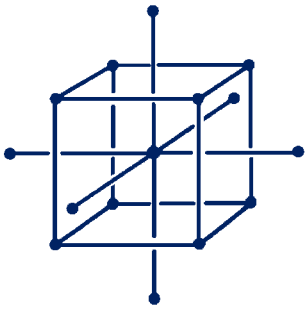
Special Publication • Special Publication • Special Publication • Special Publication • Special Publication



SPECIAL PUBLICATION©
ASQ Statistics Division

Special Publication • Special Publication • Special Publication • Special Publication • Special Publication

SPECIAL PUBLICATION **Summer 1998**

DATA "SANITY": STATISTICAL THINKING APPLIED TO EVERYDAY DATA

DAVIS BALESTRACCI
HEALTHSYSTEM MINNESOTA

1.0 Introductory Thoughts

Despite all the talk about "improvement" and "Statistical Thinking" and mad flurries of training activity (usually resembling The Inquisition), our everyday work environments are horribly contaminated with poor statistical practice (even if it is not formally called "statistics"). *Whether or not people understand statistics, they are already using statistics*—and with the best of intentions. People generally do not perceive that they need statistics—the need is to solve their problems.

However, "statistics" is not merely a set of techniques to be used solely on projects. So, forget all the statistics you learned in school. The messy real world is quite different from the sanitized world of textbooks and academia. And the good news is that the statistical methods required for everyday work are much simpler than ever imagined...but initially quite counter-intuitive. Once grasped, however, you have a deceptively simple ability and understanding that will ensure better analysis, communication, and decision-making.

1.1 Current Realities of the Quality Improvement World

Given the current rapid pace of change in the economic environment along with the "benchmarking," "re-engineering," and "total customer satisfaction" crazes, there seems to be a new tendency for performance goals to be imposed from external sources, making improvement efforts flounder when

- Results are presented in aggregated row and column formats complete with variances and rankings,
- Perceived trends are acted upon to reward and punish,
- Labels such as "above average" and "below average" get attached to individuals / institutions,
- People are "outraged" by certain results and impose even "tougher" standards.

Acknowledgment

The Statistics Division would like to thank Davis Balestracci for his dedication in completing this publication. Anyone who has worked with Davis immediately feels his passion for this topic. That passion also exists in his book, *Quality Improvement: Practical Applications for Medical Group Practice.* (See Bibliography for more information.) Further thanks go to Stu Janis and Janice Shade who edited the publication.

Additional copies of either this publication or the Statistical Thinking Publication are available through the Quality Information Center (QIC) by calling 1-800-248-1946. A nominal fee will be charged for printing, postage and handling.

These are very well-meaning strategies that are simple, obvious,...and wrong! They also "reek" of statistical traps! The purpose of this publication is to expose eight common statistical "traps" that insidiously cloud decisions every day in virtually every work environment. It is my hope that this publication will:

- Sensitize people to the fact that taking action to improve a situation is tantamount to using statistics,
- Demonstrate that the use of data is a process,
- Help expose the severe limitations of "traditional" statistics in real world settings,
- Provide a much broader understanding of variation,
- Give a knowledge base from which to ask the right questions in a given situation,
- Create awareness of the unforeseen problems caused by the exclusive use of arbitrary numerical goals, "stretch" goals, and "tougher" standards for driving improvement,
- Demonstrate the futility of using heavily aggregated tables of numbers, variances from budgets, or bar graph formats as vehicles for taking meaningful management action, and
- Create proper awareness of the meaning of the words "trend," "above average," and "below average."

1.2 Some Wisdom from Yogi Berra

Before getting to the eight traps, let's review what seems to have evolved as the "traditional" use of statistics in most work cultures. It can be summarized by the acronym PARC. "PARC" can have several meanings: **P**ractical **A**ccumulated **R**ecords **C**ompilation; **P**assive **A**nalysis by **R**egressions and **C**orrelations (as taught in many courses). With today's plethora of computers, it can also mean **P**rofound **A**nalysis **R**elying on **C**omputers. And it only takes a cursory glance at much of published "research" to see yet another meaning: **P**lanning **A**fter the **R**esearch is **C**ompleted (also called "torturing the data until they confess").

Maybe you are getting sick of hearing: "You can prove anything with statistics," "Liars, damn liars, and statisticians," etc., etc., and it is precisely because of PARC analysis that these sayings exist! Here's the problem: Applying statistics to a data set does not make it a statistical analysis. Similarly, a good statistical analysis of a bad set of data is a worthless analysis. Why? Because *any statistical analysis must be appropriate for the way the data were collected.* Two questions must be asked when presented with any previously unseen data:

- What was the objective of these data?
- How were these data collected?

Unless these questions can be answered, *no meaningful analysis can take place.* How many times are statisticians asked to "massage" data sets? These analyses usually result in wrong conclusions and wasted resources.

Yet, how many meetings do we attend where pages and pages of raw data are handed out…and everyone starts drawing little circles on their copies? These circles merely represent individuals' own unique responses to the variation *they perceive* in the situation, responses that are also influenced by the current "crisis du jour." They are usually intuition-based and not necessarily based in statistical theory; hence, *human variation* rears its ugly head and compromises the quality of the ensuing discussion. There are as many interpretations as there are people in the room! The meeting then becomes a debate on the merits of each person's circles. Decisions (based on the loudest or most powerful person's idea of how to close the gap between the alleged variation and the ideal situation) get made that affect the organization's people. As Heero Hacquebord once said, "When you mess with people's minds, it makes them crazy!"

Returning to PARC, everyone knows that acronyms exist for a reason. Generally, when PARC analysis is applied to a data set, the result is an anagram of PARC, namely, PARC spelled backwards. (The "proof" is left to the reader!) This acronym also has several meanings, including **C**ontinuous **R**ecording of **A**dministrative **P**rocedures (as in monthly reports and financials--see above paragraph), and, in some cases, **C**onstant **R**epetition of **A**necdotal **P**erceptions (which is yet another problem—anecdotal data!)

So, how does Yogi Berra fit into all this? He once said about baseball, "Ninety percent of this game is half mental," which can be applied to statistics by saying, "Ninety percent of statistics is half planning." In other words, if we have a theory, we can plan and execute an appropriate data collection to test the theory. And, before even one piece of data is collected, *the prospective analysis is already known* and appropriate. Statistical theory will then be used to interpret the variation summarized by the analysis.

So, statistics is hardly the "massaging" and "number crunching" of huge, vaguely defined data sets. In the quality improvement and Statistical Thinking mindsets, the proper use of statistics starts with the simple, efficient planning and collection of data. When an objective is focused within a context of process-oriented thinking, it is amazing how little data are needed to test a theory.

DATA "SANITY"

Too often, data exist that are vaguely defined at best. When a "vague" problem arises, people generally have no problem using the vague data to obtain a vague solution—yielding a vague result. Another problem with data not necessarily collected specifically for one's purpose is that they can usually be "tortured" to confess to one's "hidden agenda."

2.0 How Data Are Viewed

"Not me," you say? Well, maybe not intentionally. But let's look at six "mental models" about data and statistics. The first is generally taught in school as the **research** model—data collected under highly controlled conditions. In this model, formally controlled conditions are created to keep "nuisance" variation at a minimum. Patients in a clinical trial are carefully screened and assigned to a control or treatment group. The method of treatment is very detailed, even to the point of explicitly defining specific pieces of equipment or types of medication. Measurement criteria are well-defined, and strict criteria are used to declare a site a "treatment center." Needless to say, this formal control of undesirable variation is quite expensive, but it is also necessary so as to avoid misleading values and estimates of key data. Once the research is completed and published, though, nuisance variation can rear its ugly head. When physicians apply the results, their patients may not be screened with the same criteria. Variation will present itself as each doctor performs the procedure slightly differently, and the physical set up and practice environments may differ significantly from the treatment centers in the study.

Well-done formal research, through its design, is able to (implicitly) deny the existence of "nuisance" variation! However, poorly written research proposals don't have a clue as to how to handle the non-trivial existence of lurking variation--rather than design a process to minimize it, they merely pretend that it doesn't exist (like many "traditional" statistics courses on enumerative methods)! A formal process is necessary to anticipate, name, and tame lurking variation, and it cannot be 100 percent eliminated.

The next four mental models might seem a little more familiar: **inspection** (comparison / finger pointing); **micromanagement** ("from high on the mountain"); **results** (compared to arbitrary numerical goals); and **outcomes** (for bragging). Getting a little more uncomfortable? Finally, there is the mental model of **improvement**, which has resulted in a training juggernaut in most organizations. But, wait a minute…aren't inspection, micromanagement, results, and outcomes, when one comes right down to it, also improvement?…Maybe they're dysfunctional manifestations of a desire to improve, but they hardly ever produce the real thing…"Whether or not people understand statistics…"

As you see, there is a lot more to statistics than techniques. In fact, if you read no further, the "Data Inventory Considerations," presented in Figure 2.1, should be used to evaluate the current data collections in your work culture. As the famous statistician, John Tukey, once said, "The more you know what is wrong with a figure, the more useful it becomes." These seemingly simple questions are going to make a lot of people uncomfortable. Yet, until they can be answered, no useful statistical analysis of any kind can take place. Rather than accumulating huge databases, a mental model of "data as the basis for action" should be used. Data should not be taken for museum purposes!

2.1 Operational Definitions

Items 1, 3, 4, and 5 have already been alluded to, but Item 2 on operational definitions requires some special explanation. A statement by W. Edwards Deming that bothered me for quite a while was, "There is no true value of anything." (p. 113 of Henry Neave's *The Deming Dimension*).

Figure 2.1

"Data Inventory" Considerations

1. What is the **objective** of these data?
2. Is there an unambiguous **operational definition** to obtain a consistent numerical value for the process being measured?
   Is it **appropriate** for the stated objective?
3. How are these data **accumulated/collected?**
   Is the collection **appropriate** for the stated objective?
4. How are the data currently being **analyzed/displayed?**
   Is the analysis / display appropriate, given the way the data were collected?
5. What **action,** if any, is currently being taken with these data?

   Given the objective and action, is anything "wrong" with the current number?

DATA "SANITY"

One day, I suddenly "got" it. When it comes right down to it, one merely has a process for evaluating a situation and, through some type of measurement process, transforms a situational output into a physical piece of data—no way is 100% right, no way is 100% wrong, and *no way is 100% perfect*. It depends on the objective, and even then, the people evaluating the situation must agree on how to numerically characterize the situation so that, regardless of who is put into the situation, *the same number would be obtained*—whether the evaluator agrees with the chosen method or not. Otherwise, *human variation* in perception of what is being measured will hopelessly contaminate the data set *before* any statistical methods can be used.

Have you run into a situation where any resemblance between what you designed as a data collection and what you got back was purely coincidental? One of my favorite Dilbert cartoons shows Dilbert sitting with his girlfriend, and he says, "Liz, I'm so lucky to be dating you. You're at least an eight," to which she replies, "You're a ten." The next frame shows them in complete silence, after which he asks, "Are we using the same scale?" to which she replies, "Ten is the number of seconds it would take to replace you."

Example 1
I attended a presentation of three competitive medical groups where mammogram rates were presented to potential customers. After the presentation, a very astute customer stated that as a result of the way each group defined mammogram rates, it made it impossible for him to make a meaningful comparison among them. Furthermore, and he smiled, he said that each group defined the rate in such a way that it was self-serving. So, for the objective of internal monitoring, the three individual definitions were fine; however, for the objective of comparing the three groups, a different, common definition was needed.

Example 2
In looking at Cesarean section rates, there are situations, twins being an example, where one of the babies is delivered vaginally while the other is delivered via Cesarean section. So, how does one define Cesarean section rate--As a percent of labors or as a percent of literal births? Do stillborns count? No way is perfect—the folks involved just need to agree! What best suits the objective or reason for collecting these data?

Example 3
There was a meeting where an organizational goal to "reduce length of stay by eight percent" was discussed. Sounds good…but, unfortunately, it meant something different to everyone in the room. Not only that, this hospital had six (!) published reports on "length of stay" that didn't match—not by a long shot. When presented, everyone in the room said, "I don't understand it…they're *supposed* to be the same!" My response was, "Well, they're not, so can we kindly get rid of five of these and agree on how length of stay should be measured for the purposes of this initiative?" As Tukey said, "The more you know what is wrong with a figure…"

Example 4
Here's an example of the recent phenomenon of using "report cards" to inform consumers and motivate quality in health care. These numbers were published, but what does it mean? The three ranking systems give quite different results, particularly in the case of Hospital 119. Not only that, different people will have different motives for looking at the data. Physicians will ask, "How am I doing?" Patients will ask, "What are my chances for survival?" Payers will ask, "How much does it cost?" And society as a whole is interested in whether the resources are being spent effectively. Whose needs do these ranking systems address? Are some better than others? Are the operational definitions clear? One data set does not "fit all."

Hospital Rankings
Adjusted Preoperative Mortality Rates

Hospital #	System A	System D	System E
104	9	8	7
105	4	3	2
107	3	6	4
113	7	7	8
115	5	4	9
118	8	10	6
119	10	2	3
122	2	5	5
123	6	9	10
126	1	1	1

Risk Adjustment Strategies:

System A Stratified by Refined DRG Score (0-4)

System D Stratification by ASA-PS Score (2-5)

System E Logistic Regression Model including ASA-PS Score, gender, age, and diagnosis with intracranial aneurysm, cancer, heart disease, chronic renal disease, and chronic liver disease.

2.2 The Use of Data as a Process

In line with the division's emphasis on Statistical Thinking, I would like to present the use of data in this perspective. Statistics is not merely the science of analyzing data, but the **art** and science of **collecting** and analyzing data. Given any improvement situation (including daily work), one must be able to:

1) Choose and define the problem in a process / systems context,
2) Design and manage **a series of** simple, efficient data collections,
3) Use comprehensible methods presentable and understandable across **all** layers of the organization, virtually all graphical and NO raw data or bar graphs (with the exception of a Pareto analysis), and
4) Numerically **assess** the current state of an undesirable situation, **assess** the effects of interventions, and **hold the gains** of any improvements made.

3.0 Process - Oriented Thinking

What is a process? All work is a process! Processes are sequences of tasks aimed at accomplishing a particular outcome. Everyone involved in the process has a role of supplier, processor or customer. A group of related processes is called a system. The key concepts of processes are:

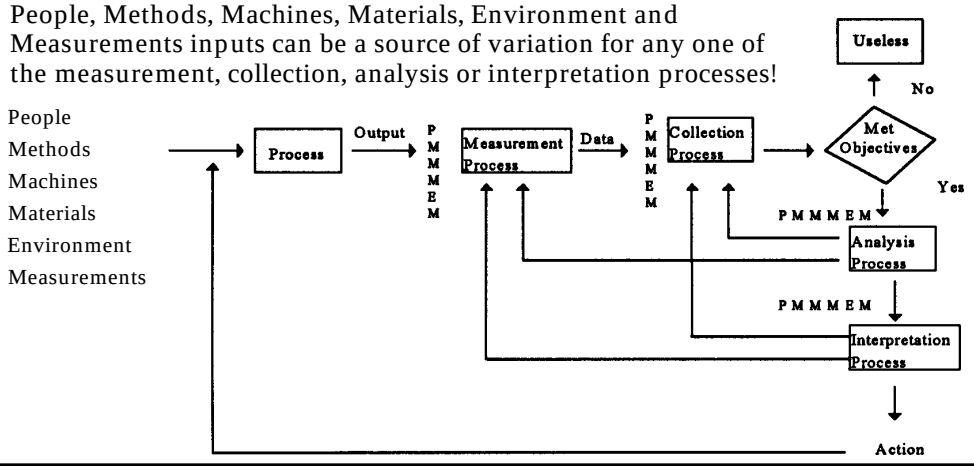
- A process is any sequence of tasks that has inputs which undergo some type of conversion action to produce outputs.
- The inputs come from both internal and external suppliers.
- Outputs go to both internal and external customers.

Process-oriented thinking is built on the premise of:

- Understanding that all work is accomplished through a series of one or more processes, each of which is potentially measurable.
- Using data collection and analysis to establish consistent, predictable work processes.
- Reducing inappropriate and unintended variation by eliminating work procedures that do not add value (i.e., only add cost with no payback to customers).

Process-oriented thinking can easily be applied to data collection. The use of data is really made up of four processes, each having "people, methods, machines, materials, measurements (data inputs via raw numbers), and environment" as inputs. (See Figure 3.1.) *Any one of these six inputs can be a source of variation for any one of these four processes!*

Figure 3.1 – Use of Data as a Process
People, Methods, Machines, Materials, Environment and Measurements inputs can be a source of variation for any one of the measurement, collection, analysis or interpretation processes!



Think of any process as having an output that is transformed into a number via a **measurement** process. If the objectives are not understood, the six sources of variation will compromise the quality of this measurement process (the "human variation" phenomenon--remember the length of stay data?).

These measurements must be accumulated into some type of data set, so they next pass to a **collection** process. If the objectives are clear, the designed collection process is well-defined. If not, the six sources of variation will act to compromise the process (Actually, it is virtually guaranteed that the six sources will compromise the collection process anyway!).

If the objectives are passive and reactive, eventually someone will extract the data and use a computer to "get the stats." This, of course, is an **analysis** process (albeit not necessarily a good one) that also has the six sources of inputs as potential sources of variation. Or, maybe more commonly, someone extracts the data and hands out tables of raw data and cursory summary analyses at a meeting that becomes the analysis process (which I call "Ouija boarding" the data).

Ultimately, however, it all boils down to interpreting the variation in the measurements. So, the **interpretation** process (with the same six sources of inputs) results in an action that is then fed back in to the original process.

Now, think back for a minute to the many meetings you attend. How do unclear objectives, inappropriate or misunderstood operational definitions, unclear or inappropriate data collections, passive statistical "analyses," and shoot-from-the-hip interpretations of variation influence the agendas and action? In fact, *how many times are people merely reacting to the variation in these elements of the DATA process* --and making decisions that have NOTHING to do with the process being studied? So, if the data process itself is flawed, many hours are spent "spinning wheels" due to the contamination from the "human" variation factors inherent in the aforementioned processes—People make decisions and react to their perceptions of the DATA process and NOT the process allegedly being improved!

Do not underestimate the factors lurking in the data process that will contaminate and invalidate statistical analyses. Objectives are crucial for properly defining a situation and determining how to collect the data for the appropriate analysis. Statistical theory can interpret the variation exposed by the analysis. The rest of this publication will concentrate on discussing the impact of "human variation" on common statistical analyses and displays, while teaching the *simple* statistical theory needed for everyday work.

4.0 Eight Common Statistical "Traps"

Organizations tend to have wide gaps in knowledge regarding the proper use, display and collection of data. These result in a natural tendency to either react to anecdotal data or "tamper" due to the current data systems in place. In this section, we will discuss the most common errors in data use, display and collection. This is by no means an exhaustive list of the potential errors, but early recognition may help an organization keep efforts on track. An overview of the Eight Most Common Traps appears in Overview 4.0. The traps are discussed in detail below.

Overview 4.0

Eight Common Traps

TRAP	PROBLEM	COMMENT
Trap 1: Treating **all** observed variation in a time series data sequence as special cause.	Most common form of "Tampering"—treating common cause as special cause.	Given two numbers, one will be bigger! Very commonly seen in traditional monthly reports: Month-to-Month comparisons; Year-Over-Year plotting and comparisons; Variance reporting; Comparisons to arbitrary numerical goals.
Trap 2: Fitting inappropriate "trend" lines to a time series data sequence.	Another form of "Tampering"—attributing a specific type of special cause (linear trend) to a set of data which contains only common cause. Attributing an *inappropriate* specific special cause (linear trend) to a data time series that contains a different kind of special cause.	Typically occurs when people always use the "trend line" option in spreadsheet software to fit a line to data with no statistical trends. Improvement often takes place in "steps," where a stable process moves to a new level and remains stable there. However, a regression line will show statistical significance, implying that the process will continually improve over time.
Trap 3: Unnecessary obsession with and incorrect application of the Normal distribution.	A case of "reverse" tampering–treating special cause as common cause. Inappropriate routine testing of all data sets for Normality.	Ignoring the time element in a data set and inappropriately applying enumerative techniques based on the Normal distribution can cause misleading estimates and inappropriate predictions of process outputs. Mis-applying Normal distribution theory and enumerative calculations to binomial or Poisson distributed data.

