Two Routes to Process Improvement

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Abstract: Having an effective model for the nature of data will inevitably identify two different paths to process improvement. One path seeks to operate a process up to its full potential while the other path seeks to operate to meet requirements. An understanding of the different techniques needed for each path is essential for successfully improving any process.

In the classroom, two plus two is always equal to exactly four. Yet when a manufacturer tries to lay down a two micron film on a two micron substrate, the result is seldom equal to exactly four microns. About the best that we can hope for is that the result will be four microns thick on the average. And this is the basic difference between *numbers* and *data*.

Numbers inhabit the mathematical plane, where 1 is always 1, and 2 is always 2, and there is no uncertainty. Here it can truly be said that two numbers that are not the same are different.

On the other hand, data belong to the real world. They are generated by some underlying process. As the process varies, the data will also vary. This variation introduces things that we never dreamed of in arithmetic. For example, when we use numbers to express our data, we suddenly find that two numbers that are different may in fact represent the same thing! So when it comes to using data, we have to understand how to deal with variation or we are liable to end up being misled or confused.

Since it is the underlying process that produces the variation, we will need a model for the structure of an underlying process in order to gain some insight into the origins of variation within our data. This paper will provide such a model.

Cause-and-Effect Relationships

No matter what your process, no matter what your data, all data display variation. Any measure you can think of that will be of interest to your business will vary over time. The reasons for this variation are many. There are all sorts of causes that have an impact on your process and the process outcomes. It is not unrealistic to think that your processes and systems will be subject to dozens, or even hundreds, of cause-and-effect relationships. And this multiplicity of causes has two consequences: it makes it easy for you to pick out an explanation for why the current value is so high, or so low; and it makes it very hard for you

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to know if your explanation is even close to being right. In order to make any headway in understanding data we need to start with a discussion of these cause-and-effect relationships.

To this end we need to perform a thought experiment. Begin by thinking about any product characteristic that you are familiar with. We will call this Characteristic No. 1. Next list all of the cause-and-effect relationships that you can think of that will have an impact upon your Characteristic No. 1. In most cases you will have dozens of cause-and-effect relationships. For purposes of this illustration we will assume that you have named 21 cause-and-effect relationships. Because of these cause-and-effect relationships, we would expect the values for Characteristic No. 1 to vary about some average value in the manner shown in Figure 1.

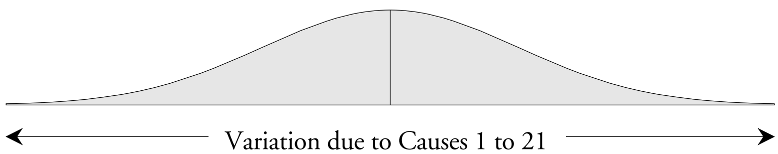

Figure 1: The Original Distribution of Characteristic No. 1

Now some of these causes will have large effects upon our characteristic, while others will have smaller effects. In Figure 2 we use bars to show the effects of each of the 21 causes upon Characteristic No. 1. As each cause varies within some range of interest the bar shows the amount by which Characteristic No. 1 varies. Thus, the height of each bar shows how much of the variation in Characteristic No. 1 can be attributed to each individual cause. With perfect knowledge about effects of each cause upon our product characteristic we could arrange these causes in order of descending impact to create the Pareto diagram shown.

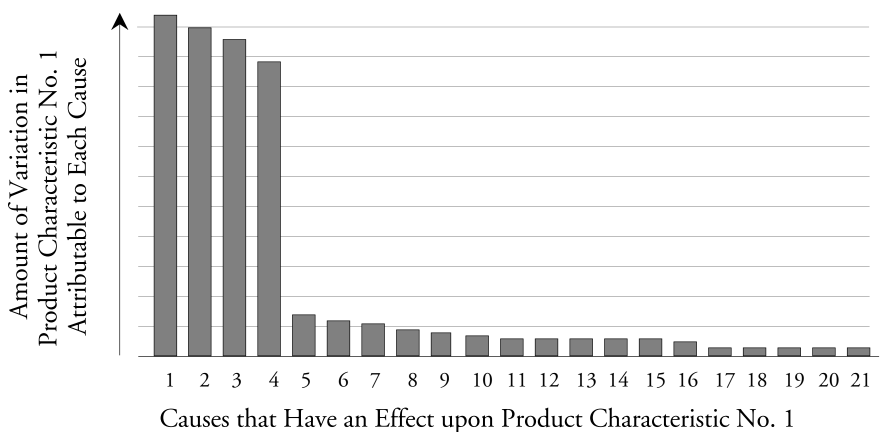

Figure 2: A Pareto Diagram of Causes and Their Effects for Characteristic No. 1

In Figure 2 it is the causes with the large bars (the dominant causes) that will provide the greatest leverage for changing the average value of the product characteristic. Causes with small bars will provide little opportunity to change the average product characteristic. Therefore, the producer will typically select the levels of the dominant causes to obtain the desired average level for the product characteristic.

Moreover, when the levels for the dominant causes are held constant these causes will no longer contribute to the variation in the product characteristic. Here, Causes 1, 2, 3, and 4 account for 79% of the total variation in the product characteristic while Causes 5 through 21 account for the remaining 21%. By controlling the levels of Causes 1, 2, 3, and 4 the producer not only determines the average value for Characteristic No. 1, but also eliminates 79% of the variation in the product characteristic. This can be seen in Figures 3 and 4.

