A DMAIC Makeover

In 50 Words Or Less

- Define, measure, analyze, improve and control (DMAIC) is about process improvement, so start with by finding the process measure.
- Move data collection into the define phase, and monitor the right control chart.
- Add a detailed process map and discover opportunities for new data collection in the measure phase.

by Rip Stauffer

Enhance Six Sigma by setting project baselines at the beginning

DEFINE, MEASURE, ANALYZE, improve and control (DMAIC) is the common roadmap for Six Sigma projects. There are a number of variations, but most use the same sequence of major steps and a fairly standard set of deliverables at each phase.

But there are potential weaknesses in this roadmap that could be addressed with a simple, proven adjustment to DMAIC. A case study describing the effectiveness of this adjustment can be found in the online sidebar "Data Collection Case Study" at www.qualityprogress.com.

DMAIC is a phase-gated project life cycle, offering a standard process that can be taught and a common language for project players. It defines expectations in each step of the project.

There are many variations of the content, but most experts will include something close to what's in ASQ's Six Sigma Black Belt body of knowledge. Each phase generally includes some or all of the following tasks and concepts:

- **Define:** chartering, project management, scoping. Some variants require that you determine progress metrics.
- **Measure:** data collection, measurement systems analysis (MSA), basic graphical methods, process mapping, central limit theorem, descriptive statistics, some distributions and capability analysis, transforming non-normal data, calculating defects per million opportunities and process sigma.

- **Analyze:** multivari studies, correlation and regression, hypothesis testing, analysis of variance, contingency table analysis and nonparametric tests.
- **Improve:** design of experiments and failure mode effects analysis.
- **Control:** statistical process control (SPC) and MSA revisited.

DMAIC in this form has proven to be a useful model for lots of improvement projects and as a basis for sequencing learning objectives in Black Belt training. A couple of inherent weaknesses, though, are based on common but often flawed assumptions.

Weaknesses of some DMAIC models

Donald Wheeler suggested some flaws in most DMAIC approaches:[1]

1. Failing to investigate what can be accomplished by operating the process up to its full potential.
2. Automatically choosing a path toward improvement that should only be taken when there is a proven need.
3. Assuming you can identify the appropriate inputs to study. When a process is operated unpredictably, it is subject to the effects of unknown, dominant, assignable causes.

The first flaw is the primary weakness. Translated, it means the failure to develop a well-defined baseline of performance in the define phase leads to problems with quantifying benefits realistically, rework in later phases and—in some cases—project failure.

So you need to agree on an answer to the question: What makes a good baseline? To answer that question, let's examine some elements of good, rigorous analysis.

Four statistical problems

If statistics as a practice is to be of any use, it has to be about insight. It's not about math practice. Confusing mathematical complexity with analytical rigor is, well, confusing. Wheeler said, "The best analysis is the simplest analysis that gives the most insight."[2]

When working in processes, an analyst should consider all of the four statistical problems described by Wheeler:

1. Descriptive statistics.
2. Probability theory.
3. Statistical inference.
4. Homogeneity.

Most statistics books and courses and most Six Sigma-related treatments of statistics thoroughly cover the first three issues while ignoring the fourth. Many references discuss statistics only in the context of enumerative studies, with an emphasis on sampling from populations. Data homogeneity is assumed, based on good, random samples from homogeneous populations. For enumerative studies of a reasonably static population, this view is often effective.

In any process improvement paradigm, however, the assumption of homogeneity is much trickier. Process improvement studies are inherently analytic studies, dealing with the cause system underlying a dynamic process. No population exists; we don't extrapolate from a sample to a population, but rather from the present to the future.

Before you can characterize a distribution, you have to know whether the data are homogeneous: Did they all come from the same universe (process)? If not, you can't say anything real about the distribution. Most tests and tools used to deal with the data are only as good as the assumption of homogeneity.