4.1 Trap 1: Treating All Observed Variation in a Time Series Data Sequence as Special Cause
The Pareto Principle is alive and well: A disproportionate amount of the implicit (and unbeknownst) abuse of statistics (resulting in tampering) falls into this trap. It can also be referred to as the "two point trend" trap—If two numbers are different, there HAS to be a reason (And smart people are very good at finding them)! Well, there usually is ("It's always something…ya know!")…but the deeper question has to go beyond the difference between the two numbers. The important question is, "Is the PROCESS that produced the second number different from the PROCESS that produced the first number?"

A favorite example of mine is to imagine yourself flipping a (fair) coin 50 times each day and counting the number of heads. Of course, you will get exactly 25 every time…right? WHAT - YOU DIDN'T? WHY NOT?!?!? Good managers want to know the reason!! Maybe the answer is simply, "Because." In other words, the process itself really hasn't changed from day to day—You are just flipping a coin 50 times and counting the number of heads (honestly, I trust—but I wonder, what if your job depended on meeting a goal of 35? Hmmm…). On any given day you will obtain a number between 14 and 36 (as demonstrated in the discussion of Trap 3), but the number you get merely represents common cause variation around 25.

A trendy management style 10 years ago was MBWA (Management By Walking Around), but it will virtually never replace the universal style characterized by Trap 1—MBFC (Management By Flipping Coins). Once you understand Statistical Thinking, it is obvious that *any set of numbers needs a context of variation within which to be interpreted.* Given a sequence of numbers from the coin flipping process, can you intuit how ludicrous it would be to calculate, say, percent differences from one day to the next or this Monday to last Monday? *They are all, in essence, different manifestations of the same number,* i.e., the average of the process.

Eight Common Traps continued

TRAP	PROBLEM	COMMENT
Trap 4: Incorrect calculation of standard deviation and "sigma" limits.	Since much improvement comes about by exposing and addressing special cause opportunities, the traditional calculation of standard deviation typically yields a grossly inflated variation estimate.	Because of this inflation, people have a tendency to arbitrarily change decision limits to two (or even one!) standard deviations from the average or "standard". Using a *three* standard deviation criterion with the *correctly* calculated value of sigma gives approximately an *overall* statistical error risk of 0.05.
Trap 5: Misreading special cause signals on a control chart.	Just because an observation is outside the calculated three standard deviation limits does not necessarily mean that the special cause occurred at that point.	A runs analysis is an extremely useful adjunct analysis preceding construction of any control chart.
Trap 6: Choosing **arbitrary** cutoffs for "above" average and "below" average.	There is actually a "dead band" of common cause variation on either side of an average that is determined from the data themselves.	Approximately half of a set of numbers will naturally be either above or below average. Potential for tampering appears again. Percentages are especially deceptive in this regard.
Trap 7: Improving processes through the use of arbitrary numerical goals and standards.	Any process output has a natural, inherent capability within a common cause range. It can perform only at the level its inputs will allow.	Goals are merely wishes regardless of whether they are necessary for survival or arbitrary. Data must be collected to assess a process's natural performance relative to a goal.
Trap 8: Using statistical techniques on "rolling" or "moving" averages.	Another, hidden form of "tampering"--attributing special cause to a set of data which could contain only common cause.	The "rolling" average technique creates the **appearance** of special cause even when the individual data elements exhibit common cause only.

Example 1 — "We Are Making People Accountable for Customer Satisfaction!": The Survey Data
A medical center interested in improving quality has a table with a sign saying "Tell Us How Your Visit Was." Patients have the opportunity to rank the medical center on a 1 (worst) to 5 (best) basis in nine categories. Monthly averages are calculated, tabulated, and given to various clinic personnel with the expectation that the data will be used for improvement.

Table 4.1

Month	Ov_Sat	% Change
1	4.29	*
2	4.18	-2.6
3	4.08	-2.4
4	4.31	5.6
5	4.16	-3.5
6	4.33	4.1
7	4.27	-1.4
8	4.44	4.0
9	4.26	-4.1
10	4.49	5.4
11	4.51	0.5
12	4.49	-0.4
13	4.35	-3.1
14	4.21	-3.2
15	4.42	5.0
16	4.31	-2.5
17	4.36	1.2
18	4.27	-2.1
19	4.30	0.7

Nineteen monthly results are shown in Table 4.1 for "Overall Satisfaction" as well as the summary "Stats" from a typical computer output. Management also thought it was helpful to show the percent change from the previous month, and they used a rule of thumb that a change of 5% indicated a need for attention.

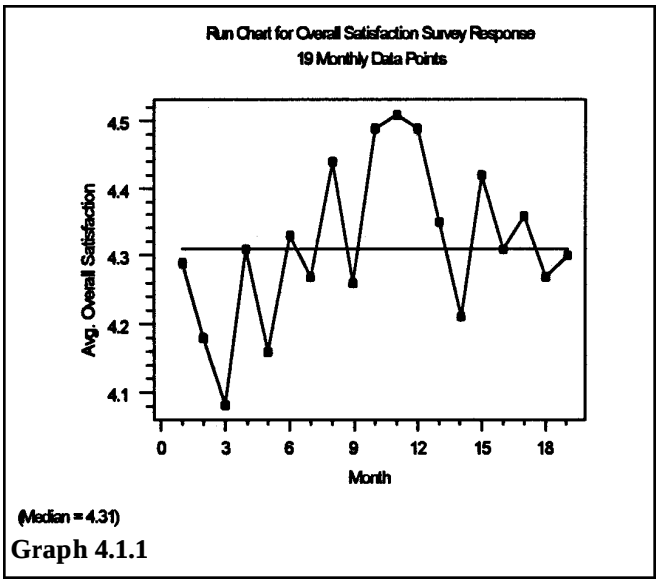
With the current buzz phrase of "full customer satisfaction" floating about, does this process of data collection and analysis seem familiar to you? Is this presentation very useful? Is it ultimately used for customer satisfaction…or do you think they might react defensively with an "inward" focus?

What about the *process* producing these data?

If you learn nothing else from this publication, the following technique will cause a quantum leap in the understanding of variation in your work culture. And the good news is that it is simple and very intuitive.

As I will try to convince you in the discussion of Trap 3, any data set has an implicit time element that allows one to assess the process producing it. Especially in this case where the time element is obvious, i.e., monthly data, one should develop a "statistical reflex" to produce at least a **run chart**: a time series plot of the data with the overall **median** drawn in.

Mean	Median	Tr Mean	StDev	SE Mean	Min	Max	Q1	Q3
4.3174	4.3100	4.3200	0.1168	0.0268	4.0800	4.5100	4.2600	4.4200



Graph 4.1.1

Why the median and not the mean you may ask? Once again, this will be made clear in the discussion of Trap 3. Let's just say that it is a "privilege" to be able to calculate the average of a data set, and a run chart analysis assesses the "stability" of a process to determine whether we have that privilege. Think back to the example of flipping a coin 50 times—it averages 25 heads, but any given set of 50 flips will produce between 14 and 36. A run chart analysis of a (non-cheating) series of results from 50 flips would probably allow one to conclude that the process was indeed stable, allowing calculation of the average.

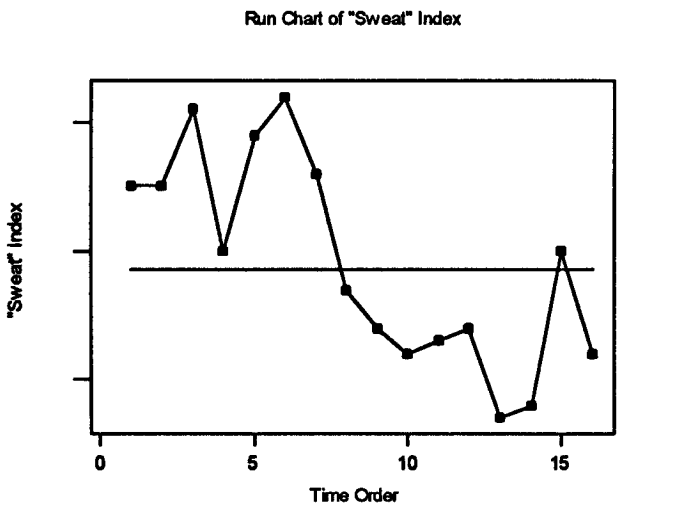
The median is the empirical midpoint of the data. As it turns out, this allows us to use well-documented statistical theory based on…flipping a fair coin! So, a run chart analysis allows folks to still use "MBFC," but with a basis in statistical theory. In the current set of data, 4.31 is the median—note that we have 19 numbers: eight are bigger than 4.31, two happen to equal 4.31, and nine are smaller.

Our "theory" is that overall satisfaction is "supposed" to be getting better. Remember (for a *very* brief moment!) the "null hypothesis" concept from your "Statistics from Hell 101" courses—in essence, "Innocent until proven guilty." Plot the data on a run chart, as shown in Graph 4.1.1, assuming it all came from the same process. What are some patterns that would allow us to conclude that things had indeed become better?

"Look for trends," you say. However, the word "trend" is terribly overused and hardly understood. This will be thoroughly discussed in the Trap 2 section. For now, it is safe to conclude that there are no trends in these data.

Looking at the chart, think of it as 17 coin flips (two data points are on the median, so they don't count). Think of a point above the median as a "head" and a point below the median as a "tail." The observed pattern is four tails (called a "run of length 4 below the median" (remember to skip the point exactly on the median) followed by a head (called a "run of length 1 above the median") followed by tail, head, tail, then four heads, a tail, then two heads followed by two tails. Could this pattern be obtained *randomly*? I think your intuition would say yes, and you would be right. But how about some robust statistical rules so we don't treat common cause as if it's special cause?

Suppose our theory that this process had improved was correct? What might we observe? Well, let me ask you—how many consecutive heads or consecutive tails would make you suspicious that a coin wasn't fair? As it turns out, *from statistical theory*, a sequence of eight heads or tails in a row, i.e., eight consecutive points either *all* above the median or *all* below the median, allows us to conclude that the sequence of data observed did not come from one process. (A point *exactly* on the median neither breaks nor adds to the count.) In the case of our overall satisfaction data, if our theory of improvement was correct, we might observe a sequence of eight consecutive observations *below* the median *early* in the data and / *or* a sequence of eight consecutive observations *above* the median *later* in the data. We see neither.



Graph 4.1.2

Now imagine a situation illustrated by the run chart depicted in Graph 4.1.2. This was a very important "sweat" index whose initial level was considered too high. Note that there are eight observations above the median and eight observations below the median, by definition. An intervention was made after observation 6. Did the subsequent behavior indicate process improvement? There could be as many interpretations as there are people reading this. What does statistical theory say?

Observations 6-10 *do not* form a trend (to be explained in Trap 2). Applying the rule explained in the previous paragraph, the first "run" is length seven as is the next run. These are followed by two runs of length one. So, according to the given statistical "rules," since neither of these are length eight, there is no evidence of improvement(!). What do you think?

There is one more test that is not well known, but extremely useful. Returning to the coin flipping analogy, do you expect to flip a coin 16 times and obtain a pattern of seven heads followed by seven tails then a head then a tail. Our intuition seems to tell us "No". Is there a statistical way to prove it?

Table 4.2 tabulates the total number of runs *expected* from common cause variation if the data are plotted in a run chart. For example, the "sweat" index has a total of four "runs," two above and two below the median. Looking in the table under "Number of Data Points" at 16 and reading across, we *expect* 5-12 runs from random variation. However, *we did not get what we expected;* we got four. Hence, we can conclude that the special cause "created" after observation 6 did indeed work, i.e., we have evidence that points to "guilty." Generally, a successful intervention will tend to create a smaller than the expected number of runs. It is relatively rare to obtain more than the expected number of runs and, in my experience, this is due mostly to either a data sampling issue or…"fudged" data. In other words, the data are just *too* random.

Table 4.2
Tests for Number of Runs Above and Below the Median

Number of Data Points	Lower Limit for Number of Runs	Upper Limit for Number of Runs
10	**3**	**8**
11	**3**	**9**
12	**3**	**10**
13	**4**	**10**
14	**4**	**11**
15	**4**	**12**
16	**5**	**12**
17	**5**	**13**
18	**6**	**13**
19	**6**	**14**
20	**6**	**15**
21	**7**	**15**
22	**7**	**16**
23	**8**	**16**
24	**8**	**17**
25	**9**	**17**
26	**9**	**18**
27	**9**	**19**
28	**10**	**19**
29	**10**	**20**
30	**11**	**20**
31	**11**	**21**
32	**11**	**22**
33	**11**	**22**
34	**12**	**23**
35	**13**	**23**
36	**13**	**24**
37	**13**	**25**
38	**14**	**25**
39	**14**	**26**
40	**15**	**26**
41	**16**	**26**
42	**16**	**27**
43	**17**	**27**
44	**17**	**28**
45	**17**	**29**
46	**17**	**30**
47	**18**	**30**
48	**18**	**31**
49	**19**	**31**
50	**19**	**32**
60	**24**	**37**
70	**28**	**43**
80	**33**	**48**
90	**37**	**54**
100	**42**	**59**
110	**46**	**65**
120	**51**	**70**

There are nine runs in the overall satisfaction data. Since two points are on the median, these are ignored in using the table. So, with 17 (= 19 - 2) observations, we would expect 5-13 runs if the data are random—exactly what is observed. It seems to be a common cause system.

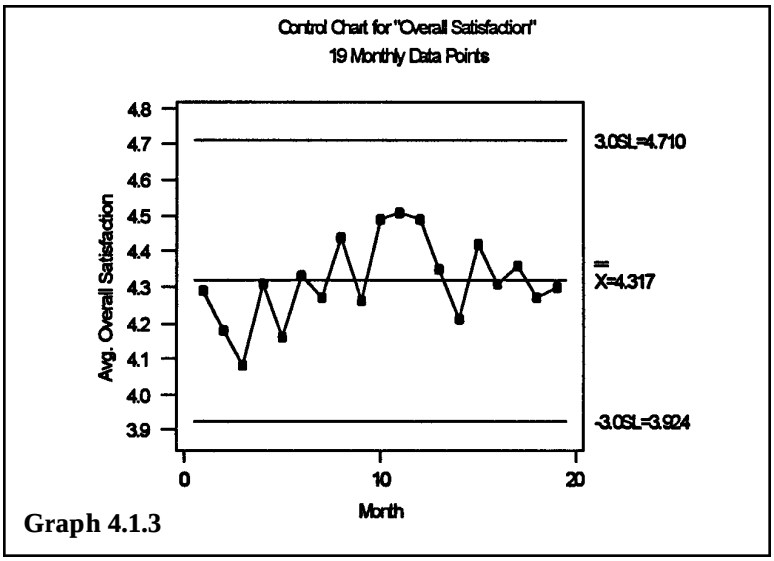
Some of you may wonder what a control chart of the data looks like. (If not, perhaps you should!) The calculations of the common cause limits are discussed in Trap 4, and a control chart of the overall satisfaction data appears in Graph 4.1.3. If the process is stable, the data from a "typical month" will fall in the range (3.92 - 4.71).

The control chart is the final piece of the puzzle. The process has been "stable" over the 19 months, and all of the months' results are in the range of what one would expect. Would you have intuited such a wide range? *"It is what it is…and your process will tell you what it is!"*

Oh, yes, how much difference between two months is too much? *From the data,* and as discussed in Trap 4, this is determined to be 0.48. (For those of you familiar with Moving Range charts, this is simply the upper control limit.) Note that this figure will virtually never correspond to an arbitrarily chosen percentage or amount such as 5 or 10 %—*the data themselves will tell you!* And it is usually more than your management's "Ouija board" estimate of what it "should" be.

So, all this effort over 19 months and nothing's changed. Actually, what is the current process as assessed by this data set? It seems to be processing a "biased" sample of data (based on which customers choose to turn in a card), exhorting the workforce according to "Ouija board," and treating common cause as special cause. A number will be calculated at the end of the month and will most likely be between 3.92 and 4.71. Normal variation will allow one month to differ from the previous month by as much as 0.48(!) units.

The current survey process is perfectly designed to get the results it is already getting! Are you saying, "But that's not a very interesting process"? You're right! So…why continue?



Graph 4.1.3

Table 4.3

Arrests	Vfib	ROSC	%Vfib	%ROSC	Mo/Year
18	6	1	33.33	16.67	6/94
17	8	1	47.06	12.50	7/94
15	6	4	40.00	66.67	8/94
19	6	1	31.58	16.67	9/94
21	6	1	28.57	16.67	10/94
21	8	1	38.10	12.50	11/94
23	7	1	30.43	14.29	12/94
25	7	1	28.00	14.29	1/95
21	1	0	4.76	0.00	2/95
30		2	30.00	22.22	3/95
27	8	0	29.63	0.00	4/95
24	9	3	37.50	33.33	5/95
24	9	1	37.50	11.11	6/95
19	2	0	10.53	0.00	7/95
14	2	0	14.29	0.00	8/95
21	7	2	33.33	28.57	9/95
32	5	0	15.63	0.00	10/95
19	4	1	21.05	25.00	11/95
28	9	2	32.14	22.22	12/95
28	10	1	35.71	10.00	1/96
28	8	1	28.57	12.50	2/96
17	5	2	29.41	40.00	3/96
21	7	2	33.33	28.57	4/96
24	3	1	12.50	33.33	5/96

Tot_Arr	Tot_Vfib	Tot_ROSC	%Vfib	%ROSC	Period
261	81	16	31.03	19.75	6/94-5/95
275	71	13	25.82	18.31	6/95-5/96

Note: Vfib is a term for ventricular fibrillation
ROSC stands for "Return Of Spontaneous Circulation."

Example 2 — An Actual QA Report (But What do the Data Say?)

The data in Table 4.3 were used to create a quality assurance report. The report was published, sent out, and people were expected to…???????? It was obviously some type of mid-year report comparing the performance of two consecutive 12 month periods.. The monthly data were given as well as the individual aggregate 12-month summaries. This was an emergency medicine environment, and the data set represented the process for dealing with cardiac arrests.

I have taken direct quotes from this report. (For non-healthcare readers, think about some of the quality assurance summary reports floating around your facility.)

"We are running a slightly higher number of cardiac arrests per month. The total amount of cardiac arrests has risen from a mean of 21.75 (June 94- May 95), to 22.92 (June 95- May 96). This is an increase in 14 cardiac arrests in the last 12 months."

Comment:

You're right…275 is a bigger number than 261, but what's your point? Let's use the "innocent until proven guilty" approach and look at a run chart of the 24 months of data (Graph 4.1.4a). The graph shows no trends, no runs of length 8, eight runs observed and 6-14 expected. Sounds like common cause to me!

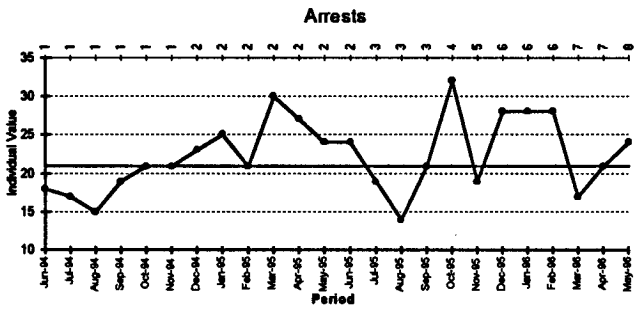
Why Not an "Xbar-R" Chart?

Those of you familiar exclusively with the "Xbar-R" chart will probably notice its conspicuous absence in this publication. Yes, it is intentional. The purpose of this publication is to expose the myriad *unrecognized* opportunities for statistics in everyday work: mainly, the processes used to manage the basic products and services delivered to your customers, as well as all relationships involved.

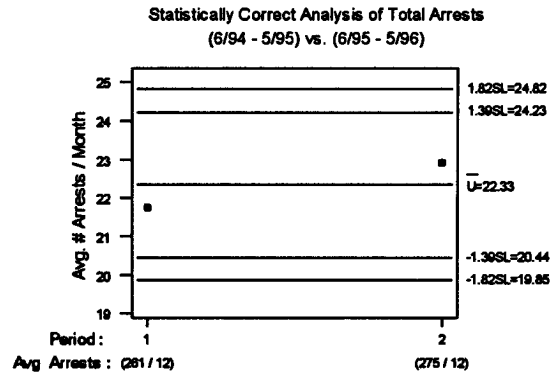
Many of you have used "classical" statistics (t-tests, designed experiments, regressions, etc.) to improve your organization's products and services themselves; however, this is only a "drop in the bucket" for the effective use of Statistical Thinking and methods. In fact, recent experiences seem to support that greater appreciation for and use of Statistical Thinking within the context of your organization's products and services will actually accelerate the appreciation and use of their power for improving the quality of these products and services. *These are two separate issues,* with the Statistical Thinking aspects of overall context going virtually unrecognized until relatively recently. The purpose here is to create awareness of this issue and convince you that it will create a beneficial synergy with your current statistical usage.

