Management Services: A Magazine of Planning, Systems, and Controls

Volume 7 | Number 3 Article 5

5-1970

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Recommended Citation

Nigra, Alphonse L. (1970) "Quality Control of Data Through Statistical Control," *Management Services: A Magazine of Planning, Systems, and Controls*: Vol. 7: No. 3, Article 5.
Available at: https://egrove.olemiss.edu/mgmtservices/vol7/iss3/5

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Sampling techniques for quality control, common in industry and in financial auditing, could equally well be applied to all data flowing through a system. Here two basic statistical techniques for control are reviewed—

QUALITY CONTROL OF DATA THROUGH STATISTICAL CONTROL

by Alphonse L. Nigra
Allied Chemical Corporation

EVERYONE agrees that a good system, whether it be an accounting system or a management information system or a data processing operation, must have both "timely" and "good" input and other operating data. Another way to say this is that the "actual" or "live" data going into the system must have values that are not too far out of line with the values used to design the system. But "timely" and "good" data available at the time of design may change to something less than "good" with the passage of time. This need for maintaining timely data at a satisfactory acceptance level becomes more critical when input data from many remote places are fed directly into a central computer installation.

I think each one of us could quickly define what he means by "timely" in terms of specific values, such as one hour, one day, etc. But what do we mean when we say "good" data or a "satisfactory acceptance level" for data? Let me, therefore, define what I mean by a satisfactory acceptance level. A secretary typing a letter to a president would want it to be letter perfect. A letter to someone in her own department might be acceptable with one or two minor errors. A working draft need only be understandable and may contain a number of errors. The president's letter has no room for tolerance; it must have zero defects. The other two must fall within certain tolerances to be acceptable.

Most operations we wish to control fall within the tolerance classification and are performed in an environment composed of variable factors that may or may not be within an acceptable tolerance. When the variable factors fall

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within the acceptable tolerance a satisfactory number of times we can say that the operation is "under control." In general, variations fall into two broad categories: *chance* variations and those due to *assignable causes*. Chance variations, which may be due to any number of complex minor causes, occur in a random manner and there is very little we can do about them for a given system or operation. On the other hand, variations due to assignable causes can be traced and corrected. One statistical control procedure is to design a control chart that shows standards of expected normal variation due to chance causes. Then, when variations resulting from one or more of the assignable causes are superimposed on the control chart, they "stick out like a sore thumb" and tell us that something basic has changed.

Thus "good" data will always fall within a pre-established tolerance that is acceptable for our particular system or operation.

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Control of data

Variation is inherent in the environment we wish to control. The inherent multitude of chance causes, few of which can be predicted with certainty, also occur in other environments, such as manufacturing, transportation, warehousing, etc. Here the pattern of variation may affect the dimension of a finished part, the strength of an acid, the number of arrivals for a time period, etc. However, for these environments we have developed techniques to control their variations. The techniques require sampling inspection, and perhaps the most familiar use of sampling inspection is in quality control work.

I know of no reasons why these sampling inspection techniques cannot be used to control data for all types of systems used in business. The two basic techniques I have in mind are as follows:

1. Data may be inspected at any given point for timeliness and quality and compared to acceptable standards. The statistical control procedure will tell us whether a *satisfactory* amount of these data are meeting our standards.

2. Data may also be inspected to determine whether the system, process, or operation generating them is "under control." If not "under control," corrective action can be taken quickly before a great quantity of bad information is generated by our data processing machines. It is this system that uses control charts with their designed control limits within which sample items must fall in order for the operation to be considered "under control." (See example at the end of this article.) Since these limits are designed to allow for expected normal variations due to chance, whenever a sample value falls outside these limits, an inference is made that a stable system of chance causes no longer exists. Action is then taken to find the cause of the apparent change. If such a cause exists, the operation may be brought back into control or compensation made for the change in the pattern of variation.

It is these two statistical techniques, already in use in many areas of manufacturing and processing operations, which, I suggest, can be used to control all types of data used in various management information and accounting systems. And it is the second technique or process control concept for which the better known *Models of Statistical Control,* called "Control Charts," are designed. Allow

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2

me to point out at this time that a control chart need not be a graph on the wall where sample values are posted by hand. It can also be programed for a computer to use, and the computer can also select the sample values and "post" them to its "computerized control chart." Exception reports can then be printed out and responsible personnel can take corrective action.