Fortunately, in process studies, there are powerful tools for checking homogeneity in data collected over time. In May 1924, Walter Shewhart sent Western Elec-

Four process states / FIGURE 1

	Some nonconforming product produced	100% conforming product produced
Process displays control	**Threshold state** • Process in control. • Some non-conforming product. • Must either: change processes or change specifications. • Sorting is only a temporary fix. • Control charts: maintain process in control and evaluate efforts at improvement state.	**Ideal state** • Process in control. • 100% conforming product. • Control charts: maintain process in control and give timely warning of any troubles. • Quality and conformance can change in a moment.
Process displays lack of control	**Chaos state** • Process out of control. • Some non-conforming product. • Assignable causes still dominate. • Random fluctuations due to assignable causes will eventually frustrate efforts at process improvement. • The only way out of chaos is to first eliminate the assignable causes.	**Brink of chaos** • Process out of control. • 100% conforming product. • All may seem OK, but assignable causes determine what is produced by the process. • Quality and conformance can change in a moment.

Source: Donald J. Wheeler and David S. Chambers, *Understanding Statistical Process*, SPC Press, 1992. Published with permission.

tric's director of inspection a memo and a sample of the first statistical control chart.[3] Shewhart's three-sigma control limits provided an economic filter defining a trade-off between finding most of the real signals and reacting to false signals. He knew that many managers react to any movement in a metric, tampering with stable systems and increasing the variation in the system.

Process control charts provide strong evidence of data homogeneity and can often be used in place of some hypothesis tests when comparing processes. These charts are, of course, used in SPC and often provide opportunities for ongoing improvement.

Unlike SPC or *kaizen*, however, Six Sigma is not about continual improvement but is about breakthrough.

What is breakthrough?

Wheeler and David S. Chambers pointed out that any process exists in one of four states and is defined by its performance in the two dimensions of a state of statistical control and its ability to meet specifications:[4]

- Chaos—neither stable nor meeting specifications.
- Brink of chaos—not stable, but meeting specifications.
- Threshold state—stable, not meeting specifications.
- Ideal state—stable, meeting specifications.

These four states (see Figure 1) should be considered in the define phase of any Six Sigma project to help answer the vital question: "Is this project worth doing?"

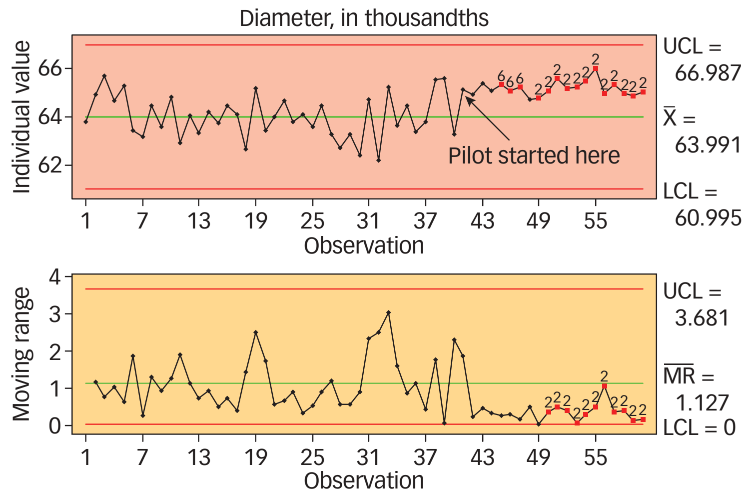
Processes on the brink of chaos or in the state of chaos will have to be stabilized before any project can start. Because you can't predict the outcomes today, you can't begin to estimate what improvements would be needed.

Processes in the ideal state might require a project to reduce variation, but those might be very costly. Economically, it makes the most sense that Six Sigma projects would be aimed at processes in the threshold state.