Within this context, the "bread and butter" tool is the control chart for individuals (I-Chart, also called X-MR charts). Don Wheeler's excellent book, *Understanding Variation,* also uses I-Charts exclusively to explain the concept of variation to management. The "traps" explained in this publication take Wheeler's situations several steps further.

One further aspect of using I-Charts is that, unlike Xbar-R charts, the control limits correspond to the natural limits of the process itself. On an Xbar chart, the control limits represent the natural limits of subgroup averages, which are rarely of interest other than for detecting special causes. Thus, when using I-charts, it makes sense to use the control limits when talking about the "common cause range," while it would be inappropriate on an Xbar chart.



Graph 4.1.4a



Graph 4.1.4b

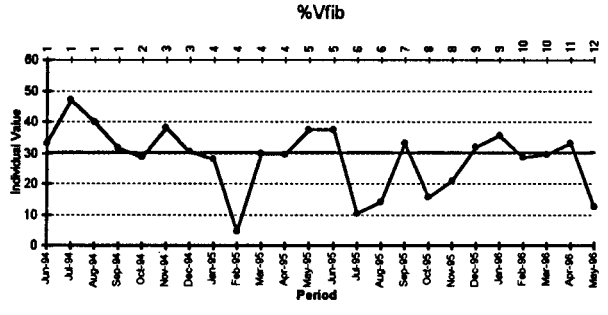
Next to the run chart, in Graph 4.1.4b, is a "statistically correct" analysis of the data that compares the two years within a context of common cause. One would also conclude common cause, i.e., no difference between the two years, because both points are inside the outer lines. Now, don't worry if you don't understand that "funny looking" graph—**that's the point!** You come to the same conclusion by doing a run chart that you come to by using a more sophisticated statistical analysis that isn't exactly in a non-statistician's "tool kit."

Now, watch how treating the "difference" between the two years as special cause rears its ugly head in the next conclusion.

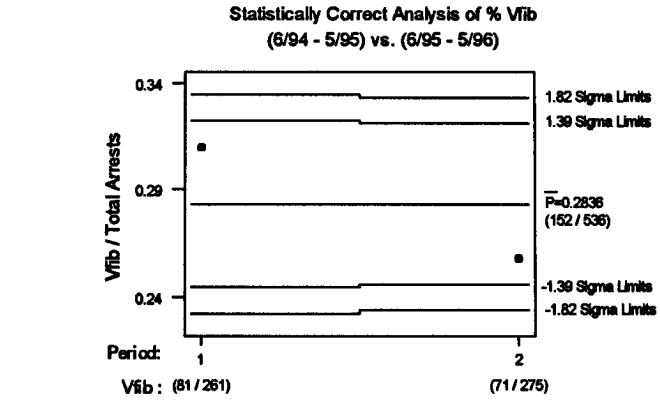
"Next we interpreted the data relating to Vfib Cardiac Arrests…This could be significant to our outcome, and directly resulting in the decrease seen in ROSC over the last year. This indicates a need for more sophisticated statistical analysis. It was already shown that the number of cardiac arrests has increased by a mean of 1.17 per month. Now we are adding to that increase, a decrease of times we are seeing Vfib as the initial rhythm. From June 1994 to May 1995 we arrived on scene to find Vfib as the initial rhythm with an overall mean of 6.75 times. That gave us a capture rate of 32.03%. This last year, June 1995 - May 1996, we are arriving to find Vfib as the initial rhythm with an overall mean of 5.92, and a capture rate of 25.81%. This obviously means that over the last year, we have responded to more cardiac arrests and found them in more advanced stages of arrest."

Comment:
Excuse me!…How about a run chart of the %Vfib response as shown in Graph 4.1.5a?

Let's see—no trends, no runs of length 8, twelve runs observed and 8-17 runs expected--Common cause here, too.



Graph 4.1.5a



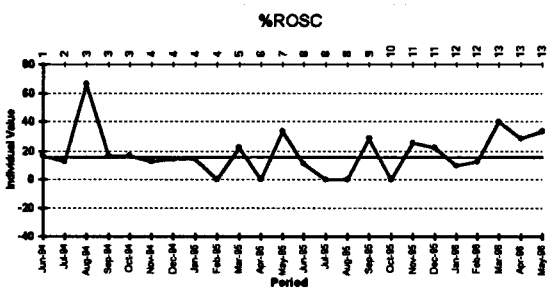
Graph 4.1.5b

The common cause conclusion is also confirmed by the "statistically correct" analysis in Graph 4.1.5b. This response is a percentage and this technique for percentages will be shown in discussion of Trap 6. But once again, who needs "fancy" statistics? The run chart analysis has told the story (and quite a different one from the report's conclusion!).

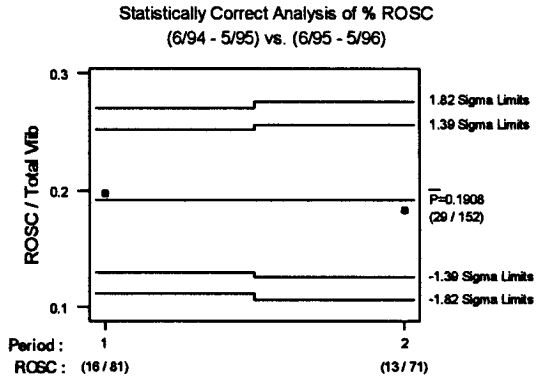
"This shows us that in our first year of data, (June 94- May 95), we had a mean of 6.75 calls a month in which Vfib was identified as the initial rhythm. Of those 6.75 calls, 1.33 calls had some form of ROSC resulting in a 19.75% of ROSC. In our second year, (June 95- May 96), we had a mean of 5.92 calls a month in which Vfib was identified as the initial rhythm. Of those 5.92 calls, 1.08 calls had some form of ROSC, resulting in a 18.31% of ROSC."

Comment:
Is this correct?! How about a run chart?

Graph 4.1.6a shows—No trends, no runs of length 8, thirteen runs observed and 8-17 expected—Common cause. The "statistically correct" analysis, shown in Graph 4.1.6b, concurs with the run chart analysis—common cause.



Graph 4.1.6a

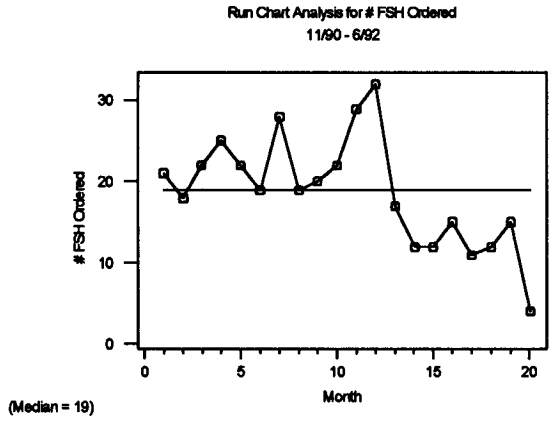


Graph 4.1.6b

4.2 Trap 2: Fitting Inappropriate "Trend" Lines to a Time Series Data Sequence.

Example 1 — The Use (Mostly Abuse!) of Linear Regression Analysis
A clinical CQI team was formed to study menopause. One task of the team was to reduce inappropriate ordering of FSH testing for women 40-44 years old. (FSH stands for "follicle stimulating hormone," which is sometimes used to determine the onset of menopause.) The lab reported the total number of FSH tests performed each month. Guidelines were issued in October '91 (Observation 12). Were they effective? Let's look at the run chart in Graph 4.2.1.

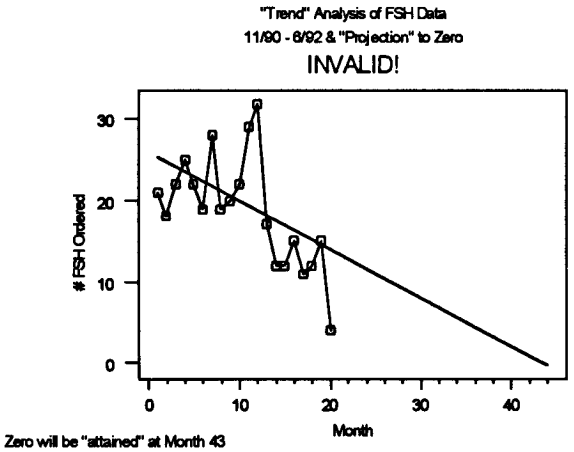
From the discussion of Trap 1, we can see that the last run has length 8, which occurs right after the intervention. We can conclude that the intervention was indeed effective. (How does this analysis, using statistical theory to reduce "human variation," compare to a meeting where the 20 numbers are presented in a tabular format, the data are "discussed," and the final conclusion is, "We need more data"?)



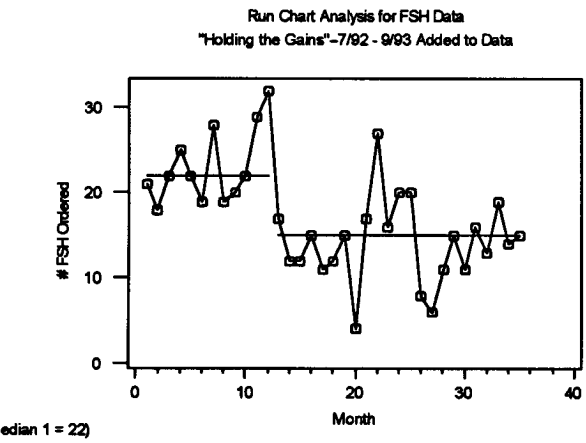
Graph 4.2.1

Fitting an Inappropriate Trend Line to the Data
It is not uncommon for data like these (especially financial indices) to be analyzed via "trend" analysis with linear regression. The result is shown graphically in Graph 4.2.2. From the p-value of 0.005, the regression is "obviously" significant.

Of course, people never plot the data to see whether the picture makes sense because "the computer" told them that the regression is "significant." Graph 4.2.2 shows the reason the regression is so significant: we are in essence fitting a line to two points, i.e., the averages of the two individual processes! In bowing down to the "almighty p-value," we have forgotten to ask the question, "Is a regression analysis *appropriate* for the way these data were collected?" (Remember, the computer will do anything you want.) If a plot prior to the regression analysis doesn't answer the question, then it needs to be answered via diagnostics generated from the regression



Graph 4.2.2



Graph 4.2.3

analysis (residuals versus fits plot, lack-of-fit test, normality plot of the residuals, and if possible, a time ordered plot of the residuals) — which this analysis would "flunk" miserably despite the "significant" p-value.

As if using regression analysis isn't bad enough, I have seen incorrect models like these used to "predict" when, for example, the number of inappropriate FSH tests will be zero (almost two years from the last data point)--- Assumptions like these are not only wrong, but dangerous! Even good linear models can be notoriously misleading when extrapolated.

Process-oriented thinking must be used to correctly interpret this situation. Here, someone merely changed a process, the intervention seems to have worked, and the new process has settled in to its inherent level. The number of FSH tests will not continue to decrease unless someone makes additional changes. People don't seem to realize that more changes occur in a "step" fashion than in linear trends.

In other words, once statistical rules determined that the intervention had the desired effect, subsequent data were plotted with a median based on the new process (see Graph 4.2.3). This plotting could act as an "audit" to make sure that the gains were held.

Note the excessively high value at month 22 (confirmed by control chart analysis). This led to an interesting discovery regarding the operational definition of the situation. It turns out that FSH testing is also used for infertility workups for women in the 40-44 age group. So, the number as reported by the lab is not one hundred percent "clean" for the clinical objective of menopause testing. In the special cause month, chart reviews showed that an abnormally high number of tests were for infertility purposes.

As health care personnel can attest, chart reviews can be a notorious drain on resources. So, the current process of counting all the FSH tests was *good enough* for the objective of "holding the gains." Should a special cause become apparent, it may be necessary to do chart audits, *but only then*. In other words, take the energy that would be absorbed by making the FSH data for menopause technically correct "down to a gnat's eyelash" and put it where the return on investment will be more beneficial.

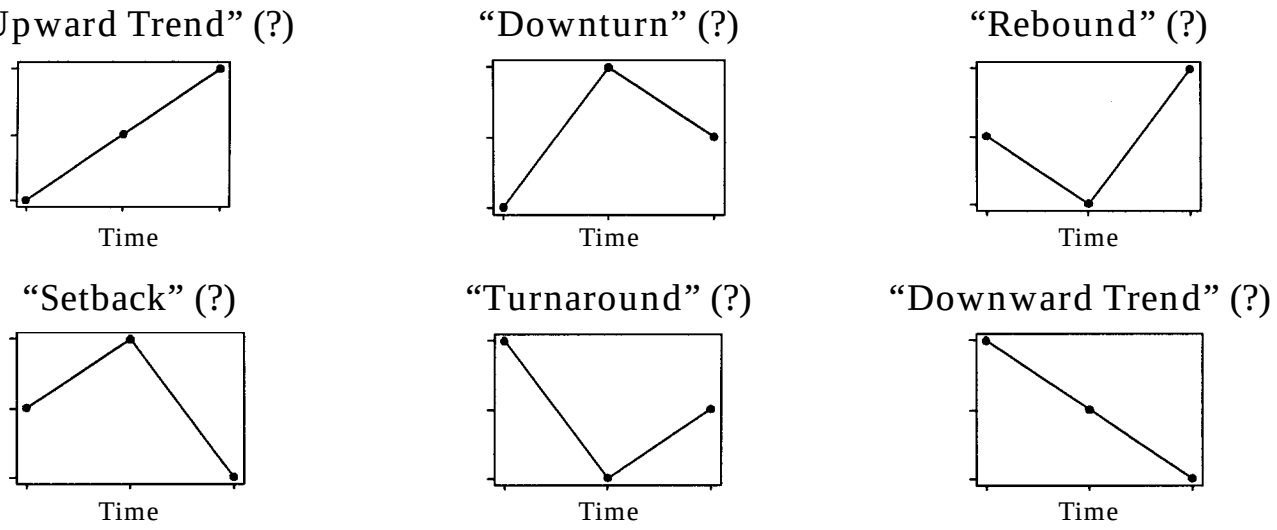
Statistical Definition of Trend

So, what does constitute a "trend"? Figure 4.1 was constructed with typical "monthly" and "quarterly" meetings in mind where organizational productivity and financial results are discussed. Why three data points? Because monthly meetings discuss "this month" vs. "last month" vs. "twelve months ago" and quarterly meetings discuss the last three months' results.

Do you realize that, given any three different numbers, there are six *random* sequences in which they can occur? These are shown in the figure along with fairly standard "explanations." Is there a slight chance that common cause could be treated as special cause?

Figure 4.1

Six Possible (& RANDOM) Sequences of Three Distinct Data Values

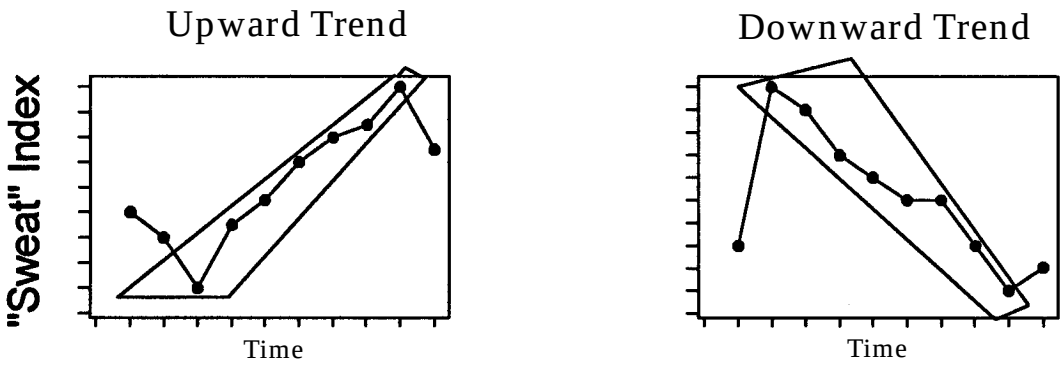


Now, it so happens that two patterns (the first and the last) fit a commonly held prejudice about the definition of a "trend." However, these are two patterns out of just six possibilities. So, to arbitrarily declare three points a trend without knowledge of the process's common cause variation results in a "2 out of 6" (or "1 out of 3") chance of treating common cause as special. Hardly odds worth taking without the context of a control chart to further interpret the extent of the variation.

So, how many data points does it "statistically" take to declare a "trend" with a low level of risk? Extending the concept presented above, it generally takes a run of length seven to declare a sequence a true trend. This is shown pictorially in Figure 4.2. Note that if the number of data points is 20 or less, a sequence of length six is sufficient. This could be useful when plotting the previous year's monthly data with the current year-to-date monthly data. (By the way, should you ever have the luxury of having over 200 data points, you need a sequence of 8 (!) to declare a trend.)

Figure 4.2

Graphic Representation of a Trend



Special Cause – A sequence of SEVEN or more points continuously increasing or continuously decreasing – Indicates a trend in the process average.

Note 1: Omit entirely any points that repeat the preceding value. *Such points neither add to the length of the run nor do they break it.*

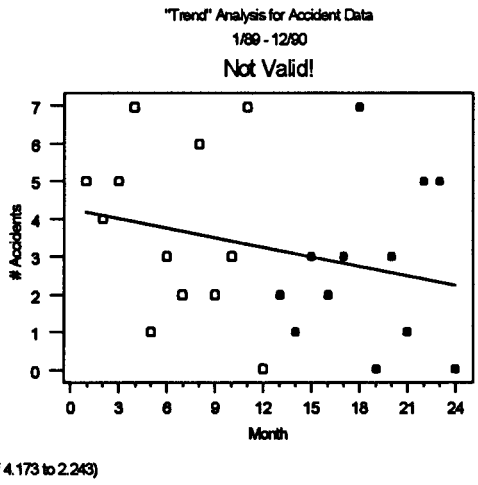
Note 2: If the total number of observations is **20 or less**, **SIX** continuously increasing or decreasing points can be used to declare a trend.

Example 2 — "How's Our Safety Record in 1990 Compared to 1989? What's the trend?"
A manufacturing facility had 45 accidents in 1989. This was deemed unacceptable, and a goal of a 25% reduction was set for 1990. 32 accidents occurred (28.9% reduction using the "Trap 1" approach). Time to celebrate…or is it?

Actually, an engineer was able to show that accidents had decreased even further. Using "trend" analysis (most spreadsheet software offers an option of putting in a "trend line"—talk about "delighting" their customers!), he was able to show that accidents had gone from 4.173 at January 1989 down to 2.243 by December 1990—a reduction of 46.2%! (See Graph 4.2.4).

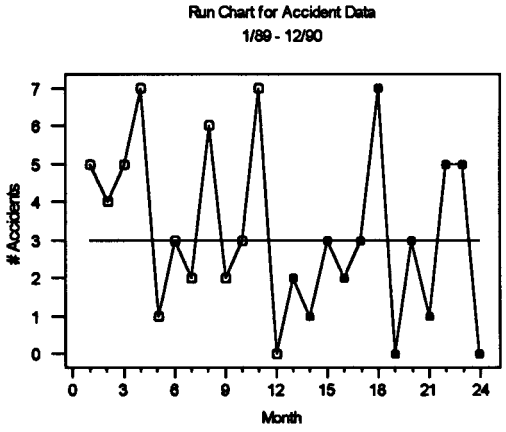
Now, here's a case where the p-value isn't significant at all, but it does indicate how clever frightened people can be when faced with an "aggressive" goal. What is the correct statistical application in this case?

Why not consider this as 24 months from a process, "plot the dots" in their time order, and apply runs analysis as shown in Graph 4.2.5? There are no trends, no runs of length eight, and 10 runs (6 to 14 expected). Therefore, *this system demonstrates common cause behavior:* Given two numbers, one was smaller--and it also happened to coincidentally meet an aggressive goal.



This is NOT a 46.2% Reduction in Accidents!

Graph 4.2.4



Correct analysis: **NO CHANGE!**
Any one month: 0-9 Accidents
End of the year: 20-57 Accidents Total
NEED COMMON CAUSE STRATEGY!

Graph 4.2.5

A Common Misconception
A very common misconception holds that if a process has only common cause variation, one is "stuck" with the current level of performance unless there is a major process redesign. I have a sneaking suspicion this is the reason people inappropriately use statistical methods to "torture a process until it confesses to some type of special cause explanation." Major opportunities for improvement are missed because of this fallacy. All a common cause diagnosis means is that little will be gained by investigating or reacting to individual data points. It allows us the "privilege," if you will, of aggregating the data, then "slicing and dicing" them via stratification by process inputs to look for major "pockets" of variation. Can we locate the 20% of the process causing 80% of the problem (Pareto Principle)? Only if stratification did not expose hidden special causes do we need to consider a major process redesign.