Statistical control has proven itself to be a valuable tool in such important areas as:

- Work sampling of all types
- Control of quality in manufacturing operations and other types of continuous processing operations
- Control over voluminous clerical or document handling operations
- All types of waiting line systems
- Such items as labor turnover, costs, accident rates, etc.
- Monitoring solutions obtained from decision models.

As we have already discussed, all types of data going into an operation may be sample inspected for timeliness and quality and compared to acceptable standards. For example:

- Sales and Invoicing Data:
  - Timeliness. Length of time between receiving order and shipping material and invoicing customer.
  - Quality. Validity of customer name and address, shipping instructions, product description, prices, discounts, terms, accounting and sales codes, etc.
- Purchasing and Accounts Payable Data:
  - Timeliness. Length of time between placing order and receiving material. Length of time for processing paperwork so vendor discounts will not be lost, etc.
  - Quality. Validity of approvals and matching of documents (purchase orders, receivers, invoices, etc.). Validity of customer name, address, prices, accounting and purchasing codes, freight charges, etc.

Our statistical control procedure will tell us whether a satisfactory amount of these data are meeting our standards.

In contrast to the above where data going into an operation or process are controlled, we have the control chart technique, which can be used to determine whether the operation or process is "under control." For example:

- Data Banks, the processing of personnel and payroll information:

  To capture all this necessary information a large number of different data processing programs are usually used, and the data may come in from many different plants, offices, and other locations. The cost to check the completeness and accuracy of the employee data files would be quite expensive. On the other hand, a statistical program may be written to extract a limited number of employee files on a continuing basis, examine them completely, and tell us those areas where vital information is going "out of control."

- Management Information Systems:

  Such systems are usually dependent on decision models. Since decision models are designed at a point in time they tend to be static in that they may not readily adapt themselves to the instability of the decision environment. Thus, the specific set of values used for input parameters at time of design could change considerably with the passage of time. For example, an optimum procurement program will be less than optimum if the actual procurement lead time is more or less than the

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lead time initially determined and used to design the decision model. Control charts are valuable in such a situation because they are a means for converting static programs designed at a specific point in time to controlled dynamic programs that will function at good efficiency levels in non-steady-state environments.

– Feeding Voluminous Data to a Computer from Many Locations: It may be hard to visualize that information fed continuously into present or future data processing equipment, with its tremendous speed and large memory and storage capacities, could ever overflow the capacity of these machines and stack up in the field like too many airplanes trying to make a landing. But consider for a moment the problem of airlines issuing reservations and tickets by the millions from thousands of different locations. The airlines have long ago faced this problem, and other companies that are rapidly feeding an increasing amount of information to their computers may soon be faced with the same problem. Thus, it is well to note now that the most economical answer to the problem need not be additional or newer and better machines. The answer can well be the design of decision models to provide optimum levels of service capabilities in various waiting line systems feeding data to the computer. However, the optimum level of our decision model will not be achieved if the statistically described arrival pattern is out of control with respect to the derived model. It is here that control charts may be used to monitor the solution obtained from the decision model and provide a warning to the decision maker that the inputs to his model need revision.

As you can see from the preceding, I visualize usage of statistical control not only in such basic areas as sales, purchasing, receivables, and payables but also in the rapidly expanding areas of management information systems and the decision models that are being designed to fulfill many other business needs.

In most operations, perfection can only be achieved at an extremely high cost. Thus, rather than strive for perfection, some state less than perfection may be optimum in terms of cost. This concept is shown graphically in Figure 1 on page 41.

Cost curves

Figure 1 shows the costs for different levels of quality as decreasing as we move further away from perfection. On the other hand, the cost to our operation is shown as increasing when quality moves away from perfection. The total cost is shown as the sum of these two curves, and the optimum quality area is that point where total cost is nearest its minimum.

In practice the two curves might not follow the continuous and smooth forms shown in Figure 1. Also, it may be difficult to quantify these two functions; however, the concept is important, not because it can specify an optimum quality level precisely, but rather because it illustrates that some quality level less than perfection is usually desirable.