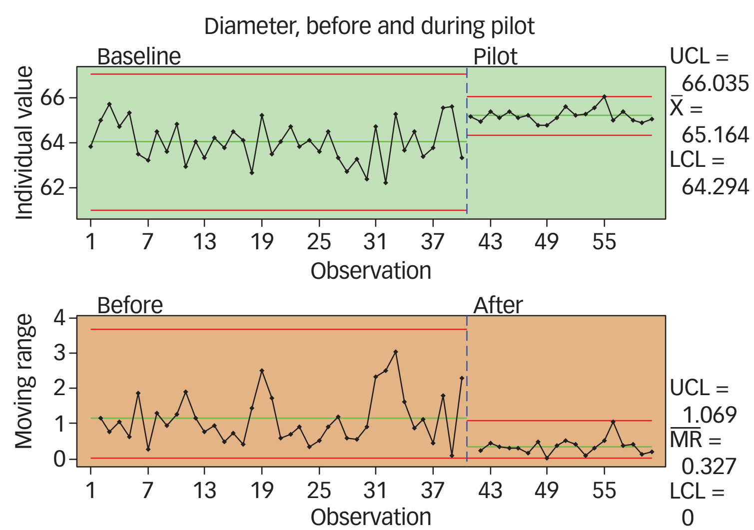
The DMAIC roadmap outlines a journey that finds and manipulates variables, seeking to change the process outcomes. Breakthrough change aims to move the performance to new levels, creating shifts in the mean and the dispersion.

This concept is illustrated in Figures 2 and 3. The mean and the average moving-range from the baseline have shifted appreciably, yielding evidence of stability around a new mean with substantially reduced variation. This shows you can't define breakthrough without the ability to separate common cause from special cause.

Breakthrough evidence / FIGURE 2



Breakthrough confirmation / FIGURE 3



UCL = upper control limit; LCL = lower control limit; MR = moving range

Therefore, one minimum requirement for the baseline of any project's progress measure is reasonable evidence of a state of statistical control. Saying, "Reduce yield loss in the production process from 10% to 1%" is meaningless if you don't know what is meant by 10%. Is it last quarter's number? A best guess from a

ONLINE CASE STUDY

Read a case study with nine more figures showing the effectiveness of the method described in this article at www.qualityprogress.com.

line worker? A monthly average? If you don't know it's been stable over time, it's just one number. The next one will probably be different. How can that be the basis for a project lasting four to six months?

If it's the average from a process displaying statistical control, however, it can be considered a coherent baseline, because you have a sound basis to estimate the range within which the process is likely to perform in its current configuration.

Thus, any performance baseline derived without regard for statistical control is suspect, providing a poor basis for project justification. In addition, the normality tests often overemphasized in Six Sigma projects are sometimes completed using sets of data that have not been checked for homogeneity. Results of such tests are irrelevant if the data come from an out-of-control process. So, when we start a project without a baseline, we have little basis for understanding the gap between current performance and desired states.

Simple change

To date, the existence of a state of statistical control has been largely undervalued in Six Sigma projects. Project baselines are sometimes set on the strength of a single number and are generally not even explored until a team is well into the measure phase of the DMAIC cycle. Training manuals and BOKs treat SPC as an afterthought—something tacked on in the control phase.

Sample projects / TABLE 1

Organization	Project	Results
Healthcare administration	Accounts receivable	$940,000 annualized savings
Healthcare administration	Accounts payable	$270,000 annualized savings
Manufacturing	Supplier quality	$1.2 million annualized savings
Investment bank	Cycle time reduction	$160,000 annualized savings
Investment bank	Call center interactive voice response penetration	$180,000 annualized savings
Manufacturing	Yield improvement	>$5 million revenue
Manufacturing	Coated film yield improvements	$8.4 million annualized savings
Manufacturing	Wood processing yield	$1.6 million annualized savings
Financial services	Hiring cycle-time reduction	$550,000 annualized savings
Manufacturing	Clean room yield	$280,000 annualized savings
Hospital	New surgical protocol adoption	Reduced from >18 months to < 3 months

My proposal is to look at this from the viewpoint of all that has been learned about data analysis since Shewhart. Let's stop assuming homogeneity in the data and start gathering evidence for it early.