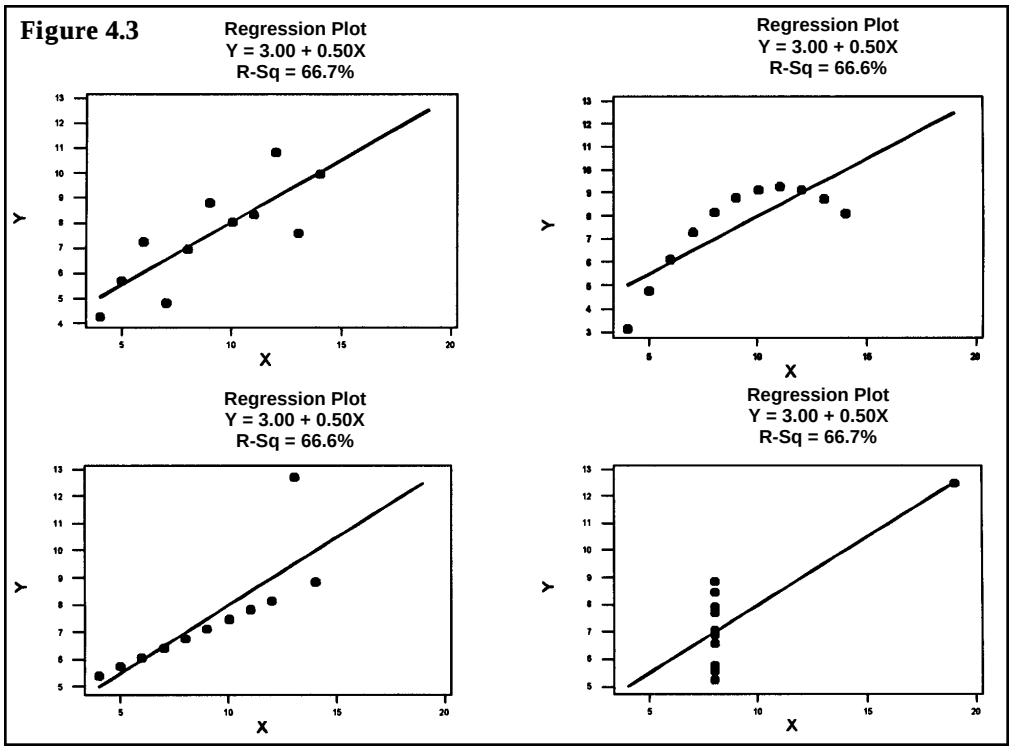
These data on accidents actually have two interesting stories to tell. Suppose a safety committee met monthly to analyze each accident of the past month and, after each analysis, put into effect a new policy of some kind. Think of an accident as "undesirable variation." (A process-oriented definition is: An accident is a hazardous situation that was unsuccessfully avoided.) Isn't looking at each accident individually treating them all as special causes? Yet our analysis showed that a common cause system is at work. Doesn't the runs analysis demonstrate that *the current process of analyzing each accident separately is not working* because no special cause has been observed on the run chart?

Wouldn't a higher yield strategy be to aggregate the 77 accidents from both years and use stratification criteria to look for the process's overall tendencies (type of accident, time of day, machines involved, day of the week, product involved, department, etc.)? A month's worth of three accidents does not yield such useful information, but the fact that the process is common cause allows one to use *all* the data from any "stable" period to identify "Murphy's" pattern of chaos!

Example 3 — Another Variation of "Plot the Dots!!!"
Figure 4.3 displays plots from four famous data sets developed by F. J. Anscombe. They all have the *identical* regression equation as well as all of the statistics of the regression analysis itself!

Yet, the only case where subsequent analysis would be fruitful based on the regression would be the first plot. The other three would "flunk" the diagnostics miserably. However, "plotting the dots" in the first place should dissuade anyone from using this regression analysis. The computer will do anything you ask it to…

Figure 4.3



4.3 Trap 3: Unnecessary Obsession With and Incorrect Application of the Normal Distribution, or "Normal distribution?…I've never seen one!" (W. Edwards Deming (1993 Four-Day Seminar))

What is this obsession we seem to have with the Normal distribution? It seems to be the one thing everyone remembers from their "Statistics from Hell 101" course. Yet, it does not necessarily have the "universal" applicability that is perceived and "retrofitted" onto, it seems, virtually any situation where statistics is used.

For example, consider the data below (made up for the purposes of this example). It is not unusual to compare performances of individuals or institutions. Suppose, in this case, that a health care insurer desires to compare the performance of three hospitals' "length of stay" (LOS) for a certain condition. Typically, data are taken "from the computer" and summarized via the "stats" as shown below.

Example 1 — "Statistical" Comparison of Three Hospitals' Lengths of Stay

Table 4.4

Variable	N	Mean	Median	Tr Mean	StDev	SE Mean	Min	Max	Q1	Q3
LOS_1	30	3.027	2.900	3.046	0.978	0.178	1.000	4.800	2.300	3.825
LOS_2	30	3.073	3.100	3.069	0.668	0.122	1.900	4.300	2.575	3.500
LOS_3	30	3.127	3.250	3.169	0.817	0.149	1.100	4.500	2.575	3.750

Given this summary, what questions should we ask? This usually results in a 1-2 hour meeting where the data are "discussed" (actually, people argue their individual interpretations of the three "Means") and one of two conclusions is reached: Either "no difference" or "we need more data".

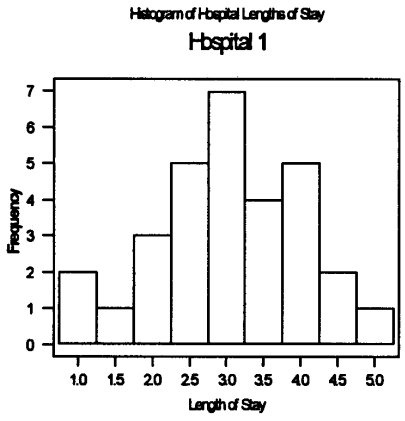
However, let's suppose one insurer asks for the raw data used to generate this summary. It seems that they want their "in-house statistical expert" to do an analysis. From Table 4.4, we know there are 30 values. With some difficulty, the raw data were obtained and are shown for each hospital.

"Of course," the first thing that must be done is test the data for Normality. A histogram as well as Normal plot (including Normality test) are shown below for each hospital. (See Graphs 4.3.1a - f).

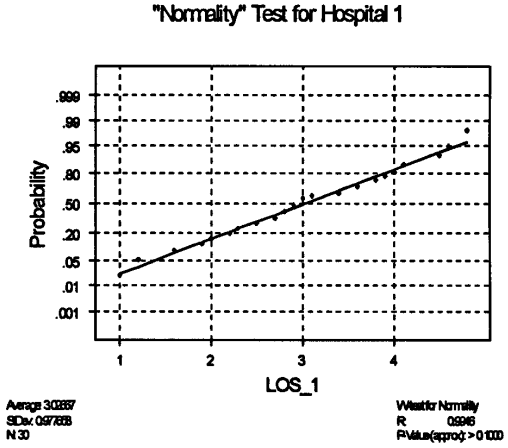
The histograms appear to be "bell-shaped," and each of the three data sets passes the Normality test. So, this "allows" us to analyze the data further using One-Way Analysis of Variance (ANOVA). The output is shown in Table 4.5 along with, of course, the 95% confidence intervals.

Raw Data

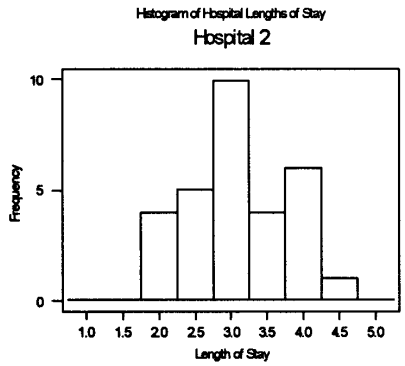
	LOS_1	LOS_2	LOS_3
1	1.0	3.4	4.5
2	1.2	3.1	3.0
3	1.6	3.0	3.6
4	1.9	3.3	1.9
5	2.0	3.2	3.7
6	2.2	2.8	4.0
7	2.3	2.6	3.6
8	2.5	3.2	3.5
9	2.3	3.3	2.5
10	2.7	3.1	4.0
11	2.9	3.4	2.5
12	2.8	3.0	3.3
13	2.7	2.8	3.9
14	3.0	3.1	2.3
15	2.8	2.9	3.7
16	2.9	1.9	2.6
17	2.9	2.5	2.7
18	3.1	2.0	4.2
19	3.6	2.4	3.0
20	3.8	2.2	1.6
21	3.6	2.6	3.3
22	3.4	2.4	3.1
23	3.6	2.0	3.9
24	4.0	4.3	3.3
25	3.9	3.8	3.2
26	4.1	4.0	2.2
27	4.1	3.8	4.2
28	4.6	4.2	2.7
29	4.5	4.1	2.7
30	4.8	3.8	1.1



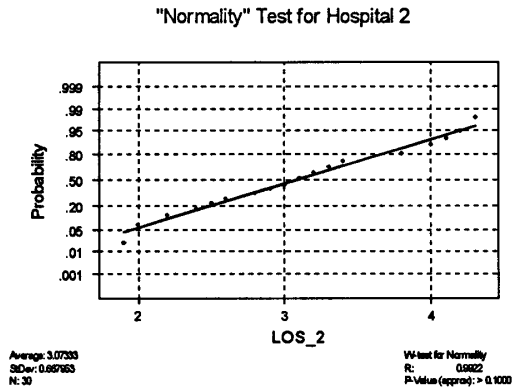
Graph 4.3.1a



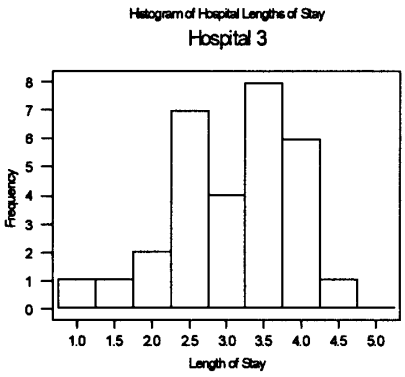
Graph 4.3.1b



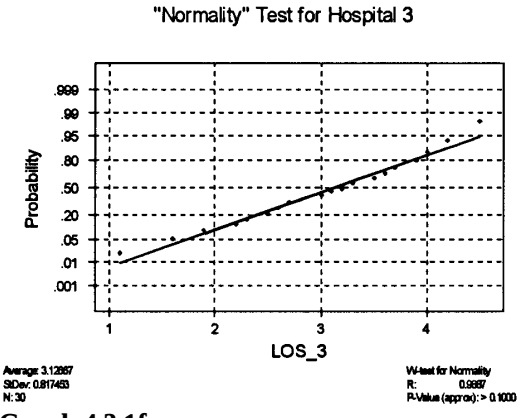
Graph 4.3.1c



Graph 4.3.1d



Graph 4.3.1e



Graph 4.3.1f

Table 4.5

A More Formal, "Rigorous" (and Wrong) Analysis: ANOVA (Analysis of Variance)

One-Way Analysis of Variance

Analysis of Variance for LOS

Source	DF	SS	MS	F	P
Hospital	2	0.150	0.075	0.11	0.897
Error	87	60.036	0.690		
Total	89	60.186			

Individual 95% CIs For Mean
Based on Pooled StDev

Level	N	Mean	StDev	----+---------+---------+---------+--
1	30	3.0267	0.9777	(----------*----------)
2	30	3.0733	0.6680	(----------*----------)
3	30	3.1267	0.8175	(----------*----------)
				----+---------+---------+---------+--
Pooled StDev =		0.8307		2.80 3.00 3.20 3.40

p-Value > 0.05: Therefore, "no statistically significant difference"

From the ANOVA table, the p-value of the analysis is 0.897. Since this is greater then 0.05, we conclude that no difference exists among these three hospitals. This is further confirmed by observing the extensive overlap of the three 95% confidence intervals.

WAIT A MINUTE! Has anyone asked the questions, "How were these data collected?" and "Is this analysis appropriate for the way the data were collected?" Some readers may be thinking, "What do you mean? The data are Normally distributed. Isn't that all we need to know?" Back to process-oriented thinking…

Suppose we're told that these represent 30 monthly data points for each hospital, and the lengths of stay are averages computed at the end of the month for all patients discharged with that condition. Further inquiry confirms that these numbers are indeed in their naturally occurring time order. How about starting with a simple plot of the data for each hospital in this time order (Graph 4.3.2)?

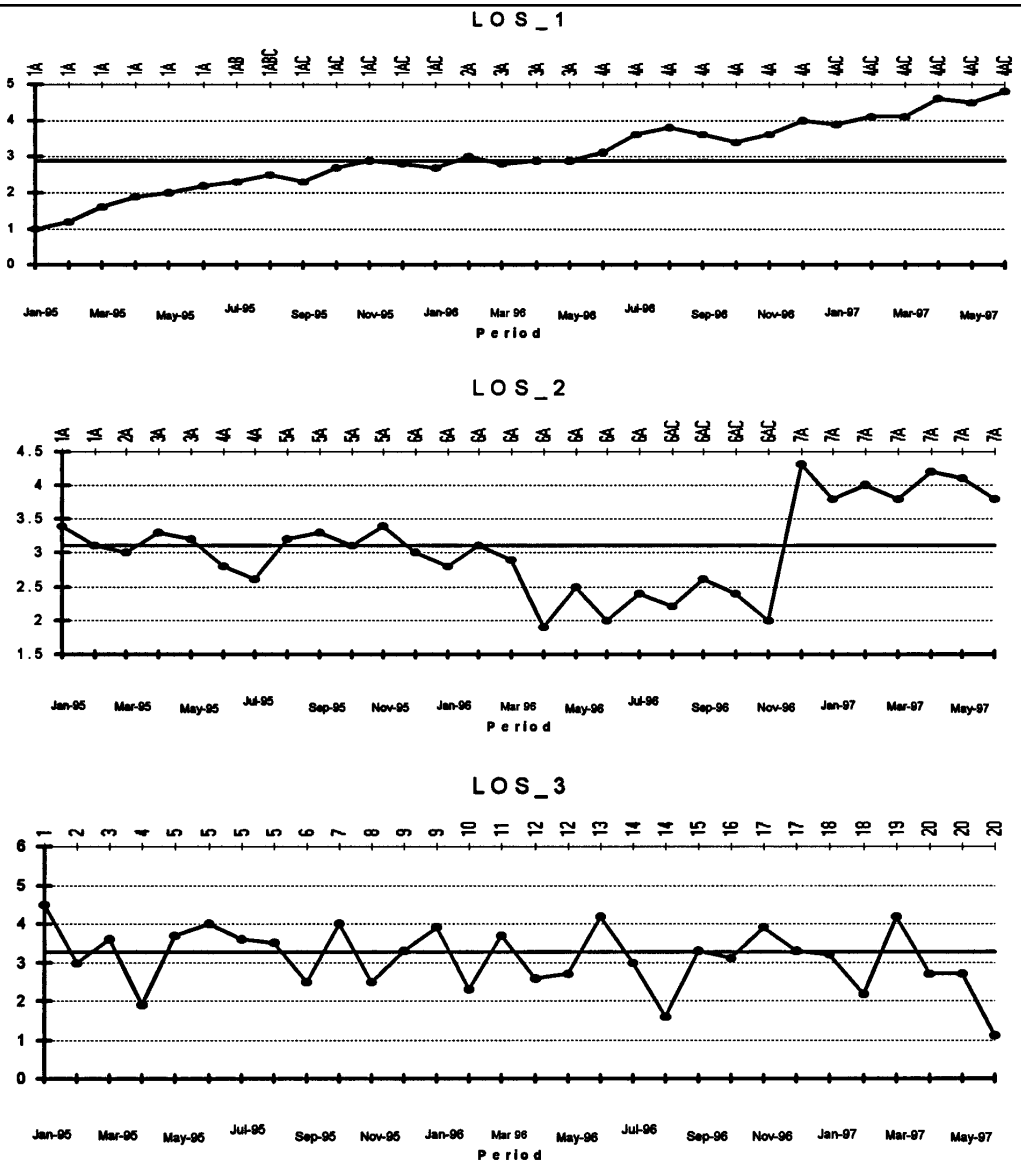
Suppose these three plots had been shown at the meeting instead? Now would people know what questions to ask? Would the ensuing discussion be slightly more fruitful than the "Ouija-boarding" of the means in the summary table (Table 4.4)?

In fact, now that the data have been plotted, how can we interpret the "Means" of hospitals 1 and 2? It's like saying, "If I stick my right foot in a bucket of boiling water and my left foot in a bucket of ice water, on the average, I'm pretty comfortable." Yet, how many meetings do you attend where tables of aggregated raw numbers are passed out, "discussed," and acted upon?

In his wonderful book, *Understanding Variation*, Donald Wheeler quotes Walter Shewhart as saying, "A data summary should not mislead the user into taking any action that the user would not take if the data were presented in a time series."

In other words: **"Plot the Bloody Dots!!!!!"**

Note that merely "plotting the dots" will ensure an extremely beneficial discussion *without the benefit of any summary statistics or statistical analysis.* How much simpler could it be? But, unfortunately, it's so counter-intuitive to most past teaching and experience.



Graph 4.3.2

No Difference?!

Example 2 — The Pharmacy Protocol--"Data Will Be Tested for the Normal Distribution"

More Tampering

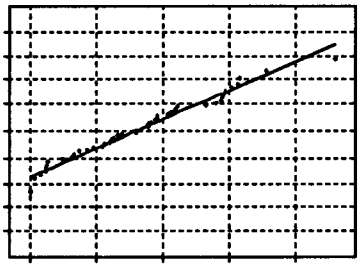
Using the most expensive antibiotic is appropriate under certain conditions. However, money could be saved if it was only prescribed when necessary. In an effort to reduce unnecessary prescriptions, an antibiotic managed care study proposed an analysis whereby individual physicians' prescribing behaviors could be compared. Once again, armed only with the standard "stats" course required in pharmacy school, a well-meaning person took license with statistics to invent a process *that would have consequences for extremely intelligent people* (who have little patience for poor practices). Real data for 51 doctors are shown in Table 4.6 along with direct quotes from the memo.

"If distribution is normal—Physicians whose prescribing deviates greater than one or two standard deviations from the mean are identified as outliers."

"If distribution is not normal—Examine distribution of data and establish an arbitrary cutoff point above which physicians should receive feedback (this cutoff point is subjective and variable based on the distribution of ratio data)."

Table 4.6

MD	Total	Target	% Target	SD_True
1	62	0	0.00	4.51
2	50	0	0.00	5.02
3	45	0	0.00	5.29
4	138	1	0.72	3.02
5	190	3	1.58	2.57
6	174	4	2.30	2.69
7	43	1	2.33	5.41
8	202	5	2.48	2.50
9	74	2	2.70	4.13
10	41	2	4.88	5.54
11	32	2	6.25	6.27
12	45	3	6.67	5.29
13	30	2	6.67	6.48
14	161	12	7.45	2.80
15	35	3	8.57	6.00
16	84	8	9.52	3.87
17	147	16	10.88	2.93
18	116	13	11.21	3.30
19	166	20	12.05	2.75
20	98	12	12.24	3.59
21	57	7	12.28	4.70
22	79	10	12.66	3.99
23	76	10	13.16	4.07
24	58	8	13.79	4.66
25	50	8	16.00	5.02
26	37	6	16.22	5.83
27	42	7	16.67	5.48
28	30	5	16.67	6.48
29	101	18	17.82	3.53
30	56	10	17.86	4.74
31	39	7	17.95	5.68
32	55	10	18.18	4.79
33	101	19	18.81	3.53
34	99	19	19.19	3.57
35	52	10	19.23	4.92
36	53	11	20.75	4.88
37	52	11	21.15	4.92
38	37	8	21.62	5.83
39	41	9	21.95	5.54
40	45	10	22.22	5.29
41	68	18	26.47	4.30
42	75	21	28.00	4.10
43	59	17	28.81	4.62
44	83	24	28.92	3.90
45	192	56	29.17	2.56
46	217	64	29.49	2.41
47	79	24	30.38	3.99
48	32	10	31.25	6.27
49	38	12	31.58	5.76
50	59	21	35.59	4.62
51	37	17	45.95	5.83
Total	4032	596	14.78%	



"Data will be tested for normal distribution"

Graph 4.3.3

In fact, the test for normality (Graph 4.3.3) is MOOT…and INAPPROPRIATE! These data represent "counts" that are summarized via a percentage formed by the ratio of two counts (Target Prescriptions / Total Prescriptions). The fact that each physician's denominator is different causes problems in applying the much touted "normal approximation" to these data. In fact these data actually follow binomial distribution characteristics more closely, which allows one to easily use a normal approximation via p-charts for a summary, as we'll see in Trap 4.