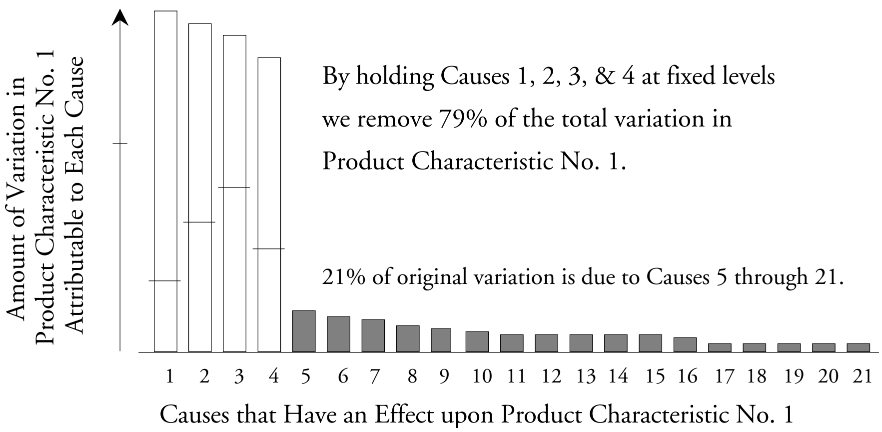

Figure 3: An Economic Production Process for Characteristic No. 1

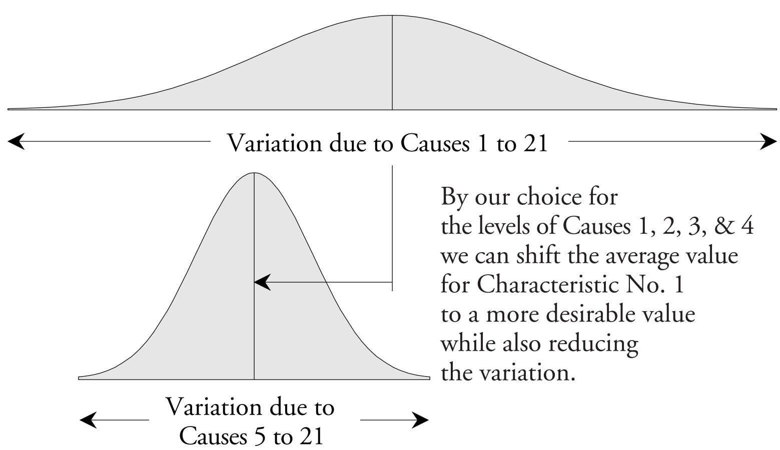

Figure 4: The Effects of Controlling Causes 1, 2, 3, & 4 for Characteristic No. 1

Because of the way variation works, the 21% of the variance that remains in Figure 3 shows up in Figure 4 as a distribution with a spread that is $\sqrt{0.21} = 0.458$ or 46% of the spread of the original distribution.

Finally, once the first four causes have been controlled it is unlikely to be economical to attempt to control any further causes. For example, Causes 5, 6, 7, and 8 only contribute 9% of the total variation in Characteristic No. 1. While it will probably cost about the same to control the second set of four causes as it does to control the first set of four causes, the payback for controlling these additional four causes will only be about one-ninth as big as it was for the first four causes. This diminishing return may be seen in Figure 5.

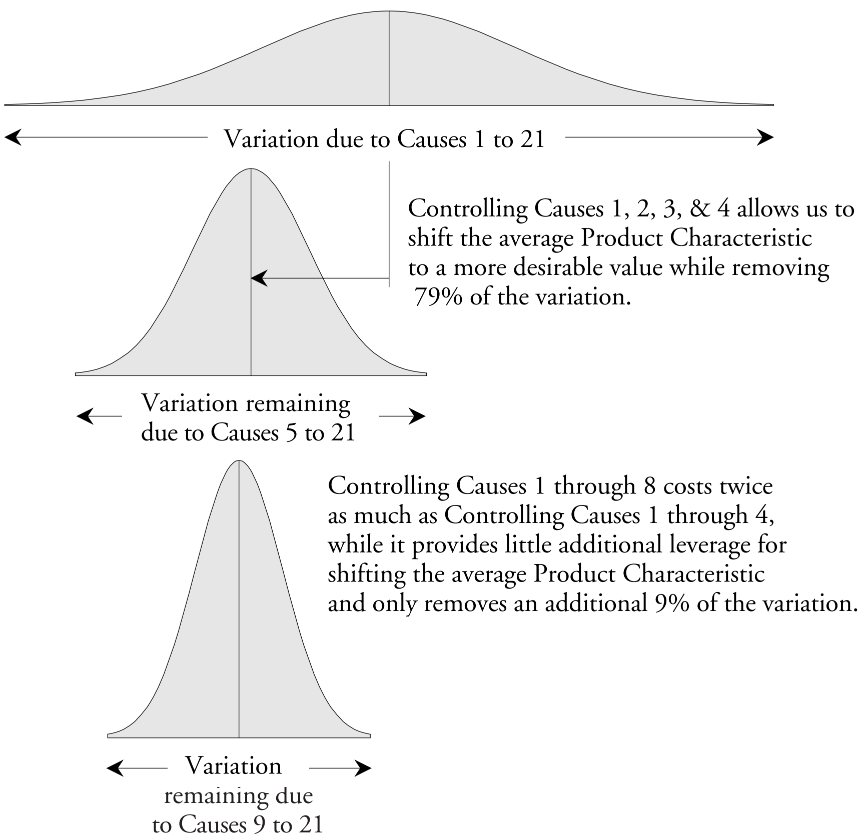

Figure 5: The Diminishing Return of Controlling Causes 5, 6, 7, & 8 for Characteristic No. 1

Economic production requires that we distinguish between those causes with dominant effects and the many causes with small effects. Controlling the levels of dominant cause-and-effect relationships is economic. Controlling the levels of other cause-and-effect relationships will not be economical.

The diminishing returns shown in Figure 5 make it unreasonable to devote resources to controlling any cause-and-effect relationships for Characteristic No. 1 beyond the first four. Thus, Causes 5 to 21 will make up the set of uncontrolled factors. It is this group that creates virtually all of the variation in the product characteristic.

Thus, the first benefit of having a conceptual model for the nature of data is that it provides a reasonable explanation for why it is not economical to try to control all of the inputs to a production process. The dominant causes are the only ones that we want to include in the set of Control Factors.