There are a number of factors that determine the size and cost of a sample or the amount of inspection necessary to achieve a desirable quality level. Let us take a moment to discuss the most important three factors. They are:

1. The amount of tolerance or quality limits we are willing to accept. In other words, our "precision" requirements.

2. Whenever our sample size is anything less than 100 per cent there is a risk that our sampling results may indicate satisfactory "precision" when actually the *true precision* in the population we are sampling may be more or less than the satisfactory precision shown by our sample. This risk is described as "reliability" or "confidence level," and it is usually very high in our favor. In other words, there may be 95 times out of 100 (95 per cent) or 99.7 times out of 100 (99.7 per cent) *when we can expect* that for the precision we have prescribed our sampling results will be correct.

– Precision and reliability are interrelated and so important that I would like to clarify their relationship with an illustration. If you wanted to visually estimate a man's height from a short distance away to within *a precision* of plus or minus one foot, I think you would agree that you have a very good chance (*reliability*) of doing so. However if you wanted to be *as precise* as plus or minus one inch in your sight estimate, then your chance (*reliability*) of doing so would be considerably less. I think you will also agree that you would need more chances (i.e., your sample size would have to be greater) in order to guess the one-inch precision than it would have to be to guess the one-foot precision. Thus, the more precision or the more reliability you want the greater the sample size (cost) you need to do the job.

3. The third important factor that affects sample size and therefore cost is the degree of variability in the data being sampled. Basically, statisticians measure variability in terms of "standard deviations." Simply, a standard deviation measures the degree to which numbers vary from their determined mean (average). Statisticians have also determined that in any normal distribution of data there will be the following dispersion of data about the mean:

Sixty-eight per cent of the data will fall within plus or minus one standard deviation (often called one sigma limit)

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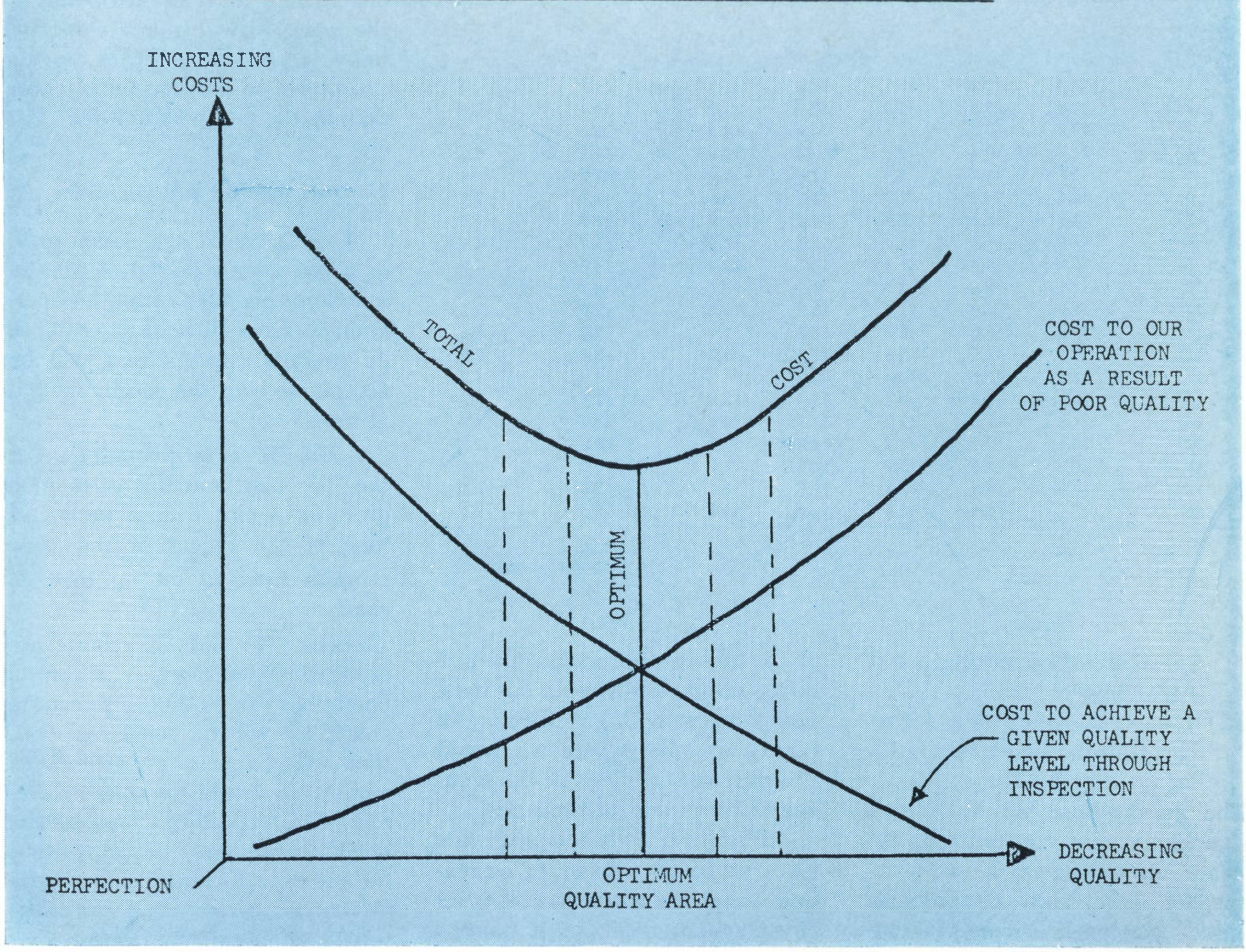
Figure 1 - Relationship Between Quality and Cost