The scary issue here is the proposed ensuing "analysis" resulting from whether the data are normal or not. If data are normally distributed, doesn't that mean that there are no outliers? Yet, that doesn't seem to stop our "quality police" from lowering the "gotcha" threshold to two or even one (!) standard deviation to find those darn outliers.

Did you know that, given a set of numbers, 10% will be the top 10%? Think of it this way: Fifty-one people could each flip a coin 50 times and be ranked by the number of heads. The average is 25, but the individual numbers would range between 14 and 36 (a 2-1/2 fold difference!) and be normally distributed[1]. Yet, looking for outliers would be ludicrous—everyone had the *same* process and lowering the outlier detection threshold doesn't change this fact! Not only that, half could be considered "above" average, the other half "below" average, and any arbitrary ranking percentage could be invoked!

Returning to the protocol, even scarier is what is proposed if the distribution is not "normal"—establish an *arbitrary* cutoff point (*subjective* and *variable*)! Remember Heero's quote, "When you mess with peoples' minds, it makes them crazy!"

[1]From the binomial distribution, $0.5 \pm 3\sqrt{\frac{(0.5)(1-0.5)}{50}} = 0.5 \pm 3(0.707) = 0.288 \rightarrow 0.712$,i.e., 28.8% - 71.2%. Multiplying by 50 flips yields a range of (50*0.288=) 14 to (50*0.712=) 36 occurrence of "heads" for any group of 50 consecutive flips. Note that the range would be different if the coin were flipped a different number of times.

By the way, the data "pass" the normality test, which brings us to…

4.4 Trap 4: Inappropriate Calculation of Standard Deviation and "Sigma" Limits.

Example 1 —A Continuation of the Pharmacy Protocol Data

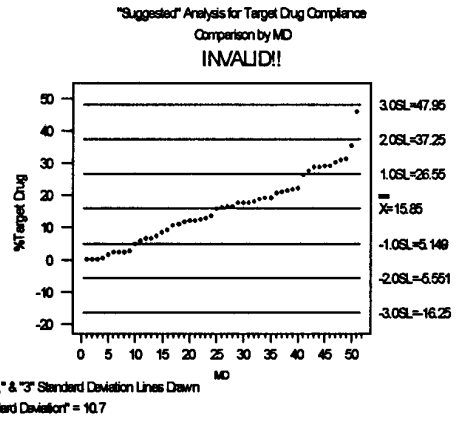
Since the data pass the normality test (see Graph 4.3.3), the proposed analysis uses "one or two standard deviation" limits based on the traditional calculation of sigma, $\sqrt{\frac{1}{n-1}\sum (X_i - \overline{X})^2}$. Applying this technique to the individual 51 percentages yields a value of 10.7. Graph 4.4.1 graphically displays the suggested analysis, with one, two, and three standard deviation lines are drawn in around the mean. So simple, obvious,…and wrong!

Suppose outliers are present. Doesn't this mean they are atypical ("boiling water" or "ice water")? In fact, wouldn't their presence tend to *inflate* the estimate of the traditional standard deviation? But, wait a minute, the data "appear" normal…it's all so confusing! So, there aren't outliers?

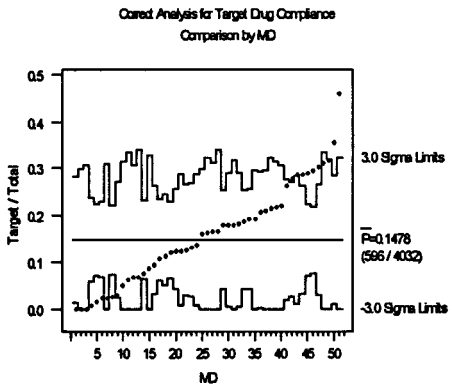
How about using an analysis *appropriate for the way the data were collected*? The "system" value is determined as the total number of times the target antibiotic was used divided by the total number of prescriptions written by the 51 physicians.(= $\frac{596}{4032}$ = 14.78%). Note how this is different from merely taking the average of the 51 percentages, which yields a value of 15.85%.)

Based on the appropriate statistical theory for binomial data, standard deviations must be calculated separately for each physician because each wrote a different number of total prescriptions. (The formula is $\sqrt{\frac{(0.1478)(1-0.1478)}{\text{Total prescriptions written by that physician}}}$. These were also given in Table 4.6 (SD_True) and we immediately notice that none of the 51 numbers even comes close to the standard deviation of 10.7 obtained from the traditional calculation.

In Graph 4.4.2, the statistically correct analysis using "three" standard deviations as the special cause threshold (known as **Analysis of Means**) is shown side by side with Graph 4.4.1. It turns out that the "conservative" three standard deviation limits *calculated correctly* are similar to the one standard deviation limits of the incorrect analysis.



Graph 4.4.1



Graph 4.4.2

Who are the Culprits???

Now that we've agreed on the analysis, what is the appropriate interpretation (a hint of Trap 6)? Anyone outside his or her (correctly calculated) individual common cause band is, with low risk of being wrong, a special cause. In other words, these physicians are truly "above average" or "below average." (Note that despite their high percentages, given the relatively small total number of prescriptions written by Physicians 48 and 49, their values could still be indicative of a process at 14.78%. Remember—"Innocent until proven guilty.")

What should we conclude? Only that these physicians have a different "process" for prescribing this particular drug than their colleagues. It is only by examining the "inputs" to their individual processes (people, methods, machines, materials, environment) that this special cause of variation can be understood. Maybe some of this variation is appropriate because of the type of patient (people) they treat or many other reasons. However, some of it may be inappropriate (or unintended) due to their "methods" of prescribing it. Remember, improved quality relates to reducing *inappropriate* variation. We can't just tell them "Do something!" without answering the natural resulting question, "Well, what should I do differently from what I'm doing now?" This will take data.

Most of the physicians, about 75%, fall within the common cause band, so this seems to represent majority behavior. A good summary of the prescribing process for this drug seems to be that its use within its antibiotic class has resulted in a process capability of almost 15%. Approximately 15% of the physicians exhibit "above average" behavior in prescribing this particular drug and 10% exhibit "below average" behavior in prescribing this drug. (It is important to look at those outside the system on *both sides*, even if only one side is of concern. If those below the system have better processes for prescribing the target drug, perhaps the other physicians could adopt them. On the other hand, this may be evidence that they are under-prescribing the target drug, resulting in higher costs due to longer lengths of stay.)

How Many Standard Deviations?

So often in my presentations, I am challenged about the use of three standard deviations to detect special cause behavior. People just can't seem to get the "two standard deviation, 95% confidence" paradigm out of their heads (Who can blame them? That's how they were taught.) Most of the time, my guess is that this is also due to their experience of using an inflated estimate of the true standard deviation.

It is also important to realize that in this example, 51 *simultaneous decisions are being made*! The usual statistical course teaches theory based making only one decision at a time. For our data set, if there were no outliers, what is the probability that all 51 physicians would be within two standard deviations of the average? $(0.95)^{51} = 0.073$, i.e., there is a 92.7% chance that *at least one* of the 51 physicians would "lose the lottery" and be treated as a special cause when, in fact, they would actually be a common cause.

Simultaneous decision-making, as demonstrated by this p-chart, is called Analysis of Means (ANOM) and was invented by Ellis Ott. Shewhart, Ott, Deming, Brian Joiner, Wheeler, and Hacquebord all recommend the use of three standard deviations—that makes it good enough for me. (Of course, given the proviso that the standard deviation is calculated correctly in the first place. In fact, Deming *hated* the use of probability limits!) I am taking a risk here (Dr. Deming, please forgive me!), but, by using three standard deviation limits, the probability of all 51 physicians being within three standard deviations is approximately $(0.997)^{51} = 0.858$, i.e., even with the "conservative" three standard deviation criterion, there is still a 14.2% chance that *at least one* physician could be mistakenly identified as a special cause.

Example 2 — Revisiting the Length Of Stay Data

The use of inflated standard deviations does not only occur in aggregated data summaries. Another common error is in the calculation of control limits. Let's revisit Trap 3's Length of Stay data for Hospital 2 shown in Table 4.7.

Many people (and control chart software programs) are under the mistaken impression that because limits on an Individuals control chart are set at three standard deviations, all they have to do is calculate the overall standard deviation, multiply it by three, then add and subtract it to the data's average. Graph 4.4.3 shows this technique applied to hospital 2's length of stay data. The traditional standard deviation of the 30 numbers is 0.668.

Table 4.7

	LOS2	MR	MR_Sort
1	3.4	*	0.1
2	3.1	0.3	0.1
3	3.0	0.1	0.1
4	3.3	0.3	0.1
5	3.2	0.1	0.2
6	2.8	0.4	0.2
7	2.6	0.2	0.2
8	3.2	0.6	0.2
9	3.3	0.1	0.2
10	3.1	0.2	0.2
11	3.4	0.3	0.2
12	3.0	0.4	0.2
13	2.8	0.2	0.3
14	3.1	0.3	0.3
15	2.9	0.2	0.3
16	1.9	1.0	0.3
17	2.5	0.6	0.3
18	2.0	0.5	0.4
19	2.4	0.4	0.4
20	2.2	0.2	0.4
21	2.6	0.4	0.4
22	2.4	0.2	0.4
23	2.0	0.4	0.4
24	4.3	2.3	0.5
25	3.8	0.5	0.5
26	4.0	0.2	0.6
27	3.8	0.2	0.6
28	4.2	0.4	1.0
29	4.1	0.1	2.3
30	3.8	0.3	*

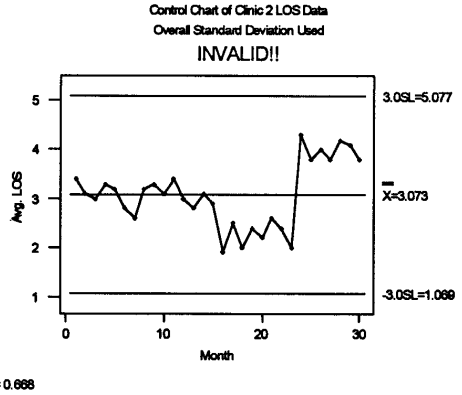
Standard deviation of LOS2 = 0.66795

Median of **MR = 0.3**

Std. Dev. = 0.3 / 0.954 = 0.314

Average of MR = 0.393

Std. Dev. = 0.393 / 1.128 = 0.348]



Graph 4.4.3

And many people tend to dogmatically apply the sacred "three sigma rule" of control charts to data, thus concluding in this case, "There are no special causes in these data because none of the data points are outside the three sigma limits."(!)

Of course, a preliminary run chart analysis would have warned us that *doing a control chart on the data as a whole was ludicrous.* The runs analysis would tip us off that the process exhibited more than one average during the time period. From the plot, it is obvious that three different processes were present during this time. The standard deviation used in control limit calculations is supposed to only represent common cause variation. Taking the standard deviation of all 30 data points would include the two special causes, thus inflating the estimate.

So, what should be done? A very common approach is to take the *moving ranges* between consecutive data points (shown in Table 4.7). Most books that use the moving range estimate sigma as the *average* of these moving ranges (in this case, 0.393) divided by 1.128, a constant from statistical theory. (In this case, sigma is estimated as 0.348.) However, what if the data contain special causes, as this data set does? It is obvious that the moving ranges from observation 15 to observation 16 (Moving range = 1) and observation 23 to 24 (Moving range = 2.3) represent more than "inherent" variation. The process clearly shifted. Granted, these do not cause as much "inflation" as using the overall standard deviation (compare 0.668 vs. 0.348), but can we protect ourselves from such occurrences, which tend to be the rule and not the exception? In fact, it is not unusual for one special cause data point to produce two consecutive overly large moving ranges.

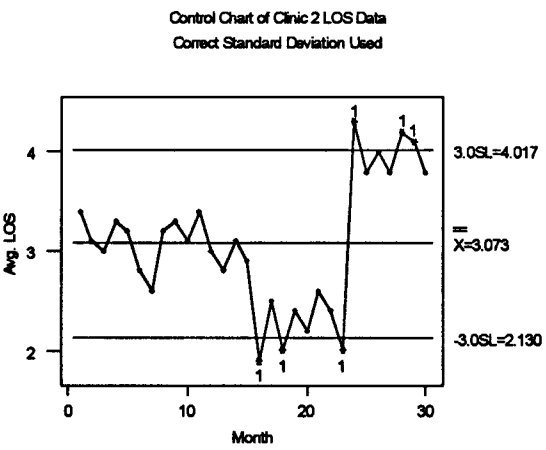
In my experience, a useful alternative is the *median* moving range, which is robust to outlying moving ranges caused by "shifts" and individual observation special causes. The only difference is that a different constant, 0.954 (once again, from statistical theory), is divided into the median moving range to obtain the estimate of the standard deviation. Note with these data, the standard deviation from the median moving range, 0.314, is the smallest of the three methods. Donald Wheeler discusses the use of the median moving range in *Understanding Variation* and Brian Joiner uses it exclusively when introducing control charts in his book *Fourth Generation Management.* I also prefer it because of the "one stop shopping" aspect of it – there's no need to estimate sigma, exclude special causes and estimate again. Minitab Statistical Software has introduced the option of using the median moving range in its Individuals control charts.

Another useful piece of information addresses Trap 1's two-point trends. The Median Moving Range can tell us how far apart any two consecutive points need to be before declaring a special cause. The product of (3.865 x (Median Moving Range)) represents the largest difference we would expect to see between two consecutive data points. Thus, a moving range greater than this value is evidence of a special cause.

Six values are outside the control limits, which leads us to…

4.5 Trap 5: Misleading Special Cause Signals on a Control Chart.

Example 1 — "When the control chart exhibits a point outside of the control limits, the point in time should be investigated to find out why" (Maybe…Maybe not)



Graph 4.5.1

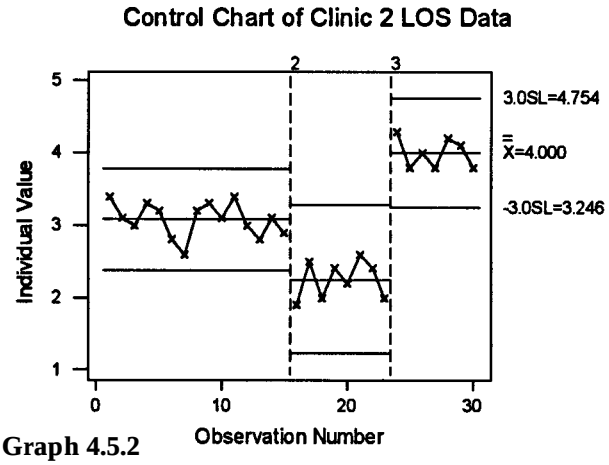
In Graph 4.5.1, the LOS data from Hospital 2 are replotted using a standard deviation of 0.314 and, unlike the previous control chart, observations now go beyond the control limits. What is the proper interpretation?

Armed only with the "one point outside three standard deviations" rule (the easiest to remember), the "naïve" interpretation would be, "Gee, we seem to have special causes at observations 16, 18, 23, 24, 28, and 29. What happened during each of those months?" [Don't laugh…I encounter this all the time…and bet that you do, too.] When you consider the fact that control charts are usually the last thing taught in a 3-4 day course on "tools" (when people's brains are already "full"), how can we reasonably expect people to not only use them properly, but also ask the right questions after the chart is obtained?

As said before, a run chart would have alerted us to the fact that different processes were at work during this time. It would be premature to do a control chart of all the data, and a control chart would probably only confuse the issue. In fact, the question should be, "What happened at observations 16 and 24?" The other points outside of the control limits (observations 18, 23, 28, and 29) were due to the fact that the process *average* had moved—*the old control limits were no longer valid at these new process levels.*

Based on the runs analysis and the standard deviation obtained from the median moving range, the correct interpretation of the data is shown in Graph 4.5.2.

Correct Interpretation



Graph 4.5.2

Example 2 —The Overtime Data
A supervisor was getting a lot of managerial "heat" regarding her overtime figures. Almost two years of bi-weekly overtime data were compiled (See Table 4.8.)

No doubt these data were "analyzed" via the bi-weekly "This period / Year-to-date / Same period last year / Last Year-to-date / Variance from Budget" paradigm. How about an analysis of the *process* producing these data?

One plot (if any is done at all) that seems to be in vogue is the "Year-to-Date Average" shown in Graph 4.5.3. Isn't it amazing how the variation decreases as the year goes on (It's almost always commented upon!)? Remember, at period 27, a new year starts and that blasted variation rears its ugly head again!

How about a run chart? From Table 4.7, the median overtime is 0.7, and "plotting the bloody dots" (Graph 4.5.4) seems to call attention to a couple of things—First, there are distinct "peaks" at periods 1, 15, and 36. Second, there is a distinct run of length 8 occurring from observations 33 to 40.

Table 4.8

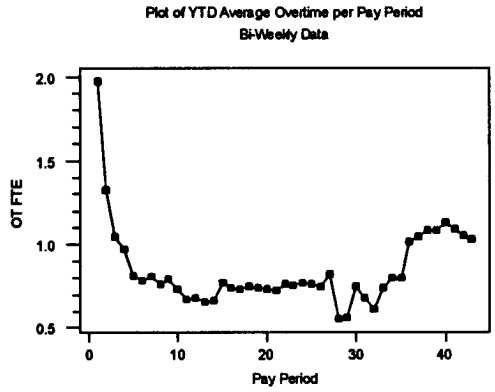
Period	OT	MR_OT	MR_Sort	
1	1.98	*	0.01	
2	0.67	1.31	0.05	
3	0.49	0.18	0.06	
4	0.74	0.25	0.11	
5	0.21	0.53	0.15	
6	0.64	0.43	0.18	
7	0.90	0.26	0.18	
8	0.45	0.45	0.21	
9	1.03	0.58	0.21	
10	0.18	0.85	0.22	
11	0.13	0.05	0.23	
12	0.70	0.57	0.23	
13	0.47	0.23	0.25	
14	0.70	0.23	0.25	
15	2.21	1.51	0.26	
16	0.34	1.87	0.29	
17	0.59	0.25	0.31	
18	1.00	0.41	0.37	
19	0.59	0.41	0.39	
20	0.58	0.01	0.39	
21	0.69	0.11	0.41	[Median]
22	1.41	0.72	0.41	[Median]
23	0.75	0.66	0.43	
24	0.96	0.21	0.43	
25	0.57	0.39	0.45	
26	0.39	0.18	0.53	
27	0.82	0.43	0.53	
28	0.29	0.53	0.56	
29	0.58	0.29	0.57	
30	1.30	0.72	0.58	
31	0.42	0.88	0.66	
32	0.27	0.15	0.72	
33	1.51	1.24	0.72	
34	1.20	0.31	0.85	
35	0.83	0.37	0.88	
36	2.99	2.16	1.14	
37	1.30	1.69	1.24	
38	1.51	0.21	1.31	
39	1.12	0.39	1.51	
40	1.68	0.56	1.69	
41	0.54	1.14	1.87	
42	0.48	0.06	2.16	
43	0.70	0.22	*	

Mean of MR_OT = 0.57143
SD = .57143 / 1.128 = 0.507

Median of MR_OT = 0.41000
SD = 0.41 / 0.954 = 0.430

Overall "Standard Deviation" = 0.58

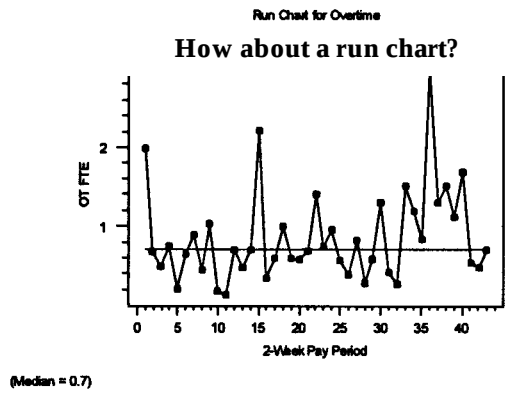
A "typical" display (if any at all) is the "Year-to-Date average":



Graph 4.5.3

Investigation showed that periods 1, 15, and 36 contained major holidays. An interesting question then becomes whether these peaks are appropriate or not. Do we expect people to work on holidays? If they do, are all their hours considered overtime? In other words, if policies were designed to keep this from occurring, they are not working. Temporarily, it may be a good idea to separate bi-weekly periods containing a major holiday and plot them on a separate chart to monitor the current state and any interventions. It would be interesting to note the behavior of the other holiday periods contained within the data.