Identifying Control Factors

Of course, before we can draw the Pareto diagram of Figure 2 we will need perfect knowledge about *all* of the cause-and-effect relationships for Characteristic No. 1. In the absence of perfect knowledge, what can we do? We generally start off as shown in Figure 6 for Characteristic No. 2 and ask R&D to sort out the gaps in our knowledge. To this end R&D will need to find the amount of variation attributable to each cause. Next they will need to identify the Control Factors, and then for each of these they will need to establish the appropriate levels for these Control Factors that should be used in production.

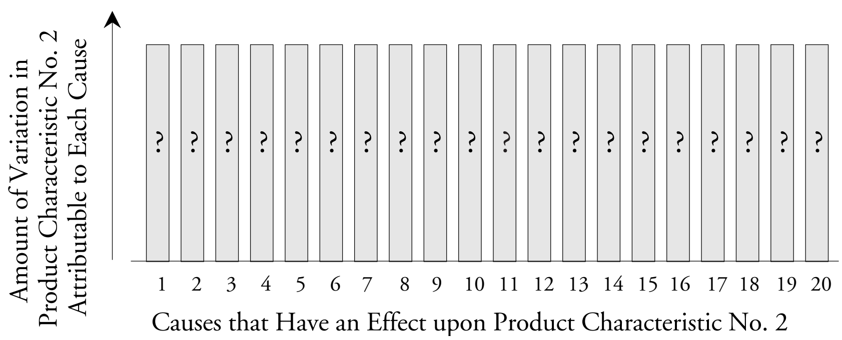

Figure 6: What We Usually Know About Causes and Effects

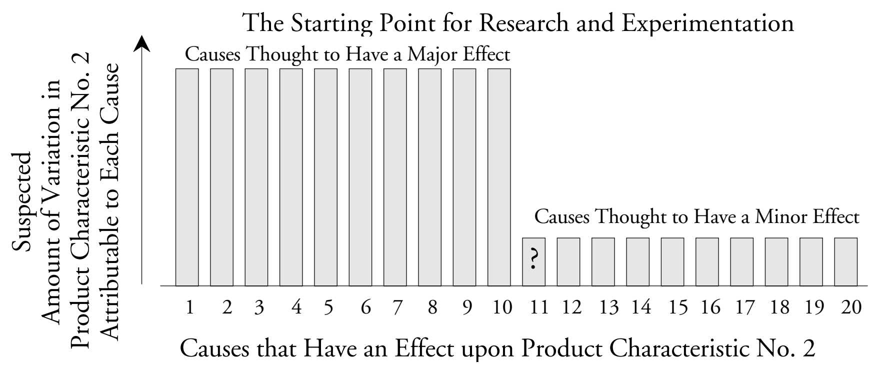

Figure 7: How R&D Chooses Which Factors to Study

Unfortunately, due to pressures of time and money, it is a rare thing for R&D to ever study all of the causes on the list. Generally they will use both theory and experience to redraw Figure 6 to look like Figure 7, and then they will tackle the cause-and-effect relationships that are thought to be the more critical (Causes 1 through 10). The remaining causes will not be studied—they will either be ignored, or randomized, or held constant during the course of the experiments performed by R&D.

Figure 8 shows the results reported by R&D for Characteristic No. 2. Among the ten causes studied they found Causes 5, 1, and 7 to be the dominant factors, collectively accounting for 77% of the variation observed by R&D. Thus, they told the Production Department that they needed to control Causes 5, 1, and 7, and they also defined the appropriate levels to use with each of these Control Factors.

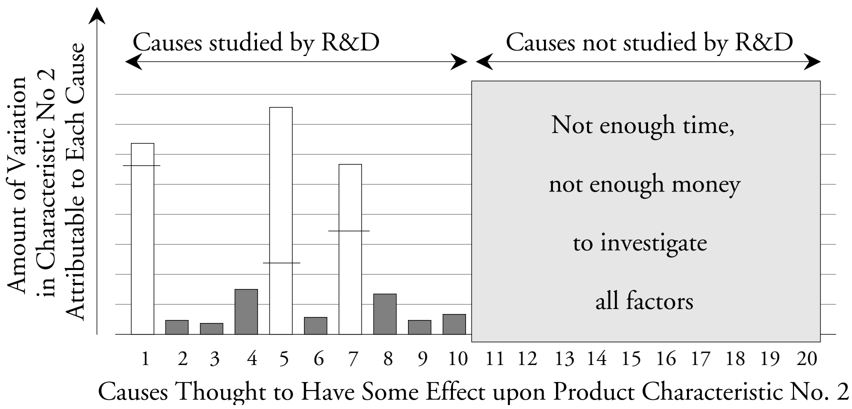

Figure 8: Causes Used to Control Characteristic No. 2

So the production process was set up using Causes 5, 1, and 7 as Control Factors for Characteristic No. 2. However, at the start of production they immediately had problems with too much variation in Product Characteristic No. 2. This resulted in a high scrap rate. So they decided to also control Cause 4. While this cost extra money, it was expected to remove an additional 6% of the variation found by R&D. Unfortunately, as seen in Figure 9, controlling Cause 4 had virtually no impact upon the process outcomes.

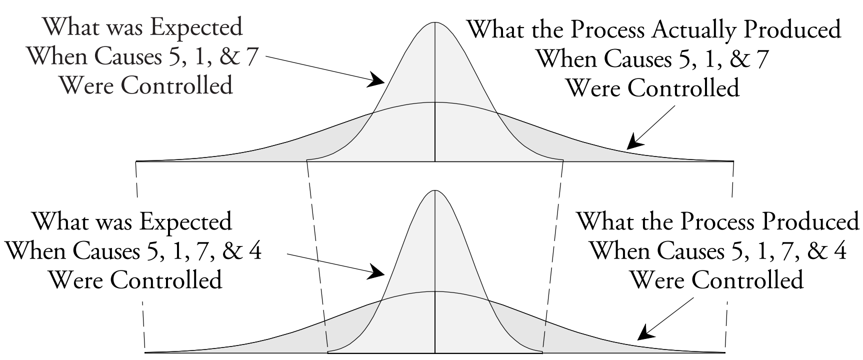

Figure 9: Expected and Observed Outcomes for Characteristic No. 2

As they fell further and further behind the production schedule, and as the mountain of scrap and rework increased, they began to talk about the "skill" that it took to make this product. Words like "art" and "magic" were used. Inspection and rework facilities were expanded, and soon the production department had settled down to a routine that W. Edwards Deming called the Western approach to production—"burn the toast and scrape it."