Ninety-five per cent of the data will fall within plus or minus two standard deviations (often called two sigma limits)

Ninety-nine and seven-tenths per cent of the data will fall within plus or minus three standard deviations (often called three sigma limits)

And in those cases where data are not sufficiently "normal" they can be resorted (stratified) into homogenous groups that will make them more "normal." Thus, while great variability in our data may require larger sample sizes or resorting, this does not prevent the use of samples or sampling inspection. In the usual design of process control charts, the natural tolerance of the process is commonly taken at three standard deviations about the mean, which provides us with a 99.7 per cent reliability.

Thus the cost to control data at some state less than perfection is very reasonable and has been applied many times in different areas of operations.

Statistical control techniques

We have already briefly discussed the two basic techniques which we will now cover in more detail. They are (1) control charts which attempt to control a process or system and (2) the various other sampling techniques that attempt to control data or items as they pass through an inspection point. Let us discuss these inspection point sampling techniques first. These techniques can be used to determine whether an item is right or wrong or good or bad (sampling by attributes), and, also, they can be used where we attempt to make a measurement of some kind, such as the number of dollars right or wrong, how good or how bad, etc. (sampling by variables). Sampling procedures are available for just attribute sampling or just variable sampling or for both at the same time. The more important of these techniques are the three that follow:

—*Acceptance Sampling* is designed so we can control the level of quality from an inspection point and be assured, with a predetermined reliability, that on the average no more than some specified percentage of defective items will pass. In the simplest use of acceptance sampling, we draw a random sample of size "n" from a total lot of data "N" and decide whether or not to accept the entire lot based on the sample. If the sample indicates a decision to reject the lot, it may then be:

(1) Subjected to 100 per cent in-

TABLE 1

Sample Number	Sample Items					Mean $\bar{X}$	Range R
1	11.5	10.8	13.1	11.6	11.4	11.7	2.3
2	10.6	12.3	12.0	12.5	11.3	11.7	1.9
3	12.8	13.5	13.2	14.2	13.8	13.5	1.4
4	11.8	10.4	12.5	12.4	12.5	11.9	2.1
5	13.0	11.7	9.6	12.8	11.4	11.7	3.4
6	12.5	11.9	11.7	11.2	10.5	11.6	2.0
7	13.4	12.4	12.6	11.8	11.9	12.4	1.6
8	12.9	11.7	12.0	11.7	12.1	12.1	1.2
9	12.4	11.4	11.4	11.7	12.4	11.9	1.0
10	11.5	13.9	13.1	11.9	10.7	12.2	3.2
11	12.0	11.9	11.9	13.2	12.2	12.2	1.3
12	13.3	11.6	10.7	13.2	11.4	12.0	2.6
13	11.9	12.5	13.8	11.6	13.0	12.6	2.2
14	12.2	12.6	12.4	13.2	11.5	12.4	1.7
15	12.3	11.4	14.1	13.1	12.1	12.6	2.7
16	11.8	12.6	12.3	11.2	10.8	11.7	1.8
17	13.8	12.3	12.4	14.0	11.3	12.8	2.7
18	10.4	11.8	13.2	12.8	11.7	12.0	2.8
19	12.0	11.2	12.1	11.7	12.1	11.8	0.9
20	11.8	12.4	13.8	11.7	13.0	12.5	2.1
Totals						243.3	40.9

spection with a sorting out of bad items, or

(2) Returned to the sender for rechecking in order to bring the lot up to standard.