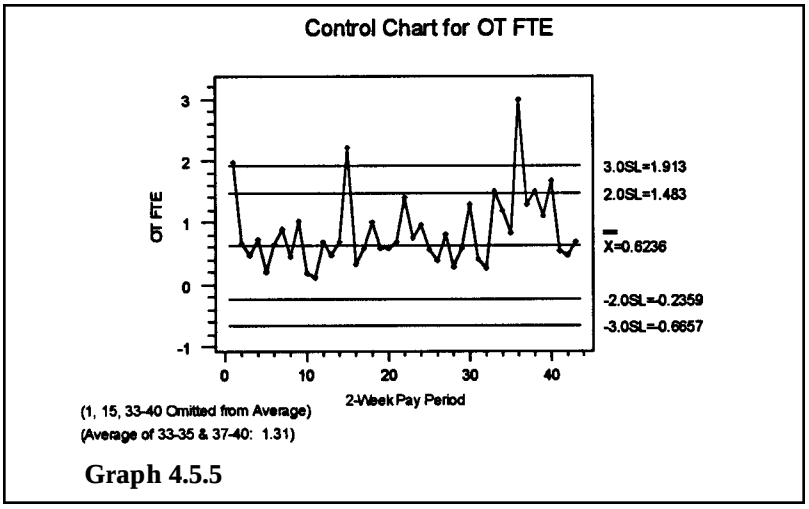
How about a run chart?



Graph 4.5.4

The run of length 8 represented a four-month period when two receptionists quit, and the supervisor was interviewing and hiring replacements--Definitely a special cause and atypical of her usual process. It's interesting to note that if turnovers were an inherent problem in the process, the control limits would probably be much wider, the process would have a higher average, and this run of 8 would not have occurred.

Comparing the various calculations for standard deviation as in Trap 4, the overall traditional calculation yields 0.58. The average moving range (which is inflated by the seven large moving ranges created by periods 1, 15, and 36; the "shift" up from period 32 to 33; and the "shift" down from 40 to 41), gives 0.507. Using the median moving range of all the data, we obtain 0.43. Note the dramatic difference in control limits when each is multiplied by three!



Graph 4.5.5

So, we know the common cause range, but what average should it enshroud? What represents this supervisor's "typical" process? Doesn't it make sense to characterize it by using the non-special cause periods, of which there are 33? This yields an average of 0.62 FTE (See Graph 4.5.5). Her process doesn't seem capable of consistently obtaining zero overtime! The lower control limit is less than zero, which means that she will *occasionally* have a period with zero overtime, but merely due to good luck. There is also the "period from hell" when she will have 1.91 FTE overtime, once again, due to no fault of her own. "Two sigma limits" (2/3 of the distance between the average and the upper and lower limits), which should cover 90-98% of the common cause variation, have also been drawn in to establish a range on the "typical" pay period — 0 - 1.48 FTE. (This comes from Wheeler's Empirical Rule.) However, what the chart seems to say is that this supervisor has a process which, as currently "designed," can *count* on 0.62 FTE of overtime. So, if all she is going to do is get "heat," she may as well put 0.62 FTE in her budget!

Note that despite periods 33-40 being a special cause, only the period containing the holiday actually goes out of the upper control limit, once again showing the importance of doing a preliminary runs analysis.

Can this process be improved? Maybe…but it will take a *common cause strategy* of *aggregating* the 33 common cause periods and doing a Pareto analysis, i.e., stratification, (if traceability to process inputs is possible) on the pattern of overtime. *Reacting to the individual high or low data points (which seems to be the current "strategy") would be a no yield strategy.*

4.6 Trap 6: Choosing Arbitrary Cutoffs for "Above" Average and "Below" Average.

Example 1 — The PTCA "Incident" Data
A cardiologist went screaming into a hospital QA director's office because two of his colleagues had "above average" numbers of incidents where patients needed to be rushed to the Operating Room during a PTCA. (PTCA is a procedure done by cardiologists.) The data are presented in the following table:

MD	# Incidents	# PTCA	# Incidents / # PTCAs	MD	# Incidents	# PTCA	# Incidents / # PTCAs
1	1	36	.0278	4*	2	58	.0345
2	4	53	.0755	5	2	110	.0455
3	4	79	.0506	**Total**	**16**	**336**	**.0476**

*The Screaming Cardiologist (Obviously "better than average" and believing his performance the "gold standard")

No doubt about it…two physicians (#2 and #3) had values above the average. Does this mean it's because of the "methods" input to their processes, as the "screamer" seems to assume? The 4.8% level of this incident doesn't seem to be acceptable to one colleague. However, is this "special cause" strategy of "find the bad apples" correct, given the data? Without a context of variation within which to interpret these percentages, are the two "above average culprits" truly, i.e., "statistically," above average?

Think back to the Pharmacy Protocol discussion in Trap 4. In that example the issue was a bogus (and inflated) calculation of the standard deviation, but at least they wanted a statistical analysis. However, when percentages are involved, it is not unusual for people to forego any semblance of statistical analysis and merely treat the difference between any two percentages as a special cause, especially when presented in tabular form.

So, using the theory of process-oriented thinking and the formula introduced in the Pharmacy Protocol discussion, we have a new question. "If this process averages 4.8% incidents, is it possible, given the total number of PTCAs performed by an individual physician, that his or her observed number of incidents is merely common cause variation reflecting this process average?"

(Think back to flipping a coin 50 times and counting the number of "heads"—even though the average is 25 (a "process" average of 50%), any one "trial" of 50 flips will yield a number of heads between 14 and 36).

Applying a "p-chart" analysis to the PTCA data results in the conclusions shown in Figure 4.4 and displayed graphically in Graph 4.6.1.

Figure 4.4

MD	Incident	PTCA	% Incident
1	1	36	2.78
2	4	53	7.55
3	4	79	5.06
4	2	58	3.45
5	5	110	4.55
Total	16	336	4.76 %

MD 1

Common Cause Range is:

$0.0476 \pm 3\sqrt{\frac{(0.0476)(1-0.0476)}{36}} = 0 - 15.4\%$

[2.8% Observed—Common cause]

MD 2

$0.0476 \pm 3\sqrt{\frac{(0.0476)(1-0.0476)}{53}} = 0 - 13.5\%$

[7.6% Observed—Common cause]

MD 3

$0.0476 \pm 3\sqrt{\frac{(0.0476)(1-0.0476)}{79}} = 0 - 12\%$

[5.1% Observed—Common cause]

MD 4

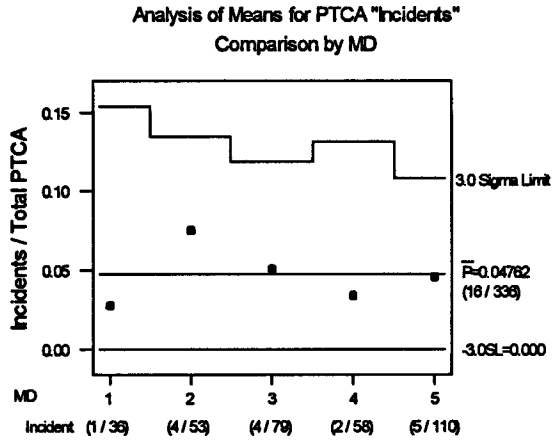
$0.0476 \pm 3\sqrt{\frac{(0.0476)(1-0.0476)}{58}} = 0 - 13.2\%$

[3.4% Observed—Common cause]

MD 5

$0.0476 \pm 3\sqrt{\frac{(0.0476)(1-0.0476)}{110}} = 0 - 10.8\%$

[4.6% Observed—Common cause]



Graph 4.6.1

Note that, despite the "messiness" of the formula, the only difference in the individual physicians' calculations is the denominator of the square root expression. The denominator represents the total "window of opportunity" for which the particular MD could obtain an "incident." In this case, it translates to his or her **total** number of PTCAs performed. Operational definition criteria can then be used to judge each PTCA as to whether the specified "incident" occurred or not.

The conclusion from the statistical analysis is that the current process is *"designed"* to obtain a 4.8% incident rate; no statistical difference exists among the performances of the five physicians. The type of variation we are dealing with is common cause, therefore, a common cause strategy would seem to be indicated. What would this entail?

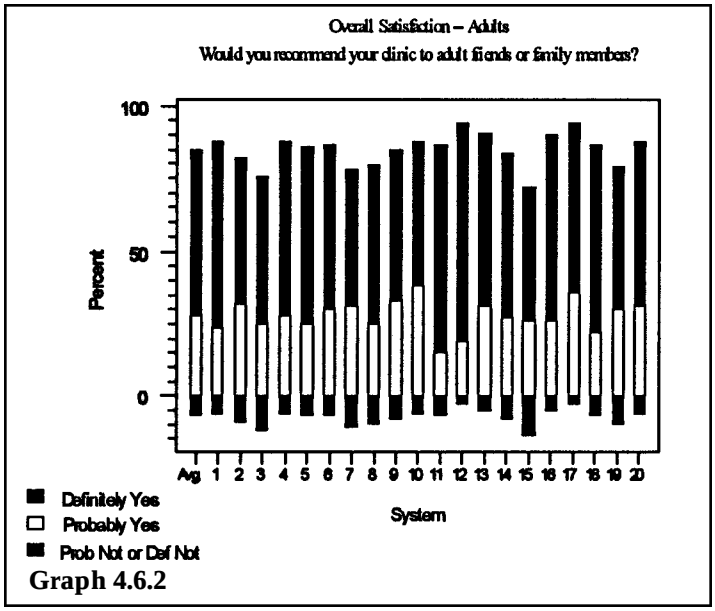
Unfortunately, sixteen incidents are a relatively small number, but the common cause strategy would dictate that they be "aggregated" then stratified via some type of Pareto analysis. The hope would be that one or two lurking process problems could be exposed to

account for a large majority of the variation. In other words, these problems would be present as a *common thread* running through a majority of the cases. Theories could then be developed and tested on the current process and subsequent plotting of data would be used to assess progress. Analysis of means could also periodically compare the current state of physician performance.

It does **not** entail subjecting each of the sixteen "incident" cases **separately** to a painstaking review then deciding to "change something" based **solely** on the circumstances of that individual case. If smart people are given an opportunity to find something, they generally will. The end result would be sixteen new policies and/or procedures that add complexity with marginal resulting value. However, this is the "simple, obvious,…and wrong" process that "common sense" seems to dictate. Isn't it obvious that this strategy treats each undesirable incident ("variation") as a special cause and isolates subsequent analysis in a vacuum?

Example 2 —Those Ubiquitous Bar Graphs: The Health System Ranking Data
This is a reproduction of a survey result published in a major metropolitan newspaper. Potential customers (patients, payers, and employers who offer health plans to their employees) were *demanding* data on how various health systems were satisfying their current customers. So, the typical customer satisfaction survey consisting of the usual vague questions was sent to 250 participants in each plan.

An approximation of the graph from the newspaper appears in Graph 4.6.2. The average of all 20 systems' data is shown as the first "bar" followed by each of the 20 systems surveyed. As you can see, the bar for each system is "stacked," with the upper portion being the percent who answered "Definitely Yes" to the question, "Would you recommend your clinic to adult friends or family members if they needed care?" the middle portion being the percent who answered "Probably Yes," and the lower portion being the percent who answered either "Probably Not" or "Definitely Not". Note that the data are "normalized" by aligning the "Probably Not or Definitely Not" numbers as the "origin" for the bars (Yes, it was actually published like this!). Each system was also "ranked" into its respective quartile for each item in the survey.



Graph 4.6.2

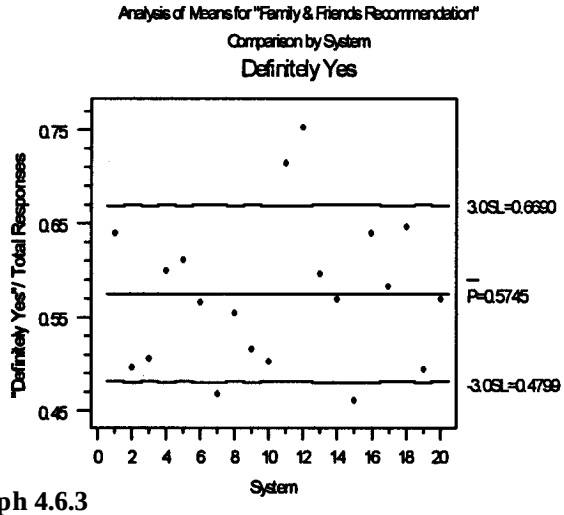
As stated previously, the lack of any context of variation makes Graph 4.6.2 impossible to interpret meaningfully. In addition, the "stacking" of various levels of responses merely adds confusion and more potential opportunities to tamper.

Another way to summarize data like these is to calculate the "average score" for each clinic and present these scores in bar graph form. The usual "top 5-10%," "bottom 5-10%," "above average," "below average," "quartile," etc. "Ouija board" criteria get applied and some type of "interpretation" results. Once again, these bars would need a context of variation to be interpreted.

One way that has been useful in my experience is to do a series of analyses. Why not use Analysis of Means to compare the number of times each health system received specifically a "definitely Yes" response relative to the total number of responses? This analysis is shown in Graph 4.6.3.

Given this system of 20 health systems, customers answer this question "definitely Yes" 57.4% of the time. The objective now is to see whether some health systems demonstrate a higher incidence of "definitely Yes" (in Deming's terms, "above" the system) as well as a lower incidence of "definitely Yes" ("below" the system). Statistically, systems 11 and 12 are above average and systems 7 and 15 are below average.

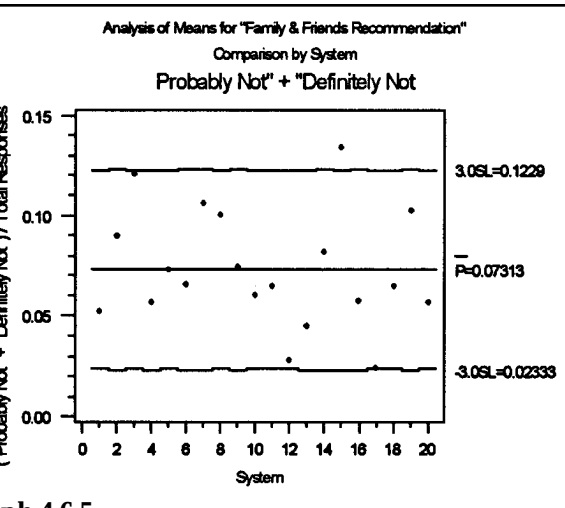
What would happen if "quartile" rankings were used instead? The marketing departments of systems 1, 16, and 18 would have undeserved "bragging rights" by joining systems 11 and 12 in the "top" quartile for customer satisfaction. Systems 2, 10, and 19 would "lose the lottery" and get branded with systems 7 and 15 in the lowest quartile (while system 3 heaves a sigh of relief).



Graph 4.6.3

"grumble factor"—sometimes, you just can't satisfy anybody! So, the combined response "probably Not" and "definitely Not" was analyzed for these 20 health systems. Graph 4.6.5 displays this analysis.

It seems that these 20 health systems just can't satisfy 7.3% of their clients. However, there is one special cause—system 15 (again!)--who is actually above average (Poor systems 3, 7, 8, and 19 who would "lose the lottery" and join system 15 in the "top quartile of dissatisfaction!"). No one seems to be exempt from the "grumble factor" as no system falls out below average, but I'm sure systems 1, 4, 12, 13, and 17's marketing departments wouldn't mind bragging that they fell in the bottom quartile for least customer satisfaction—the "least of the least satisfied."

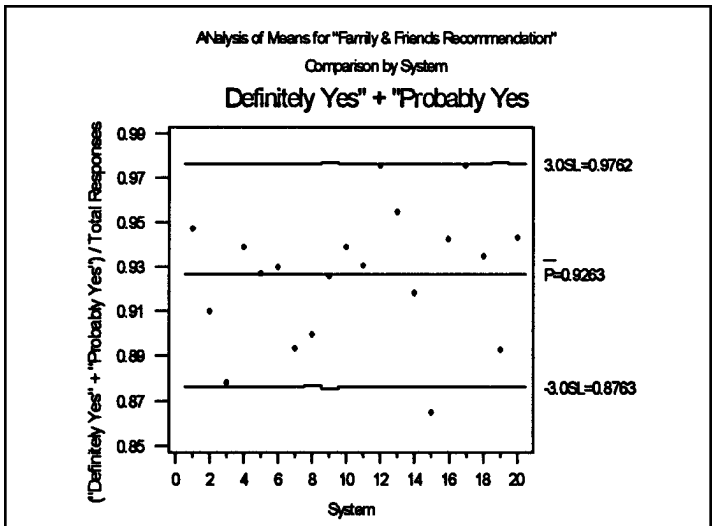


Graph 4.6.5

Next, an analysis was performed on percent incidence of obtaining either a "definitely Yes" or a "probably Yes." This "widens the net" a little bit. While some systems may not be outstanding performers, people could still be fairly satisfied with them. This analysis is shown in Graph 4.6.4.

When combined, "definitely Yes" and "probably Yes" account for 92.6% of the responses! There are no health systems "above" this system average (although systems 12 and 17 are close). System 7, previously a special cause "below" the system, has now pulled into the "pack," but system 15 remains statistically below average. (Note that, given the sample size of approximately 250, obtaining 100% "definitely Yes" and "probably Yes" would be a special cause in this process.)

Finally, I have also found it useful to look at the other "end" of the spectrum, if you will. Given a sample of human beings, there is always the presence of the

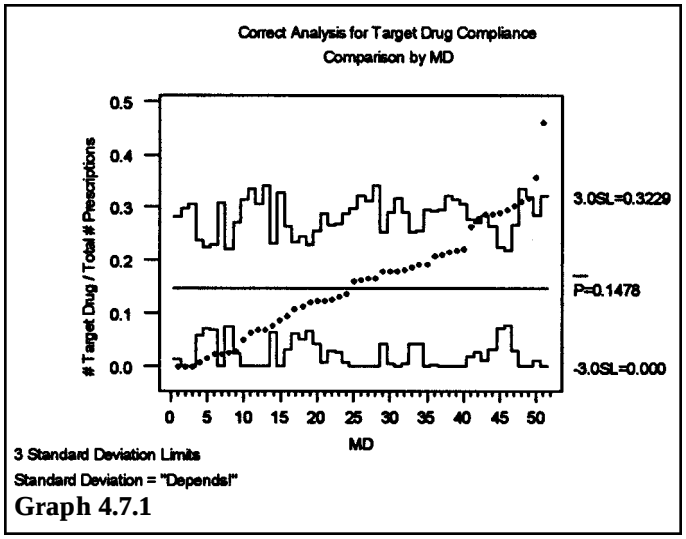


Graph 4.6.4

4.7 Trap 7: Improving Processes Through The Use Arbitrary Numerical Goals And Standards.

A statement has been attributed to Deming that is supposedly his definition of "insanity"—Doing things the way we've always done them, yet expecting different results. Imposing arbitrary numerical goals or "tougher" standards on a work environment ("typical" inputs to an organization's processes, wouldn't you say?) with the hope that these goals will somehow magically in and of themselves "improve" things is somewhat like that. This brings up another issue—measured "numbers" themselves might get better, but as far as the *actual process* itself goes…Well, never underestimate how clever frightened human beings can be when faced with a goal. (By the way, who decided that all goals must end with a zero or five—with the specific exception of an impossible situation when it is permissible to use three as a "stretch" goal?) Deming was adamant in declaring, "A goal without a method is nonsense!"

Actually, arbitrary numerical goals and standards involve two stages. The first is establishing the goal or standard itself and the second involves the processes of measuring a situation, assessing it versus the goal, then taking appropriate action on this "gap" (variation). Implicit in all of this is the question of whether people know exactly how to go about achieving the goal in a way that optimizes the system as a whole. Granted, some goals are far from arbitrary and may even be considered "facts of life"—So what? What specifically should the organization's workers do differently?



Graph 4.7.1

Example 1 — Pharmacy Protocol Data
Let's revisit the Pharmacy Protocol data. The correct analysis is shown again in Graph 4.7.1.

Suppose a goal had arbitrarily been set that "No more than 15% of prescriptions in this class should be the target drug!" (Oh-oh, ends in a five!). Since this graph captures the *actual process capability*, the effect of this goal can be assessed. *It is meeting the goal* with the exception of the truly "above average" physicians who are outside their common cause limits. The "gap" between the actual process performance and goal is zero. Even though it is meeting the goal, a special cause strategy can be used on the eight such "above average" physicians to possibly achieve some incremental improvement.