Of course, the problem was not with the set of Control Factors—by virtue of their being controlled these causes ceased to be sources of variation for the product stream. Likewise the problem was not with the other six causes studied by R&D—these causes all had small effects upon Characteristic No. 2. Nothing was wrong with the information provided by R&D, except that it was incomplete—the problem was with the factors *not* studied by R&D.

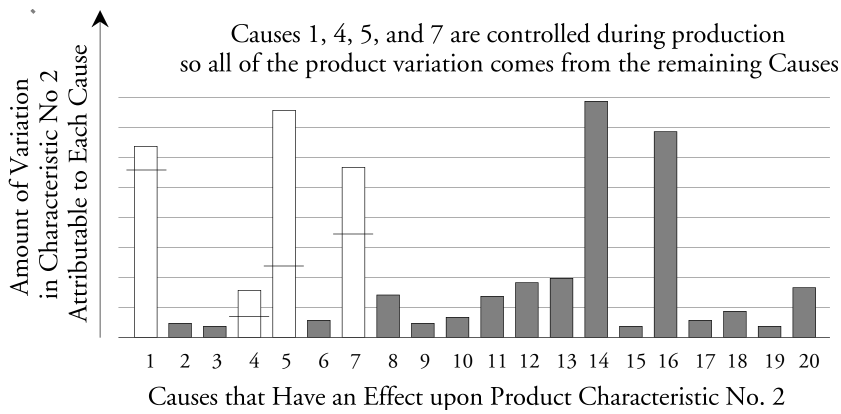

Figure 10: The Rest of the Story for Characteristic No. 2

As seen in Figure 10, Causes 14 and 16 are dominant cause-and-effect relationships for Characteristic No. 2. They are as big, or bigger than Causes 5, 1, and 7. But they were not studied. Although the manufacturer was not aware of the impact of Causes 14 and 16, the process continued to be under their influence. Since Causes 14 and 16 had not been studied, and were *thought* to be part of the lesser causes back in Figure 7, the manufacturer was not exerting any control over the levels of these two factors. As a result, when the levels of either one of these causes changed, it would result in a corresponding change in the product characteristic. While the manufacturer remained unaware of impact of Causes 14 and 16, he still suffered the consequences of their effects.

So while Causes 5, 1, and 7 need to be in the set of Control Factors, the producer also needs to have Causes 14 and 16 in the set of Control Factors as well. Having Cause 4 in the set of Control Factors is a mistake caused by the incomplete information provided by R&D.

Assignable Causes and Common Causes

If we use the Pareto principle to organize the uncontrolled factors of Figure 10 we end up with Figure 11. There we see that the set of uncontrolled factors contains two dominant cause-and-effect relationships. Such dominant but uncontrolled causes were called Assignable Causes by Walter Shewhart. The group of remaining, lesser uncontrolled factors were called Common Causes by W. Edwards Deming. Thus, we have three types of cause-and-effect relationships: Control Factors, Assignable Causes, and Common Causes. Each of these three types of cause-and-effect relationships plays a different role in how the process behaves over time.

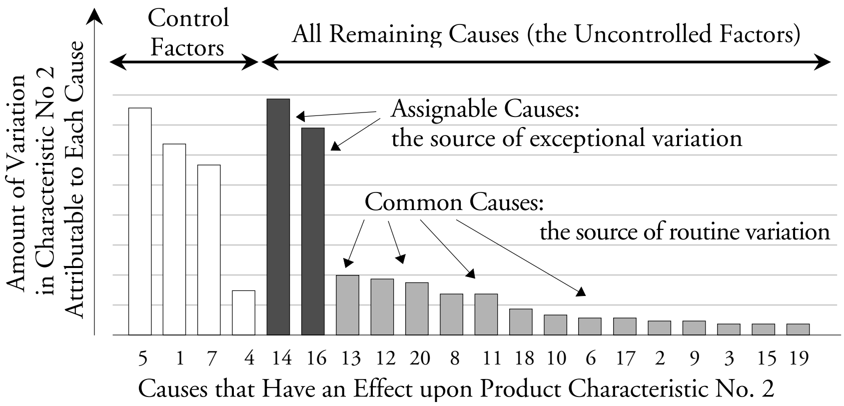

Figure 11: Three Types of Cause-and-Effect Relationships

The levels of the Control Factors used to operate the process will determine a baseline value for the average level for the product characteristic. The fact that the levels of the Control Factors are fixed means that they contribute little or no variation to the process.

Virtually all of the process variation will come from the set of uncontrolled factors. Because of their dominant effects, changes in the levels of the Assignable Causes will tend to result in noticeable changes in the process average. Over time these process changes will increase the variation displayed by the product stream. In this way, the Assignable Causes will typically be the dominant source of variation in the product stream.

Table 1: The Roles of the Three Types of Cause-and-Effect Relationships

Control Factors:	The fixed levels of these factors determine a baseline value for the process average.
Assignable Causes:	Changes in level can cause changes in the process average, which result in the bulk of the variation in the Product Stream.
Common Causes:	Large number of causes, each with a with small effect, will move values around, but will have no noticeable effect upon the process average. These small effects result in the remainder of variation in Product Stream.