The justification for acceptance sampling in terms of cost again depends on a balance between inspection costs and the probable cost of passing bad items. Various techniques have been developed for obtaining the most economical sampling plans for given situations and also for measuring the operating characteristics and efficiency of the plan.[1]

– *Estimation Sampling* may be used to determine by sampling the rate of occurrence of certain attributes within prescribed limits of precision and reliability. Thus, this method can be used to determine the portion of our data that does not conform to our established standards. Estimation sampling may also be used to estimate variables (error rates in dollars, pounds, etc.) within prescribed limits of precision and reliability. Thus, where acceptance sampling provides merely an accept or reject decision, estimation sampling attempts to give us an indication of the rate of error and/or the size of the errors occurring in our data. Estimation sampling is therefore of particular value where we would like to have some idea of the number of errors and/or their size.[2]

– *Haskins & Sells Sampling Plan* gives us results similar to estimation sampling; however, it has an advantage in that (1) it permits evaluations on a mathematically rigorous basis without the assumptions concerning normality and other data that are required with estimation sampling, (2) it automatically provides for the stratification of data, a task which is not easily accomplished with estimation sampling, and (3) it automatically weighs the effect of numerical errors (attribute errors) when monetary errors (variables) are appraised.

All of the above sampling techniques are suitable for various given situations; there are also other methods, and I am sure new methods will be developed to do a particular job as changing conditions may require it.

Our second technique is control charts. Control charts may also be constructed for variables (which is usually the case with continuous operations) and for attributes or the simple two-valued classification: yes or no, right or wrong, acceptable or not acceptable. These various charts are as follows:

Control models for variables

– An "$\bar{X}$" chart calculation gives us a plot over a period of time of sample means taken from an operation in order to help us establish an average (mean) that will be acceptable over the specific period of time.

– The "$\bar{X}$" chart's counterpart is the "R" chart, and this calculation gives us a plot over a period of time of the ranges of the same samples used to set up the "$\bar{X}$" chart.

– The "$\bar{X}$" and "R" charts are often employed together in control operations. In setting up control charts we will be concerned with their effectiveness as *operational* models. It should be noted, therefore, that Operating Characteristic or OC curves may be constructed for any type of control chart. These OC curves provide a measure of the relative ability of the control chart to detect changes in the basic pattern of variation. An example showing the construction of an "$\bar{X}$" and an "R" chart will be found at the end of this article.

Control models for attributes

- A "P" chart is used for a constant sample size when the item sampled is assessed and then placed into one of two defined classes. The *proportion* of units falling into one class may be controlled over time (or from one sample to another) with this "P" chart. This control chart is most useful in work sampling studies in that the observed *proportions* can be verified as "in control" and following a stable pattern of variation or "out of control" because of an unstable pattern.
- A "P" chart with variable sample size may also be constructed.
- A "C" chart with constant sam-

[1] See References 3, 4, 8, and 9 on page 45.

[2] See References 1, 10, and 11 on page 45.

ple size is constructed when the variable process provides numerical data to be recorded *as a number rather than a proportion.* An example of this would be the *number* of arrivals per hour at a given point requiring some service where we need to know what level of service capability we must provide for at different times of the day.

- A "C" chart with variable sample size may also be constructed.

Operating characteristic (OC) curves, which provide a measure of the relative ability of the control chart to detect changes in the basic pattern of variation, may be constructed for any of the above charts.[3]

Constructing a chart

Table I on page 42 shows a situation where 20 samples of 5 items per sample have been taken. The sample values shown in this table could represent:

- Time factors such as:
  - How long it takes a group of men to do a job
  - The length of time it takes something to move from one place to another
  - The lead time between placing a purchase order and receiving the material
- Measurement factors such as:
  - Various dimensions of non-uniform products produced or sold
  - Container or cargo dimensions used to ship products
- Cost factors such as:
  - Cost of materials
  - Labor costs
  - Yields of a process
- Weight factors such as:
  - Bulk weight shipments
  - Weights of containers filled on an assembly line
- Strength factors such as:
  - Tensile strengths
  - Acid strengths
- Etc., Etc.