But what tends to happen in these cases? Usually, *any* deviation from a goal is treated as a special cause. Altogether there are 28 physicians above 15%. So, in addition to the eight outside the system, there are 20 physicians (40%!) who would incorrectly be considered "above average" and reported as "noncompliant." Because they are within the common cause band of the process average, they can statistically be considered no different from the average. Thus, they are neither statistically different from the goal nor different than the 18 physicians (35%) who happened to "win the lottery" and end up in the common cause band below the average.

Suppose the goal had **arbitrarily** been set at 10%. (Oh-oh, ends in a zero!) Despite all wishes and exhortations, the process would remain at its current capability of 15%. How would the gap between the actual performance and the desired performance ("variation") be acted upon?

The "simple, obvious, and wrong" way would be to provide feedback to anyone who has a rate of over 10% —a horrible tampering strategy. *The process, as it currently exists and operates, would not be capable of meeting this goal. There would need to be a fundamental change in* **all** *physician behavior*, i.e., basically a common cause strategy because the observed "gap" between 15% and 10% is common cause. However, a special cause strategy could be used in studying the physicians who are statistically above the current capability of 15%. That may yield some improvement, but not necessarily of the magnitude needed to attain the goal. Now, studying the physicians who are statistically "below average" may yield some appropriate behaviors that could lead to such improvement or at least attain a performance closer to the desired goal. There are no guarantees and, unless the goal is somehow tied to a significant organizational achievement, mere discussion of the goal is a complete waste of time. Intelligent, "statistical" discussion of the "gap" between the actual and desired performance on the other hand…

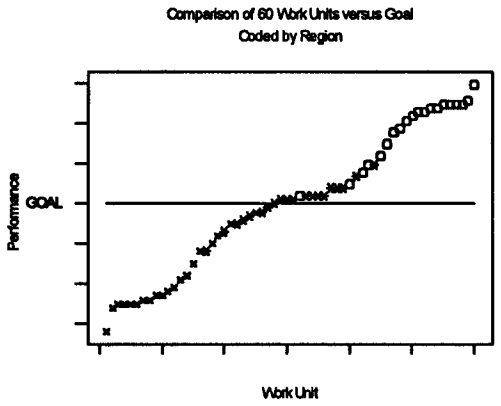
Goals in and of themselves are not bad. It depends on how they are used. Obsession with a goal itself is a no yield strategy. However, if the current process performance can be honestly measured and assessed (aside from consideration of any goal), and the *gap* (once again, "variation") between the current performance and the goal be correctly diagnosed as to whether it is common cause or special cause, an appropriate strategy will emerge to help close the gap (although it won't necessarily attain the goal). Usually, a mixture of common cause and special cause strategies is necessary; however, it is a human tendency to "default" to the "everything is a special cause" strategy.

Example 2 — Bonuses Based on Performance
There are two general ways that goals are used. The first is assessment and action based on a tabular summary of data (say at the end of the year when meeting certain goals is tied to compensation). The Pharmacy Protocol data is such an example. The time identity of the data points making up the summary is usually lost and the summary uses "aggregate" performance for the period under scrutiny. Typically, any variation of the summary from the goal is considered special cause.

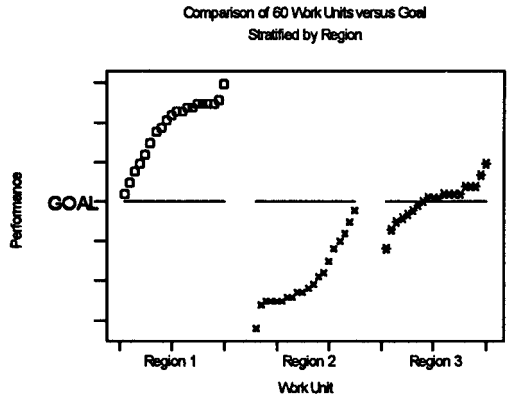
The second is assessments at various times of the year, e.g., weekly, monthly, quarterly, to evaluate current performance and "predict" relative to the year-end-achieving of set goals, usually resulting in some type of "action" to "redirect the course" (tampering?). I am indebted to Thomas Nolan and Lloyd Provost for the following scenario (from their excellent paper "Understanding Variation"). It delves deeper into the first process than the pharmacy data.

Suppose a corporate goal ("higher is better") had been set, and a company had three "regions." At the end of the year, work unit bonuses would be based on performance relative to the goal. Each region was made up of 20 work units. The 60 performances were sorted, and they are shown in the Graph 4.7.2, coded by region. How does one assign bonuses?

What if each region's data were stratified and plotted separately versus the goal (Graph 4.7.3)? Should this necessarily change the way bonuses are assigned? What about region 2? So as not to totally devastate that region, should they give a bonus to the top performer? Top 10%? Top 20%? Top Quartile? There are probably as many interpretations as there are people reading this.



Graph 4.7.2



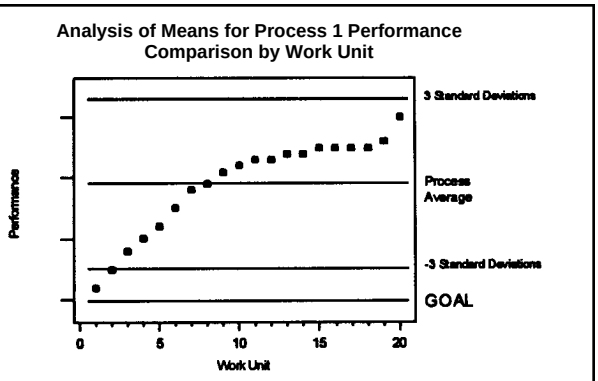
Graph 4.7.3

Raw numbers themselves cannot be interpreted unless one has a context of variation within which to put them. First of all, each region's performance must be evaluated relative to the goal by assessing whether the observed "gap" could be common cause or special cause. Next, each work unit's performance must be assessed *within the context of the process it forms* with the other units of that particular region.

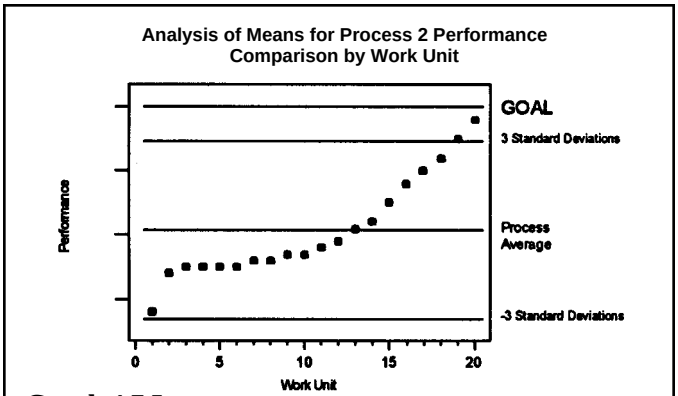
These regions represent a stratification of the "environment" input to the overall organization's process. People tend to automatically assume that the observed variation is due solely to the work "methods" of each region's and work unit's processes. However, deeper questions must be asked: "Is this variation *unintended* or *inappropriate* when compared to other regions' performances, given the other inputs to their processes?", i.e., people (both workers and customers), materials, machines and, measurements. Is the operational definition of the goal and its measurement appropriate, given the "environment" of each region?"

Below is an analysis of means for each work unit within each region. *For whatever reasons*, Region 1 (Graph 4.7.4) is "predestined" to meet the goal, i.e., meeting the goal seems to be within its inherent process capability. Should this necessarily be rewarded? It could be due to good overall management, motivated workers (resulting from good management and hiring), or merely good luck. The most interesting observation seems to be that two work units, even though they are meeting the goal, are statistically below what should be expected for this region's performance. All other process inputs being "equal," *these two performances are inappropriate!*

For whatever reasons, Region 2 (Graph 4.7.5) does not seem capable of meeting the corporate goal. Similar reasons could apply as above; however, two work units seem to have risen above the "bad hand" dealt to them. They maybe didn't achieve the goal, but they definitely achieved a statistically better performance than this region should have expected, given the region's processes. All things being equal, these two units probably have some unknown "knacks" in their work processes that, if shared with the other work units, could raise the overall level of Region 2's performance--but it would still fall short of the goal. As part of the "unintended" variation vis-à-vis Region 1 (and Region 3), are there some "knacks" Regions 1 and 3 could share that might possibly raise the level of *all* the work units in Region 2?

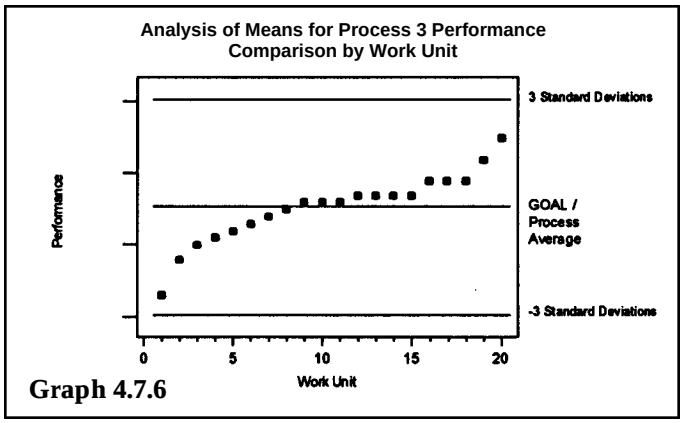


Graph 4.7.4



Graph 4.7.5

Region 3 (Graph 4.7.6) is the proverbial "lottery" relative to the goal--if the difference from the goal is treated as special cause. The "gap" between Region 3 and the goal is zero. Furthermore, the analysis of means comparing work unit performance shows no statistical differences relative to Region 3's overall average. Everyone should receive the bonus! However, discussion of Region 3's "gap" from Region 1's performance should occur to possibly expose process practices that might reduce some "unintended" variation. How much variation between Region 1 and Region 3 is "appropriate," given the inputs to their processes?

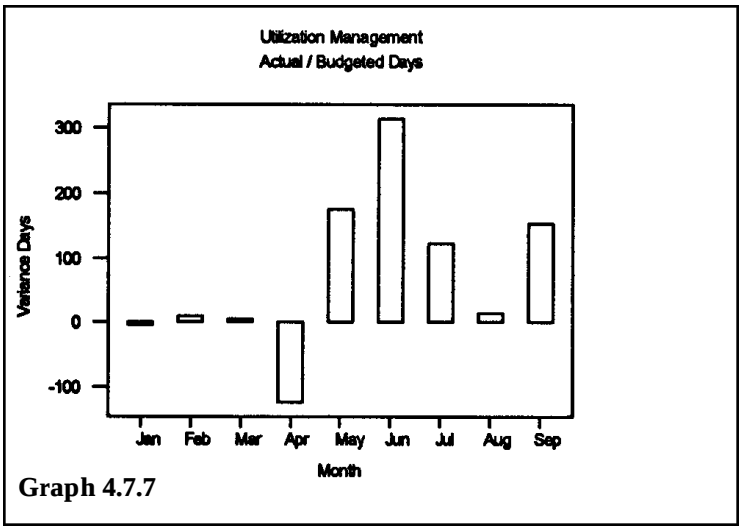


Graph 4.7.6

In summary, note how putting numbers into a statistical context through understanding the observed variation always yields a series of questions that may demand deeper knowledge of the processes being studied. A superficial "one pass" analysis of comparing numbers to goals runs the "simple, obvious, and wrong" danger—and consequences on very intelligent people.

Example 3 — "Constant Monitoring Versus Goal" Process

The Overtime example discussed under Trap 5 was an example of this, except the goal was not formalized—People just aren't "supposed to" have overtime! Also, in that case, we had a lot of data for good assessment of the process's inherent capability. What about the common situation where "the slate is wiped clean" every January and, at best, one can only use last year's data and current year-to-date for comparison to the latest set of goals?



Graph 4.7.7

Because of the impact of managed care, medical utilization is coming under closer scrutiny—using more resources does not guarantee more money! It is not unusual for organizations to appoint a utilization manager (someone with an MBA) who works "jointly" with a physician to "monitor" medical utilization. This results in monthly meetings where numerous graphs are "presented" and "discussed."

One aspect of Utilization management involves estimating the number of days patients "should" spend in the hospital for various conditions. When patients are hospitalized with these conditions, their lengths of stay can be compared with the predicted (or budgeted) lengths. If patients stay longer than "budgeted," the departments make less profit, so any deviation (or variance) the "wrong way" can be a major concern. Graph 4.7.7 is an example of utilization data.

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep
Actual Days	3120	2633	2879	2673	2877	2819	2621	2672	2671
Budgeted Days	3125	2623	2874	2798	2701	2503	2499	2658	2518
Variance Days	-5	10	5	-125	176	316	122	14	153

Note that the budget figure is treated as sacrosanct—any deviation from it is always treated as special cause! Positive variation under all conditions, of course, is "unacceptable."

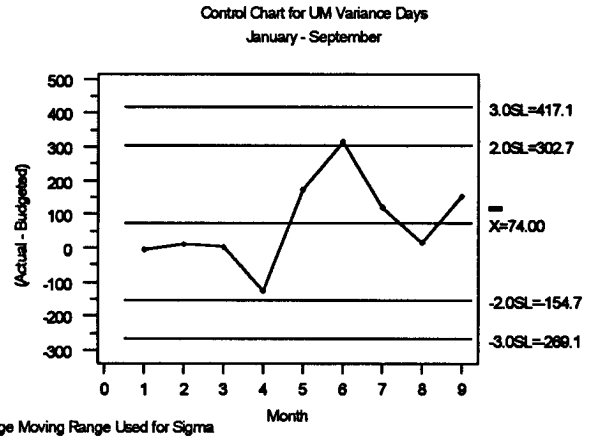
As mentioned before, we need a context of variation to interpret numbers. The time ordered nature of this data set begs for a control chart. Granted, nine data points may not be much, *but it's all the data we have.* It couldn't be any worse than the "Ouija board" discussion (and resulting action)!

Due to the small number of data points, the control chart limits in Graph 4.7.8 are based on the average moving range instead of the median. (We may also want to consider these limits "tentative" until more data are collected.)

Month	Var_Days	MR_VDays
1	-5	*
2	10	15
3	5	5
4	-125	130
5	176	301
6	316	140
7	122	194
8	14	108
9	153	139

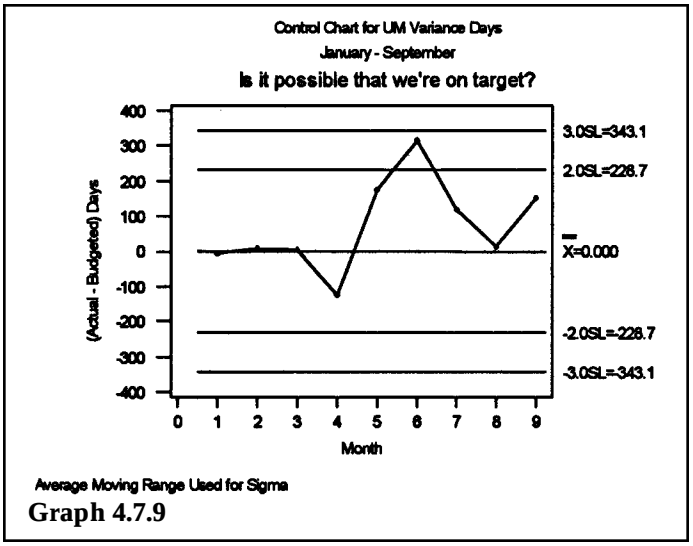
Average of MR_VDays = 129.00

Common Cause Limits: 74 + (2.66 x 129)



Graph 4.7.8

As astonishing as it seems, there are no indications of special causes--and look at the month-to-month variation! In fact, if the process operates *normally*, there is the possibility (in the "month from hell") of obtaining a positive 417 day variance randomly, even when the process has an average of 74 (90-98% of the time, the monthly variance will range between -155 and 303)! Of course, there will be a chorus of, "We have to do something!"—resulting in consequences for intelligent people.



Graph 4.7.9

Like the poor supervisor in the overtime data example, they may want to consider the implications of a positive 74-day monthly variance on their current budget. If this is not acceptable, some type of common cause strategy might be needed to achieve the goal, which would involve disaggregating and stratifying the process (if possible) to look for potential opportunity.

But, wait a minute! The question needs to be asked, "How were these data defined and collected?" Does the "variance" represent inherent utilization variance or the fact that the model used to predict "budget days" is lousy?

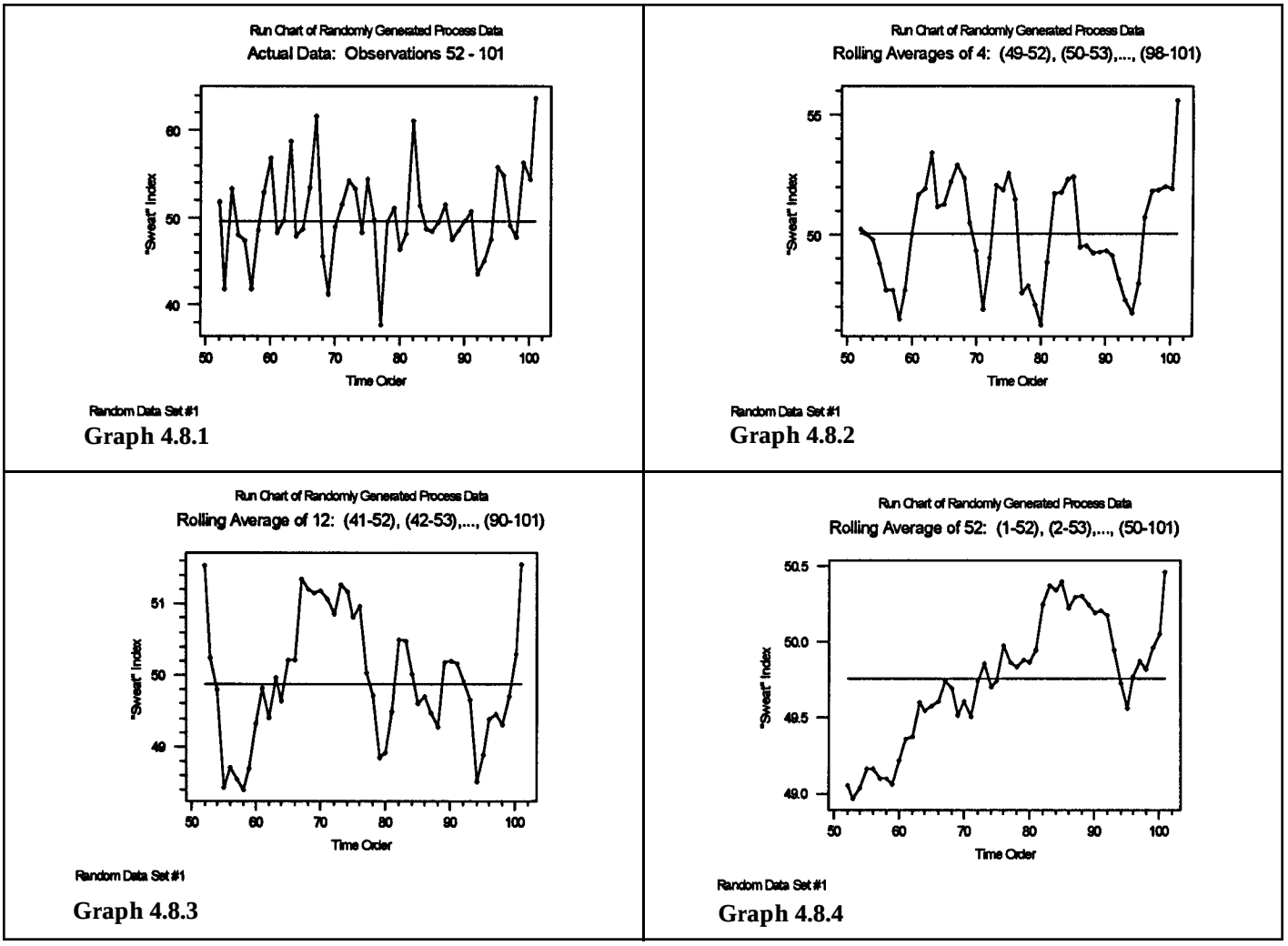
Because of the large variation, one might also be tempted to ask, "Even though the average is 74, is it possible that the process is really on budget, i.e., is the difference between 74 and 0 simply common cause variation?" How could this be tested? The control chart in Graph 4.7.9 forces an average of zero onto this process. It's interesting that no special

causes are triggered; however, the last five months have had a positive variance…what if it continued for three more months?