Because of their lesser effects, and due to their greater numbers, changes in the levels of the Common Causes will tend to cancel each other out. Individual observations may be displaced, but the overall process will show little change except for the variation introduced by all of these small changes. In this way, the Common Causes will create the remainder of the variation in the product stream.

As a result of these three types of cause-and-effect relationships, a process like that in Figure 11 will behave erratically over time, and might be pictured in the manner shown in Figure 12.

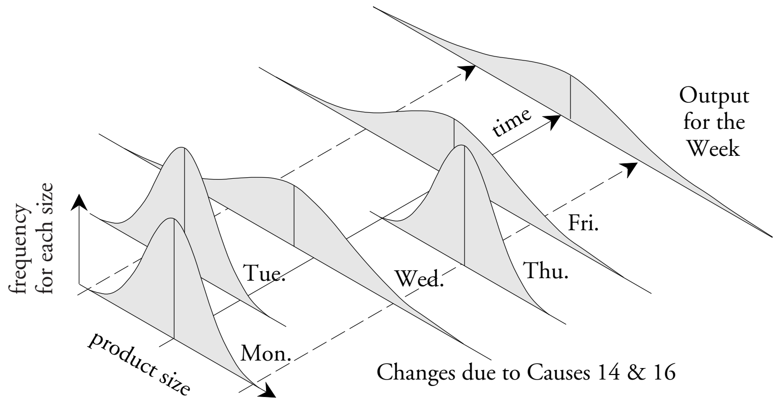

Figure 12: A Process Subject to Assignable Causes will Behave Erratically Over Time

This is why *effort spent trying to fine tune the Control Factors will be of marginal benefit as long as there are Assignable Causes present.* It does not matter what levels of Factors 5, 1, 7 and 4 we choose to use as long as we are doing nothing about Factors 14 and 16! The variation introduced by the Assignable Causes will more than obliterate any fine tuning of the average level we might achieve by adjusting the Control Factors.

You cannot optimize any system
when some of the dominant cause-and-effect relationships remain unidentified.

When the set of uncontrolled factors contains Assignable Causes, it will be worthwhile to identify those Assignable Causes and take steps to make them part of the set of Control Factors. By doing so we will be removing a major chunk of the variation in the product characteristic, while, at the same time, gaining added leverage for controlling the average level of the product characteristic. For this reason, effort spent in identifying Assignable Causes will have a high payback and should always be given priority.

But how can we separate Assignable Causes from Common Causes? This is where Observational Studies come in. Unlike Experimental Studies, where a few selected factors are manipulated to determine their effect upon a product characteristic, Observational Studies look at how the process behaves over time *while it is under the influence of all of the cause-and-effect relationships.* If the process displays erratic behavior like that shown in Figure 12, then it is likely that one or more Assignable Causes are present. And the technique for deciding whether the process is erratic or consistent is the Process Behavior Chart.

Process Behavior Charts separate the routine variation of the Common Causes from the exceptional variation of the Assignable Causes by using limits to define the bounds of routine variation. When points fall outside these limits they are interpreted as signals of the presence of Assignable Causes. By investigating the context for such points we can discover the nature of the Assignable Causes affecting our process. As we take steps to control these Assignable Causes we will remove their variation from the product stream while gaining added leverage for adjusting the process average. At some point we will reach that state shown in Figure 13 where there are no more dominant cause-and-effect relationships in the set of uncontrolled factors.

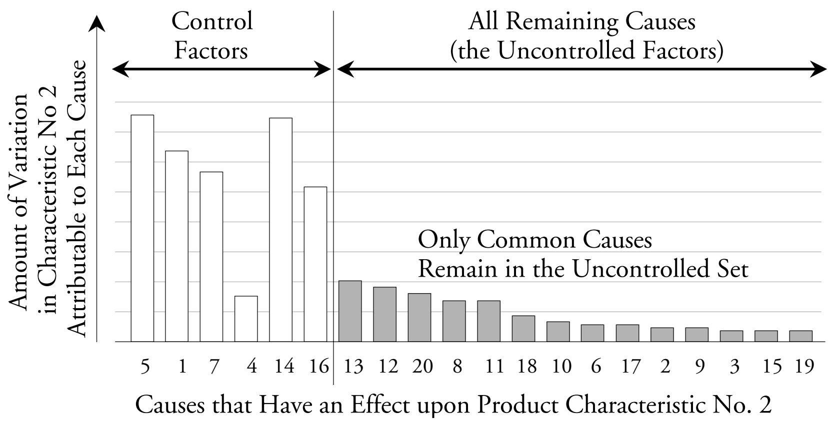

Figure 13: A Process Operating at Full Potential

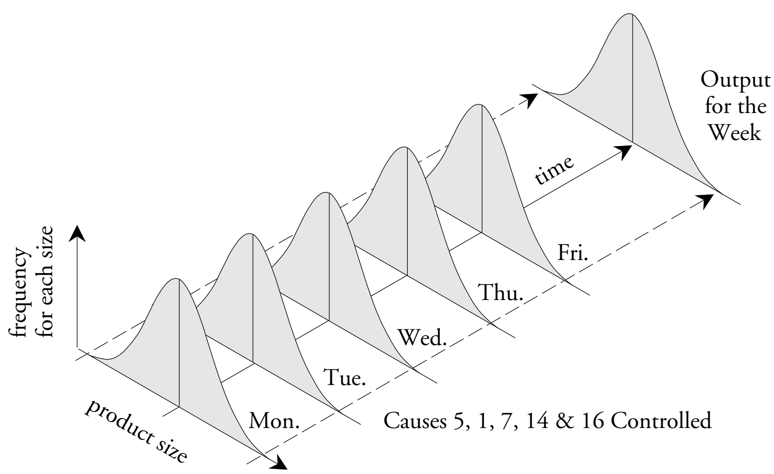

Figure 14: In the Absence of Assignable Causes the Process Will Behave Predictably

When, as in Figure 13, the set of uncontrolled factors contains nothing but Common Causes, the variation in the product characteristic will be the result of *many different cause-and-effect relationships where no one cause-and-effect relationship is dominant*. The resulting process variation will be that routine, run-of-the-mill variation which is inherent in every production process. At this point the product stream should look like the one shown in Figure 14.