The $\bar{X}$ shown in Table I is the mean or average of the five numbers shown on each line. Thus, for Sample Number 1 the $\bar{X}$ would be $11.5 + 10.8 + 13.1 + 11.6 + 11.4 = 58.4 \div 5 = 11.7$.

[3] See references 3, 4, 5, 6, and 7 on page 45.

TABLE II

FACTORS FOR THE CONSTRUCTION OF $\bar{X}$ & R CHARTS*

Sample Size, n	$\bar{X}$ Chart		R Chart	
	d_2	A_2	D_3	D_4
2	1.128	1.880	0	3.267
3	1.693	1.023	0	2.575
4	2.059	0.729	0	2.282
5	2.326	0.577	0	2.115
6	2.534	0.483	0	2.004
7	2.704	0.419	0.076	1.924
8	2.847	0.373	0.136	1.864
9	2.970	0.337	0.184	1.816
10	3.078	0.308	0.223	1.777
11	3.173	0.285	0.256	1.744
12	3.258	0.266	0.284	1.716
13	3.336	0.249	0.308	1.692
14	3.407	0.235	0.329	1.671
15	3.472	0.223	0.348	1.652
16	3.532	0.212	0.364	1.636
17	3.588	0.203	0.379	1.621
18	3.640	0.194	0.392	1.608
19	3.689	0.187	0.404	1.596
20	3.735	0.180	0.414	1.586

NOTE: For all the sample sizes shown, values in the A_2, D_3, and D_4 columns have been calculated at three sigma control limits, which give us a reliability of 99.7 per cent in our results. The d_2 column designates the expected ratio between the average range, $\bar{R}$, and the standard deviation of the process for the sample sizes shown.

*Factors taken from A.S.T.M. *Manual on Quality Control of Materials.*

The R or Range shown in Table I is the difference between the highest value and the lowest value shown on each line. Thus, for Sample Number 1 the Range or R would be $13.1 - 10.8 = 2.3$.

From the information contained in Table I we will first construct an R chart. There is a real advantage to constructing an R chart before you construct the $\bar{X}$ chart. Since we get an estimate of the variance of the sample means from $\bar{R}$ (See equation (a) below), the construction of the $\bar{X}$ chart will depend upon the *control of* our variability. Thus, if the $\bar{X}$ chart were constructed first and all the $\bar{X}$ values fell within the limits, the chart might still have to be revised if the variability was not in control when we constructed our R chart. In effect, a revised estimate of our process variation would have to be included in new limits *on both* the R and $\bar{X}$ charts.

Our R chart is constructed as follows:

1. $\bar{R}$ is obtained from equation (a) as follows:

   Equation (a) $\bar{R} = \frac{\sum_{i=1}^{m} R}{m}$

   which is simply calculated by taking the sum of the R values shown in Table I and dividing this sum by the 20 samples taken, or

   $\frac{40.9}{20} = 2.045$, or $\bar{R} = 2.05$

2. The control limits are then determined from equations (b) and (c), which are:

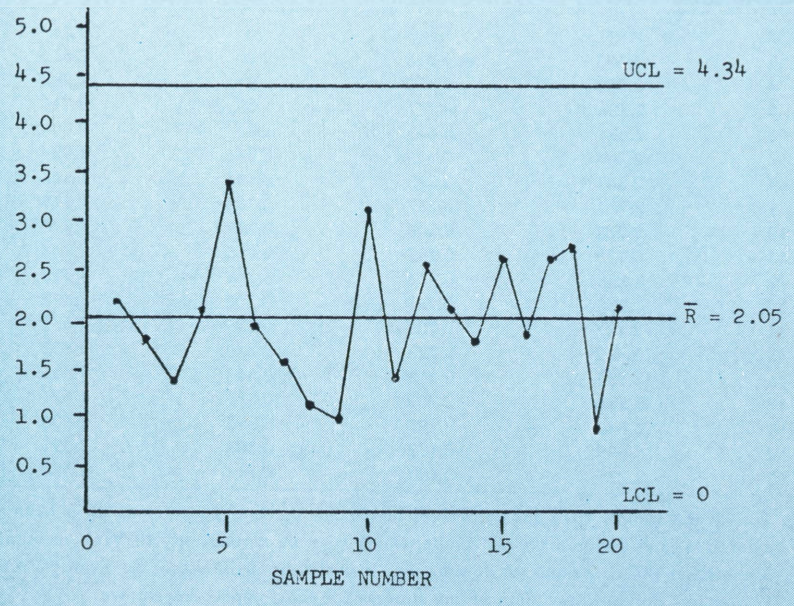
   Equation (b) $UCL_R = D_4\bar{R}$

   Equation (c) $LCL_R = D_3\bar{R}$

   where UCL = Upper Control Limit
   LCL = Lower Control Limit

and Values for D are obtained from Table II, on this page. Using equations (b) and (c) we get:

Figure 2
R Chart For Data Shown on Table I



$UCL_R = D_4\bar{R} = 2.115 \times 2.05 = 4.34$

$LCL_R = D_3\bar{R} = 0 \times 2.05 = 0$

Note that we took 20 samples of 5 *items per sample*. Therefore, in using Table II, our sample size (n) is 5.

These limits (43.4 and 0) are used to construct the R chart shown in Figure 2 on this page, and the R values shown on Table I are plotted on it. Since Figure 2 shows that all R values fall within the control limits, the R chart is accepted as a means of assessing the subsequent process variation in the process we are trying to control. Had an R value (or point) fallen outside our calculated limits, this point would have had to be discarded and our limits recalculated.

The next step is to construct the $\bar{X}$ chart. The mean of the sample means, $\bar{X}$, is found from Equation (d).

Equation (d) $$\bar{X} = \frac{\sum_{i=1}^{m} \bar{X}}{m}$$

which is simply calculated by taking the sum of the $\bar{X}$ values in Table I and dividing this sum by the 20 samples taken, or $\frac{243.3}{20} = 12.165$, or $\bar{X} = 12.17$.

The mean of the sample ranges, $\bar{R}$, has already been calculated as 2.05. Preliminary control limits for the $\bar{X}$ chart may now be calculated from equations (e) and (f) shown below:

Equation (e)
$$UCL_{\bar{X}} = \bar{X} + A_2\bar{R}$$

Equation (f)
$$LCL_{\bar{X}} = \bar{X} - A_2\bar{R}$$

(The A_2 factors are obtained from Table II)

Thus: $UCL_{\bar{X}} = 12.17 + (0.577 \times 2.05) = 13.35$

And $LCL_{\bar{X}} = 12.17 - (0.577 \times 2.05) = 10.99$

These limits are used to construct the $\bar{X}$ chart shown in Figure 3 on page 45. The $\bar{X}$ values from Table I are then plotted on this same chart.

Since Sample Number 3 exceeds the upper control limit we have an indication that at this point in time, the population from which this sample was selected was not indicative of a stable pattern of variation. Some change occurred between the time we selected Sample Number 2 and Sample Number 3. It should also be noted that after Sample Number 3, the process returned to its original state. The mean of Sample Number 3 might have exceeded our upper control limit by chance. Alternatively, the pattern of variation could have shifted some time before Sample Number 2 and not returned after this time; however, Figure 3 shows that the pattern of variation was normal after Sample Number 3. Therefore, the data of Sample Number 3 are discarded and the control limits recalculated for the remaining items. The mean of the remaining sample is

$$\frac{243.3 - 13.5}{19} = 12.09$$

and the control limits are revised to:

$$UCL_{\bar{X}} = 12.09 + (0.577 \times 2.05) = 13.27$$

$$LCL_{\bar{X}} = 12.09 - (0.577 \times 2.05) = 10.91$$

These revised limits are shown on Figure 3.

The range is not recalculated because we have assumed that the process variation did not change when Sample Number 3 was selected. Our reasons for this assumption are as follows:

