eight times before hanging up and to listen to answering machine messages to give them useful information about the household. The process that the interviewers follow, regardless of obtaining an outcome of no answer or answering machine, is estimated to be about the same amount of time. These charts are slightly limited because the smallest unit of time used by the version of the computer assisted telephone interview (CATI) software was in minutes not seconds. Figure 5 shows the control charts for the first two weeks.

Week 1 $\overline{X}$ and R charts indicate that the process is out of control. However, the average mean and range times do not look that bad. They may be slightly inflated, but remember this is the first week of calling on the study. At this point, the most critical problems to examine are the outlyers. Management needs to look into these points to determine problems that may effect the charts. Possible problems could be that the

Figure 5: Time of Non-Contact Dispositions Control Charts



front-end or user interface was complicated on this specific study. Thus interviewers were easily confused. This has an impact on the ultimate quality of data. As a result, interviewer training on general interviewing techniques, general CATI skills, and/or study specific CATI skills may need to be revised or interviewers may need more practice prior to making any calls on the study.

As the weeks progress, the $\overline{X}$ charts become more in control. In week 2, activity during shifts 26 through 28 must be examined and actions taken to eliminate these assignable causes. Finally in week 3 (chart not shown), the process was in control with an $\overline{\overline{X}}$ of 1.86 minutes and an $\overline{R}$ of 1 minute. Thus it seems as though we had a 2 week learning curve for understanding the process of the questionnaire's user-interface.

As a result, training on general interviewing techniques, general CATI skills, and/or study specific CATI skills is probably the key point on which to focus to eliminate this variability. In addition, all interviewers would benefit from an improved training due to the fact that no cyclic behavior occurred. In otherwords, interviewers and interviewer session did not consistantly differ.

5. Conclusions

In conclusion, SPC charts can be very useful in monitoring survey data quality and interviewer productivity. SPC techniques have a long history of being effectively applied to production processes. Two of the more commonly used techniques are mean, $\overline{X}$, charts and range, R, charts. These charts utilize quantifiable data and display it in graphical form. These two parameters when used in conjunction with the central limit theory provide a very effective means of monitoring quality and productivity.

Organizations that administer surveys are similar to productions systems in that it is possible to collect quantifiable data which describe the performance of the system. In order to perform their function, management of organizations which conduct surveys must be able to measure the survey process in order to monitor survey data quality and interviewer productivity. the application of $\overline{X}$ and R charts present data to management in a format that will enable them to carry out their duties.

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