Seeking to identify and control Common Causes is a low-payback strategy. When all of the dominant causes are contained in the set of Control Factors, you will have reached an economic limit on finding and removing causes of variation. At this point of economic equilibrium the product stream will have the greatest degree of uniformity that is consistent with economic production. Controlling Common Causes will be uneconomical. The process will be operating at full potential and the product stream will be predictable over time.

Thus, by providing a mechanism for separating the Assignable Causes from the Common Causes, Process Behavior Charts become the locomotive for moving a process to the point of operating at full potential. They provide an operational definition of an Assignable Cause, and they allow us to judge whether a process is or is not operating with minimum variance.

What About Meeting Requirements?

When a process is operated predictably as shown in Figure 14, it will have cause-and-effect relationships like those shown in Figure 13. Such a process will be operating at a point of economic equilibrium. It will be operating at full potential, and it will have the minimum amount of variation that is consistent with economic production. However, none of these properties will guarantee that the process will meet requirements.

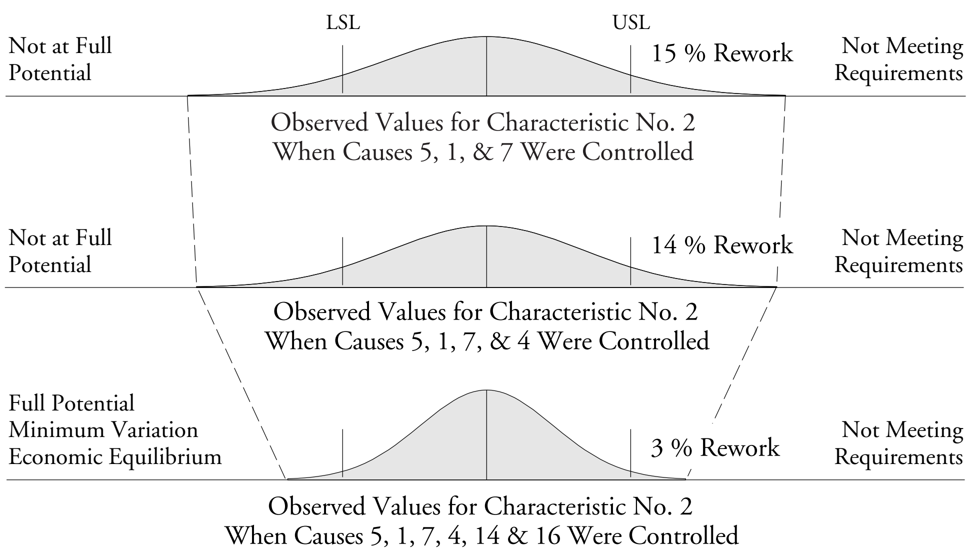

Figure 15: Outcomes for Characteristic No. 2 Corresponding to Figures 8, 10, and 13

As shown in Figure 15, a point of economic equilibrium may be less than perfect even though it may be the best we can expect to achieve without changing the process in some major way. In order to achieve greater consistency for Characteristic No. 2, and to thereby eliminate the 3% rework, we will have to upgrade or reengineer this production process. This will typically require the introduction of new technology, new equipment, new procedures, or new materials into the process. *And when we do this we are effectively adding new cause-and-effect relationships to our list.* Of course, with these new factors to consider, we end up returning to the Starting Point for Research shown in Figure 7. While we may have partial knowledge about our upgraded process, we will still have to learn how the new cause-and-effect relationships fit in with the original set of cause-and-effect relationships in order to once again select the dominant causes for our set of Control Factors.

Thus, as shown in Figure 16, when we upgrade or reengineer a predictable process we are changing the set of cause-and-effect relationships and returning to the Starting Point for Research. Experimentation will be required in order to begin to identify the new Control Factors and their appropriate levels for production. However, Experimental Studies will only provide information about some of the cause-and-effect relationships. It will tell us nothing about those cause-and-effect relationships that are not included in the experiment.

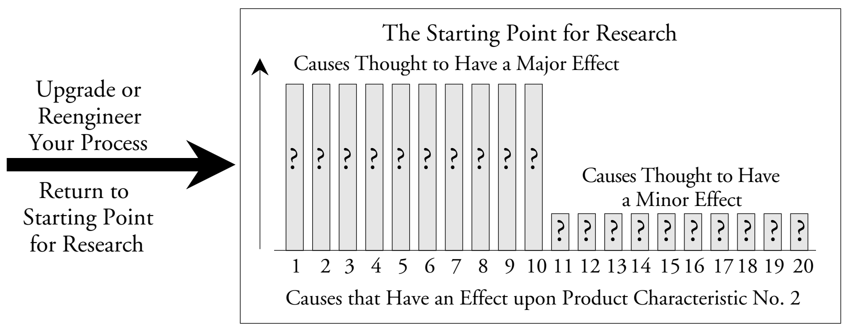

Figure 16: The Effect of Reengineering a Process

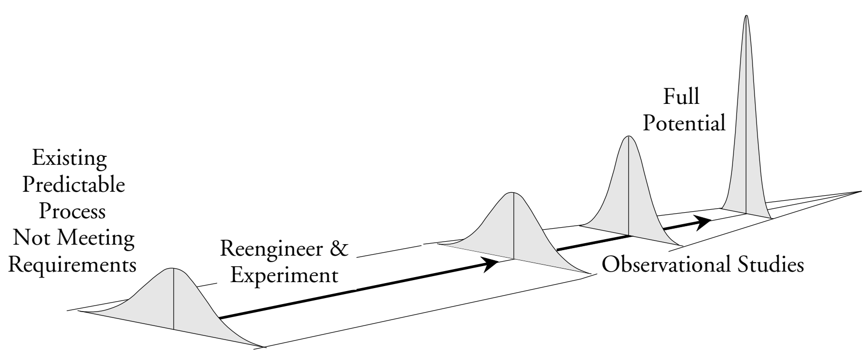

Figure 17: Reengineering and Operating at Full Potential

Therefore, before a reengineered process can be operated up to its full potential an

Observational Study will be required. As Assignable Causes are identified and made part of the set of Control Factors, the reengineered process will move toward its point of economic equilibrium with the resulting reduction of variation that inevitably follows.