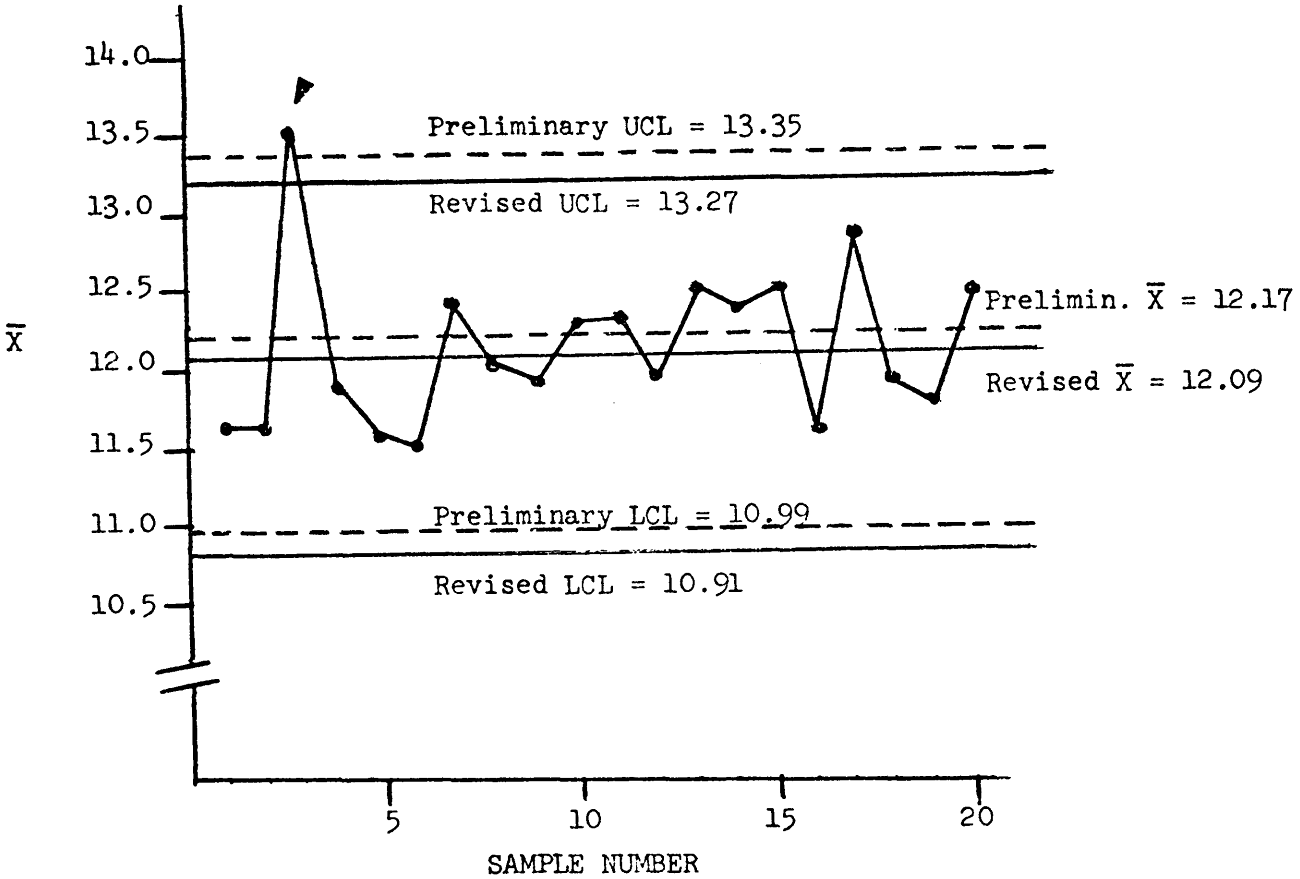
1. The mean of Sample Number 3 exceeded our upper control limit *by chance*

   OR

2. The pattern of variation shifted some time before Sam-

Figure 3

$\overline{X}$ Chart For Data Shown on Table I



ple Number 2 and did not return thereafter. However, examination of Figure 3 clearly indicates that it did return on the very next sample item and remained quite stable thereafter.

We therefore assumed that the excess mean of Sample Number 3 was caused *by chance* and therefore rejected it and recalculated our limits for the $\overline{X}$ chart. Following this reasoning, it is not necessary to recalculate our range. Both our $\overline{X}$ and R charts can now be used to monitor the operation we wish to control.

Conclusion

In order to present this material in a reasonably understandable form, statistical theory has been kept to a very bare minimum, certain statistical concepts have been defined in very simple terms that probably would not satisfy a statistician, and a great deal of material has not been covered at all. Therefore, no one should assume from a reading of just this article that he is now ready to set up models of statistical control. My purpose has been to acquaint you with the potential of these tools and not to instruct you sufficiently so you can start using them. You have only been given the 25-cent tour of the statistician's workshop and for 25 cents I felt justified in taking certain liberties with my explanations. But if you now have a few new thoughts on the matter, then, I believe, you have received your quarter's worth.

Selected References

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Published by eGrove, 1970