Note that a different series of questions are asked about the situation when it is studied as a process. And, once again, the goal itself is irrelevant—How does the "gap" behave and is a common cause or a special cause strategy needed?

4.8 Trap 8: Using Statistical Techniques on "Rolling" or "Moving" Averages—A Lurking Trap.

After reading an article by Lloyd Nelson ("The Deceptiveness of Moving Averages," Journal of Quality Technology, April 1983) and noticing how much financial departments use the technique of rolling averages, I decided to do a little simulation. How many of us have taught courses within our organizations to people from such departments without realizing the types of data to which they will return and apply techniques such as run charts and control charts?



Graph 4.8.1 **Graph 4.8.2**

Graph 4.8.3 **Graph 4.8.4**

Believe it or not, these Graphs 4.8.1 – 4.8.4 are of the same data! 101 random numbers were generated from a normal distribution with mean 50 and standard deviation of 5. The first graph (Graph 4.8.1) shows a run chart of the last 50 numbers from this sequence (observations 52-101). No trends, no runs of length 8, and it passes the total number of runs test (25 observed, 19 to 32 expected). In other words, a stable process. Of course…it was generated that way.

Now, let's simulate a commonly used financial technique known as the "four quarter rolling average," i.e., construct rolling averages of four. The next graph (Graph 4.8.2) shows the **average** of observations 49 through 52 followed by the **average** of observations 50 through 53, etc., ending with the **average** of observations 98 through 101. In other words, it's still a plot of observations 52 through 101, but with a slight twist. Note how this creates the *appearance* of special

causes—runs of length 9 and 10, 9 total runs with 19 to 32 expected, and a "special cause" increase for the last observation. This runs analysis is inappropriate for the way the data were defined and collected.

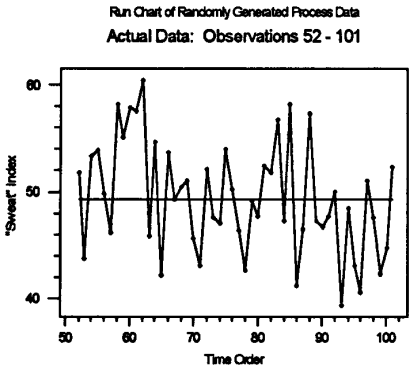
The next graph (Graph 4.8.3) simulates another commonly used technique, the "twelve month rolling average," i.e., constructing rolling averages of 12. The plot contains the average of observations 41 through 52 followed by the average of observations 42 through 53, etc., ending with the average of observations 90 through 101. Once again, it's merely plotting observations 52 through 101. Note the "runs" of length 8 and 13, and it also does not pass the expected number of runs test—11 observed versus 19 to 32 expected.

Finally, a favorite Wall Street technique seems to be the 52 week rolling average. This is simulated in the fourth graph (Graph 4.8.4). The average of observations 1 through 52 is followed by the average of observations 2 through 53, etc., ending with the average of observations 50 through 101. Note that the heavier the rolling, the more dramatic the appearance. Is it any wonder that people can look at graphs like these, see "special causes" *using rules we've taught them*, and end up "messing with people's minds?" As a result of such plots, I've had people confess to me that they were told to look for reasons for "increases" or "decreases" that seemed so obvious from the graphs, but subsequent investigation was frustrating and fruitless.

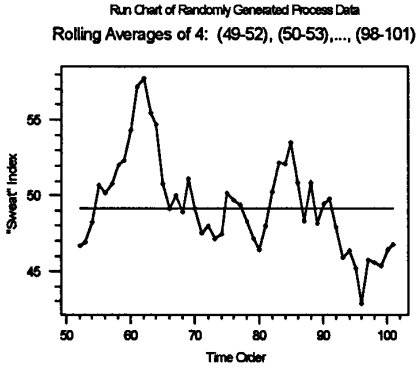
Out of curiosity, I generated one more set of 101 numbers from the same process and proceeded as before: graphs of rolling averages of 4, 12, and 52. These are shown in Graphs 4.8.5 a-d.

The process has not changed. However, notice how these graphs give a totally different impression of the process from their counterparts in the first set of data (all except the graph of the actual data of course)!

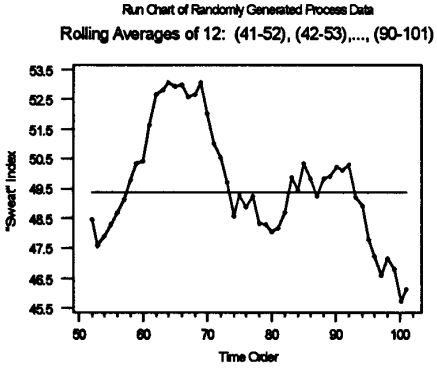
Why do people feel the need to create such indices (as Deming would say, "Simple, obvious, and wrong!")? Because they well-meaningfully want to reduce the variation so as to make better predictions. However, making the variation go away "on paper" does not make it disappear in actuality! The variation "is what it is". Besides, understanding Statistical Thinking and the difference between common causes and special causes of variation *will* allow one to make better predictions despite the presence of the heretofore feared variation!



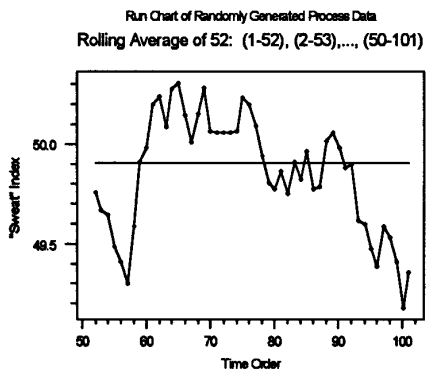
Graph 4.8.5a



Graph 4.8.5b



Graph 4.8.5c



Graph 4.8.5d

5.0 Summary

The traps and techniques speak for themselves. The purpose of this publication was to demonstrate how statistical techniques in and of themselves do not exist in a vacuum.

5.1 The Fundamentals of Variation

The following list was developed to summarize and bridge this gap between Statistical Thinking and statistical techniques (The author is indebted to his former 3M colleague, Andrew Kirsch, who originally suggested this format and drafted the first incarnation):

1) Good data collection requires planning, which is as important as the data themselves.
   - The first question must be, "What is the objective?"
2) Good data analysis requires knowing how the data were collected or will be collected. The analysis must be appropriate for the method of collection.
   - Raw data say little,
   - Graphical methods are the first methods of choice, however…
     - Bar graphs are appropriate only for stratifying via either a Pareto analysis ("count" data) or stratified histogram ("continuous" data),
     - Bar graphs of data over time "waste ink." Do a time plot / run chart of where the bars "end,"
   - The proposed analysis should be clear before one piece of data is collected.
3) All data result from a measurement process.
   - Is the measurement process agreed-upon and reliable?
   - Have vague terms been properly and operationally defined?
   - Do the people actually collecting the data understand the data's purpose and the processes of how to measure and collect them?
4) Variation exists in all things, but may be hidden by:
   - excessive round-off of the measurement,
   - excessive aggregation,
   - using "rolling" or "moving" averages.
5) All data occur as an output from some process and contain variation. This variation is caused and has sources which can be better identified through proper data collection.
6) There are sources of variation due to **inputs** to a process (People, Methods, Machines, Materials, Measurement, and Environment) and variation in **time** of these individual inputs as well as their aggregate. **Both** are reflected in the output characteristic being measured.
7) The stability of the process (over time) producing the data is of great importance for prediction or taking future action.
8) All data occur in time.
   - Neglect of the time element may lead to invalid statistical conclusions.
9) Any source of variation can be classified as either a common cause or a special cause. It is important to distinguish one from the other to take appropriate action.
   - The presence of special causes of variation may invalidate the use of certain statistical techniques,
   - Any and all data analyses must be based in sound statistical theory and help to interpret the observed variation meaningfully in terms of identifying common and special causes. This will drive subsequent questions asked and investigated with further data collection.
10) There is variation (uncertainty) even when an object is measured only once.

5.2 Final Comments from the Author

Part of me wants to apologize, yet part of me doesn't, if some of you may have felt "uncomfortably warm" while reading parts of this publication. Change is never easy, and many current practices of teaching statistical techniques via the ubiquitous "short courses" actually do more damage than ultimate good (see Butler and Rough references in Bibliography). That is not *anyone's* fault! These are good people (BOTH instructors and participants) doing their best. Kerridge makes a wonderful quote in his article (referenced in the Bibliography - he is a world-famous Deming philosophy teacher) to summarize both the current state of organizational work processes and the process of teaching statistics: "If we are actually trying to do the wrong thing, we may only be saved from disaster because we are doing it badly." Rather eye-opening, isn't it?

In my 20-year career, I've come to realize that at least half of a statistician's job relates to the psychology of change—and "those darn humans" fiercely resist being changed! Humans being humans, logic is not always persuasive (and only logicians use it as a source of income). It usually takes nothing less than a "significant emotional event" (a theory and term coined by Massey—see Bibliography) (or "hit in the gut") to motivate people to even *think* about changing.

DATA "SANITY"

Over time, and through many events out of their direct control, people have conditioned themselves to think in certain ways—their daily motivations tend to be unconscious and reflex-like. Unless these deep, hidden beliefs can be challenged, exposed, and, *through unrelenting conscious choice, replaced by new beliefs, people will generally choose not to change, even when they rationally know that the change is beneficial.* Given the current societal and organizational environments (process input!) where change has become a constant, individual behavior represents a last vestige of control—and people increase their resistance by several orders of magnitude. This unsettling climate exacerbates what is, even in the best of times, the uncomfortable, emotionally exhausting process of changing our own behaviors. The Franklin Reality Model (yes, of the Franklin-Covey Planner people--see Bibliography) is an outstanding resource for understanding this complex human phenomenon and harnessing its power for leveraging change.

I was guilty of falling into these eight traps for at least the first 10 years of my career. Not only that, I was blissfully ignorant of their true impact on overall organizational culture. In 1988, a seminar with Heero Hacquebord was my "significant emotional event" through his no-nonsense, straight-shooting style (Heero makes *me* look sedate! And Massey makes *Heero* look sedate!). When I left his seminar, I felt "punched in the gut" and *then* some. It really challenged my isolated little statistical world, and I didn't like it one bit—and I had no more excuses for feeling victimized! So, I'm truly sorry if you feel that this publication has added another source of stress that you didn't need. My last intent was to come across as "threatening," "angry," "self-righteous," or "preachy." Look at my last name (Italian) and substitute the word "passion" when tempted to think otherwise ("Blame" Heero!). You are doing the best you can with what you've been taught up till now. *Nobody's* to "blame" for anything! However, my intent was to expose you to situations that could uncomfortably make you realize that yes, indeed, there are alternatives to the status quo—and you're the one who is in control of how you consciously choose to deal with it.

Quite frankly, I am now *outraged* (and hope you are, too) at the waste caused by poor applications of what should be simple statistical theory, especially nonsensical decisions *having consequences on extremely intelligent people* (People like you!). It's so easy to take the easy (and human) way out and feel victimized by statistical ignorance, especially as used in American managerial processes. Treading a fine line, I have tried to present information in a way that would stimulate your realization that *whether or not people understand statistics, they are already using statistics.* It is my hope that you could turn any discomfort "inside out" and choose to change your behavior however you must so that your work culture can attain a more enlightened state of "data sanity." And, in the long term, despite some severely frustrating moments, everyone would ultimately win! And there's the key—changing one's own behavior. A sobering fact I have learned in my limited psychological applications: *The only person you can change is yourself!* However, can being exposed to your behavior motivate others to consciously examine their own behavior deeply and choose to do something about it? By exhibiting the behavior, you've done all you can—other people must decide for themselves...and you have absolutely no control over it.

I also have no control over how you choose to react to this publication. "Pure" logic would have kept you "safe" and virtually guarantee that you would continue (with the best of intentions) to do what you've always done—I had permission from the Statistics Division to "push" a little bit. Actually, if parts of it made you uncomfortable, *that's a very good sign.* You obviously care deeply about the use of statistics. Keep thinking about what unconscious assumptions of yours seem to be threatened. Can it motivate you to consciously change your behavior? Can you see it as empowering you not to be a victim? To paraphrase something the famous *enfant terrible* 20th century composer Igor Stravinsky once said: "You have to understand the rules before you are allowed to break them."

For my final comments, I want to describe an exercise Mr. Smith uses at the end of the Franklin Reality Model. He has us draw circles representing the various roles we play in our lives. In the middle of all this, he tells us to put a circle center of the other circles to represent ourselves. He asks us to put a number from one to ten (the higher the better) in that circle asking us to rate ourselves, individually, as a "human being." After a small wait, he challenges us if we put any number other than a "10" in that circle by saying, "The good Lord didn't make us to be '7s,' '8s,' and '9s."

My friends, you are ALL "10s." If you felt challenged by any of this material, that's good. I'm not implying that anyone's a "bad" person (You are all "10s."), but it may be necessary to choose some different behaviors for the good of yourself, your co-workers, and your organization.

Good luck and best wishes…

Davis Balestracci is a Statistical Specialist for HealthSystem Minnesota, reporting to the Chief Executive Officer. From 1985-1991, he worked for 3M during which time he won two corporate quality awards and two process technology awards for his innovative use of statistical methods. Since 1989, he has focused on adapting the quality improvement model used in manufacturing to the business management and service industries. Davis has a BS degree in chemical engineering and an MS degree in statistics.

BIBLIOGRAPHY

Andell JL. "Confessions of a Shot Messenger". *Journal for Quality and Participation.* January / February 1996.
[Ever try to implement this statistical "stuff" and get "shot" doing it? Some good suggestions to minimize the probability]

Anscombe, F.J., "Graphs in Statistical Analysis". *American Statistician.* **27, 17-21** (1973)

Balestracci D & Barlow J. *Quality Improvement: Practical Applications for Medical Group Practice, 2nd Edition.* Englewood, CO. Center for Research in Ambulatory Health Care Administration (CRAHCA), 1996. Phone: (303)-397-7888 to order. The book is also available through Quality Press.
[Despite the title, I did not write exclusively for a health care audience. People from many different fields have given feedback that the book shows how to integrate Statistical Thinking into everyday work and use it as motivation for organizational transformation]

Bennett, R et al. *Gaining Control.* Salt Lake City, UT: Franklin Quest Co., 1987.
[A text with more detail on the Franklin Reality Model]

Berwick DM. "Controlling Variation in Health Care: A Consultation From Walter Shewhart." *Medical Care.* 1991; 23(12).
[Applies Nolan / Provost (see below) variation paradigm to medicine…Eye opening!]

Brown MG. "Is Your Measurement System Well Balanced?" *Journal for Quality and Participation*. October / November 1994.
[Outstanding paper with a survey to determine organizational data needs]

Butler RS. "On the Failure of the Widespread Use of Statistics." *AMSTAT News.* March 1998.
[Gulp hard and see why the tone of my publication has an air of urgency about it]

Couch JM. "Quality Turf Wars." *Quality Digest.* October 1997.

Deming WE. "What Happened in Japan?" *Industrial Quality Control.* August 1967.
[One of the more readable Deming papers that puts statistical methods in an organizational improvement context]

Executive Learning Inc. Brentwood, TN: Executive Learning Inc. (call 1-800-929-7890 for preview & purchasing information).
[This is an excellent source for training materials for statistical tools. They have both "health care" and "manufacturing" versions]

Frances AE and Gerwels JM. "Building a Better Budget." *Quality Progress.* October 1989.
[Want to shake things up? Suggest using this simple and brilliant paper for doing your organization's next budget]

Franklin International Institute, Inc. *Gaining Control "The Franklin Reality Model"* (video). Salt Lake City, UT: Franklin International Institute, Inc., 1990. (call 1-800-654-1776)
[If you want a practical model for understanding human behavior and motivating change, there is no better video. This is a consistent class favorite.]

Grinnell JR. "Optimize the Human System". *Quality Progress.* November 1994.
[The hidden human behavior issues behind a quality transformation. Hint: It's more than "tools"]

Hacquebord, H. "Health care from the perspective of a patient: Theories for improvement." *Quality Management in Health Care.* 1994, 2(2)

Hare LB et al. "The Role of Statistical Thinking in Management." *Quality Progress.* February 1995.

Joiner Associates, Inc. *Fundamentals of Fourth Generation Management* (video series). Madison, WI: Joiner Associates Inc., 1992. Free preview cassette available. Call 1-800-669-TEAM to get on mailing list. Excellent resources.
[Outstanding video series in a Statistical Thinking format. I use it for my quality transformation class]

Joiner B. *Fourth Generation Management: The New Business Consciousness.* New York, NY: McGraw-Hill, Inc., 1994.
[Deming's philosophy integrated into everyday work. Reads like a novel]

Kerridge, D. "Dr. Deming's cure for a sick system." *Journal for Quality and Participation.* December 1996.
[Is your organization obsessed with "costs?" Maybe you should consider addressing "confusion," "conflict," "complexity," and "chaos" first]

Massey M. *Flashpoint! When Values Collide!* (video). Boulder, CO: Morris Massey Associates, Inc.
[If you want to motivate honest discussion in your culture, this and the next video will do it! These will make many people "uncomfortably warm," yet, trust me, they will be willing to talk about it. This is somewhat similar to the Franklin Reality Model, but "turns up the heat" several (hundred!) degrees. Call 1-800-346-9010 for preview and purchase information)]

Massey M. *Just Get It!* (video). Boulder, CO: Morris Massey Associates, Inc.
[Call 1-800-346-9010 for preview and purchase information.]

McCoy R. *The Best of Deming.* Knoxville, TN: SPC Press, Inc., 1994.
[If you want a collection of Deming "snippets" to restore your sanity during a bad day, highly recommended]

Mills JL. "Sounding Board: Data Torturing." *New England Journal of Medicine.* 1993; 329(16).
[Exposes "PARC" analysis for precisely what it is]

Neave HR. *The Deming Dimension.* Knoxville, TN: SPC Press, Inc., 1990.
[The best overall theoretical, yet practical explanation of the Deming philosophy]

Nelson EC. "Measuring for Improvement: Why, What, When, How, For Whom?" *Quality Connection.* Spring 1995, 4(2).

Nelson LS. "The Deceptiveness of Moving Averages." *Journal of Quality Technology.* April 1983.

Nolan TW and Provost LP. "Understanding Variation." *Quality Progress.* May 1990.
[A virtual "must read" if this publication has you wanting to learn more]

Ott ER. *Process Quality Control.* New York, NY: McGraw-Hill, 1975.
[An "old-fashioned" book with a TON of statistical "wisdom"]

Ralston F. *Hidden Dynamics.* New York, NY: AMACOM, 1995.
[*Excellent* book on change and human emotion in the workplace. I use it as a text in my second internal quality seminar and people rave about it]

Rough J. "Measuring Training From a New Science Perspective." *Journal for Quality and Participation.* October / November 1994.
[Very useful for rethinking current methods of training / education, especially related to statistics]

Turner R. "The Red Bead Experiment for Educators." *Quality Progress.* June 1998.
[If this article can't convince you that Statistical Thinking is everywhere, nothing can! Excellent demonstration of several of the "traps"]

Wheeler DJ. *Advanced Topics in Statistical Process Control.* Knoxville, TN: SPC Press, Inc., 1995.

Wheeler DJ. "Collecting Good Count Data." *Quality Digest.* November 1997.
[Don Wheeler's *Quality Digest* columns are absolute one-page "gems." Unfortunately, he no longer writes the column]

Wheeler DJ. "Description or Analysis?" *Quality Digest.* June 1996.
["Control Charts 101"]

Wheeler DJ. "46 Men and a Test." *Quality Digest*. September 1997.

Wheeler DJ. "Good Limits From Bad Data (Part II)." *Quality Digest.* April 1997.

Wheeler DJ. "Myths About Shewhart's Charts." *Quality Digest.* September 1995.

Wheeler DJ and Chambers DS. *Understanding Statistical Process Control.* Knoxville, TN: SPC Press, Inc., 1986.

Wheeler DJ. *Understanding Variation: The Key to Managing Chaos.* Knoxville, TN: SPC Press, Inc., 1993.
[If you want people to "get it," hand them one of these (or one of the "one-pagers")]

Wheeler DJ. "When Do I Recalculate My Limits?" *Quality Digest.* May 1996.
[What is this obsession people seem to have to know exactly "when" to recalculate control limits? Understand the chart first and you won't have to ask the question!]

STATISTICS DIVISION
AMERICAN SOCIETY FOR QUALITY
c/o Janice Shade
7 Sylvan Way
Parsippany, NJ 07054

Non-Profit Org.
U.S. Postage
PAID
Cedarburg, WI
Permit No. 199