On the other hand, trying to reengineer an unpredictable process will simply add to the chaos. As long as the process is subject to Assignable Causes it will do no good to work on manipulating other factors. Reengineering is premature. If you have not learned how to get the most out of your current process, what makes you think that you will be able to get the most out of a new process? Operating a process up to its full potential is a discipline. It has to be practiced. It cannot be installed or implemented. While it is important to operate to meet requirements, operating at full potential is a key element in meeting requirements in an economic manner.

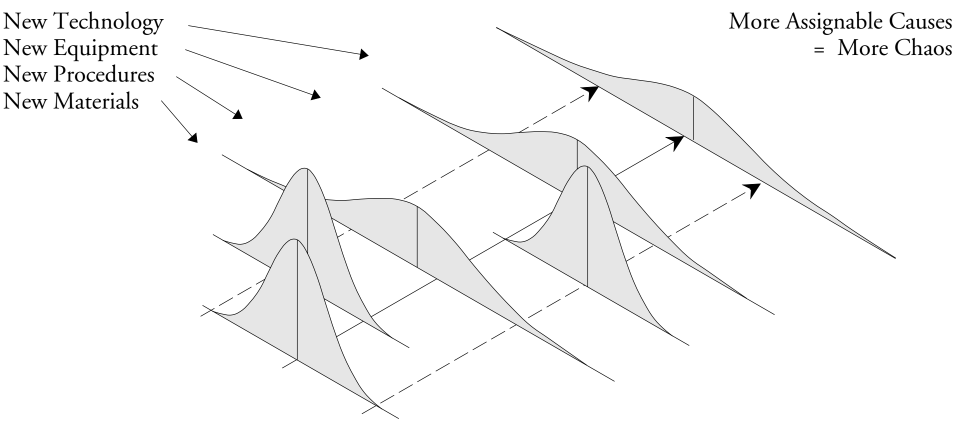

Figure 18: Reengineering an Unpredictable Process

The Fork in the Road to Process improvement

Everyone understands the need to meet requirements. If the specifications given by the customer are not met, then the customer may go elsewhere. This economical imperative is clear, yet the way to achieve this objective is hardly ever clear. Conventional wisdom tells us to upgrade our bad processes. Of course the time, trouble, and expense of reengineering a process will make this path one that we will avoid whenever possible. Fortunately, conventional wisdom also tells us to leave things alone as long as the outcomes are satisfactory. Thus, the trouble associated with reengineering and the conventional wisdom about when to work on a process will combine to create alternating periods of benign neglect and intense panic. And the changeover from neglect to panic will usually coincide with an increase in the percentage of nonconforming product.

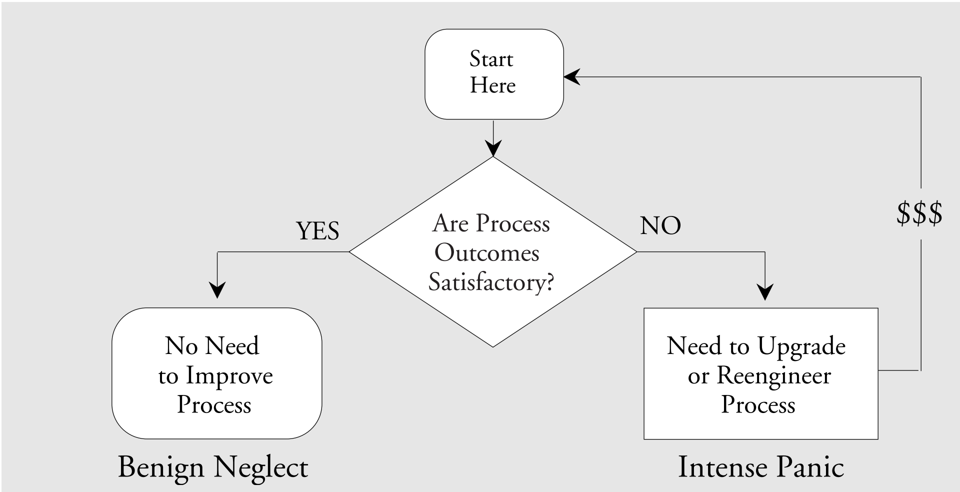

Figure 19: Conventional Wisdom About Process Improvement

As a consequence, the conventional approach to improvement is to live with our existing process as long as possible, and then, in an atmosphere of panic, to seek to reengineer the process to the point where we are no longer in trouble. Money is spent on technology, equipment, and experiments until the percentage of nonconforming product drops. Then, regardless of whether or not the technology, equipment, or experiments had anything to do with that drop, the new status quo becomes the existing *process du jour*.

However, by considering the nature of data, we have discovered a second route to process improvement. This second route does not require expensive experiments, new technologies, or new equipment. It can be used at any time by the existing personnel. It consists of using Process Behavior Charts to evaluate Observational Studies. This approach will allow you to get the most out of your existing process. Typically, the process variation can be reduced by 50% to 80%. Moreover, these reductions turn out to be effectively free due to the high payback associated with finding Assignable Causes and making them part of the set of Control Factors.

Process Behavior Charts may be used to evaluate Observational Studies on any type of process. They can be used whether the existing process is being operated predictably or unpredictably. Moreover, whenever a process is reengineered, Process Behavior Charts will complement and complete the Experimental Studies and will help in fine tuning the upgraded process.

Thus, there is a time and place for Observational Studies and a time and place for Experimental Studies. Both are needed, but you need to know how and when to use each approach. This means that there is a fork in the road to process improvement, and the fork you need to take will depend upon what type of behavior your process displays.

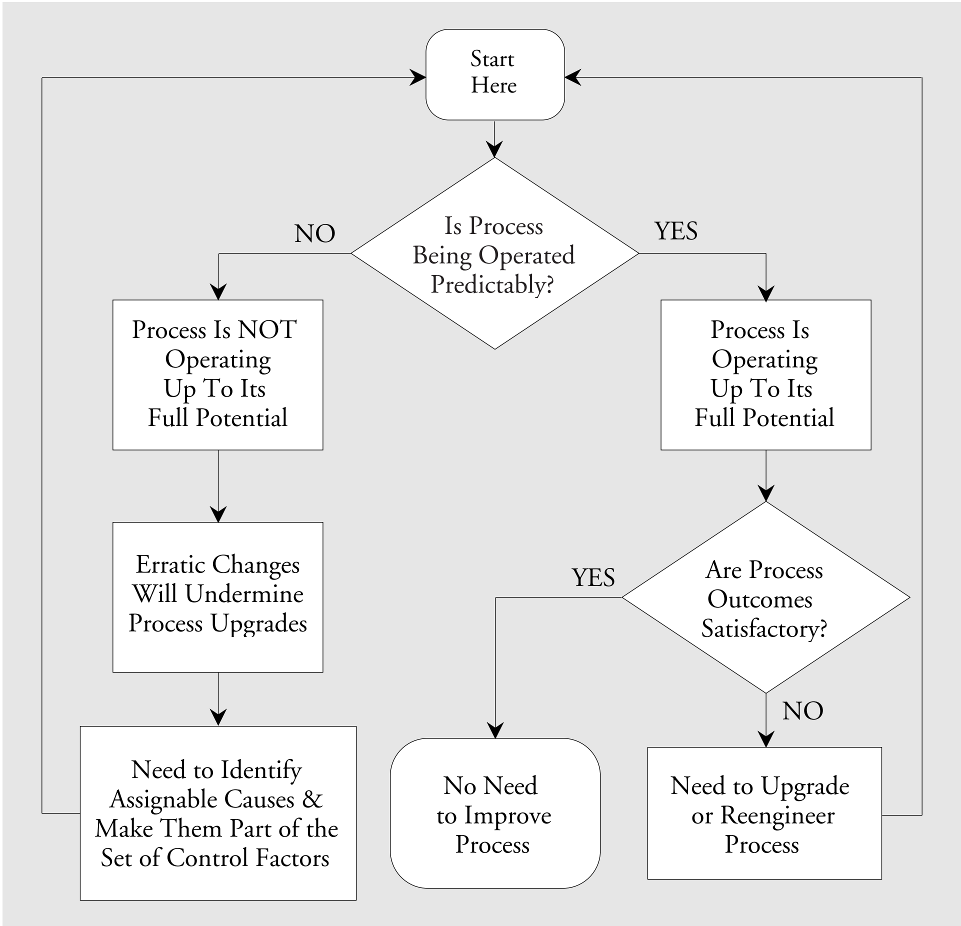

Figure 20: The Fork in the Road to Process Improvement

If your process is being operated predictably, then your process is operating at full potential and the conventional wisdom will be correct and appropriate. However, if your process is not being operated predictably, then it is not operating at full potential, and you will need to identify the Assignable Causes and make them part of the set of Control Factors. As shown in Figure 20, if you pick the wrong improvement strategy, your efforts are likely to be wasted. Upgrading an unpredictable process is a waste of time and effort, while looking for root causes of variation in a predictable process will lead to frustration. And the only way to answer the question at the fork in the road is to use a Process Behavior Chart.

Since it has proven to be easier and cheaper to operate existing processes up to their full potential than it is to upgrade and reengineer processes, any attempt to discuss process improvement that does not take advantage of Process Behavior Charts to operate processes predictably is inherently flawed and incomplete.

Shewhart's fundamental observation that some processes are operated predictably, while others are operated unpredictably, is demonstrably true. It has been proven over and over again. Ignore this fact of life and your process improvement efforts are likely to be ineffectual.

Summary

Process Behavior Charts and Observational Studies allow you to identify Assignable Causes so that you can make them part of the set of Control Factors and thereby operate a process up to its full potential. They allow you to work with existing processes, and they allow you to polish new or upgraded processes.

When adding new elements to a process as part of a process upgrade, or when designing a new process, Experimental Studies allow you to examine the impact of selected factors upon a product characteristic. However, our model for the nature of data tells us that trusting in the results of a series of Experimental Studies can never be completely satisfactory. Experiments are very successful at answering specific questions and confirming suspected relationships. They are of limited utility when we do not know what questions to ask.

The very nature of an experiment demands that we study some relationships while ignoring other relationships. For this reason, what we learn from experiments is likely to be true, but it is also likely to be incomplete. Thus, our model for the nature of data tells us that we need to complement and complete the results of any Experimental Study by using an Observational Study. For it is only with an Observational Study that we learn what our process does while *all* of the cause-and-effect relationships are present. This is the only reliable way to determine if our process contains any Assignable Causes like Factors 14 and 16. Observational Studies are a necessary step in learning from the process data and in developing a complete understanding of our processes.

The third, and perhaps the most important, implication of our model for the nature of data is that we should start any investigation of an existing process with an Observational Study. If we try to adjust, improve, or optimize an existing process without first checking for the presence of Assignable Causes we may end up playing with less than a full deck. As a result we may find ourselves erroneously adjusting the level of Factor 4 rather than working to remove the effects of Factors 14 and 16.

Thus, in addition to the tools and techniques that allow us to analyze experimental data, we will also need a way to analyze data from Observational Studies. And the primary tool for the analysis of Observational Studies is the Process Behavior Chart. Process Behavior Charts provide the only path to operating at full potential.