DMAIC is about process improvement, so you need to find the important process measure that you want to drive into a process right up front and track it. Move the data collection and tracking for that *Y* variable into define, use an appropriate control chart and monitor throughout the project.

There are a number of advantages to this approach, including:

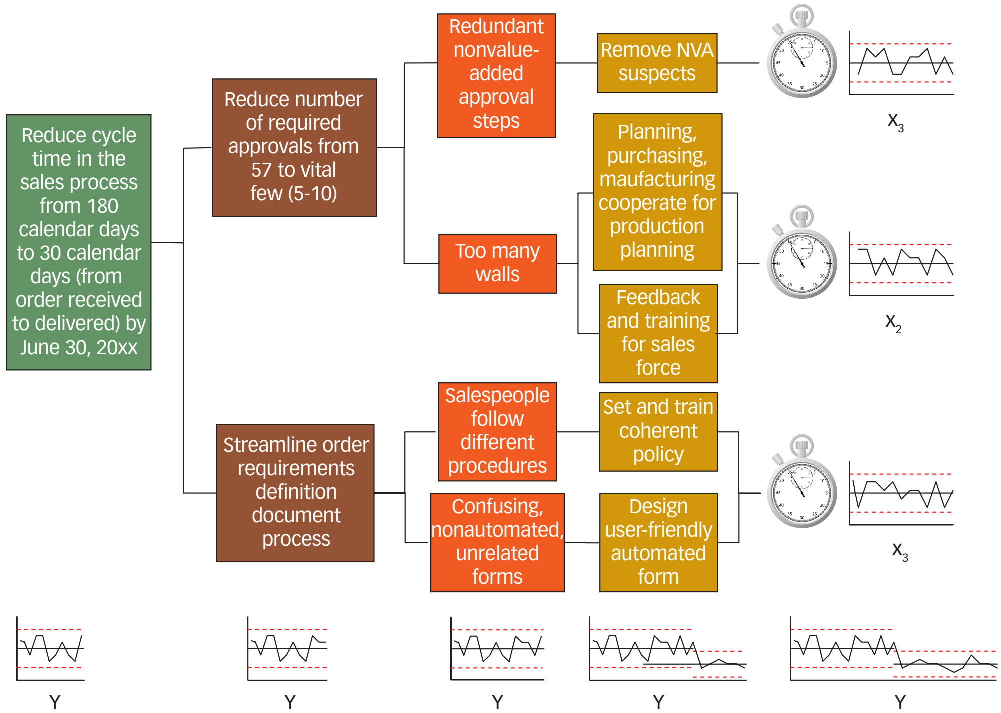
1. It's easy to prove and see results of experiments, quick hits and other actions.
2. As you move through the project, you identify and track process input variables (*x*'s). Thus, the control plan for the final improved process is built before you arrive at control.
3. There is reduction of uncertainty for tests of normality and for other hypothesis tests, usually reliant on assumptions of homogeneity.
4. Breakthrough project goals can be set rationally. A process behavior chart yields an operational breakthrough definition and an achievement benchmark.
5. There is a rational basis for project justification. The problem and its extent are quantified. You have verified there is a problem. Establishing the current state and rationally quantifying the target state should be prerequisites for sign-off on a project charter. This is why it's important to make the baseline a primary deliverable of the define phase.

What to include in measure

Because a large part of the measure phase in many current approaches is dedicated to developing the baseline, practitioners might feel that moving the baseline back into the define stage leaves the measure phase too thin. There's still plenty to do, though. For one thing, a detailed map of the process and the related discovery of opportunities for new data collection will be completed in the measure phase.

Another data-related task is stratification of the data to identify categories of interest within the structure of the baseline data. Looking at the baseline from a number of perspectives—such as using Pareto charts, box plots, histograms, control charts and hypothesis tests—focuses further efforts on the categories in which the majority of the problem dwells.

DMAIC project flow / FIGURE 4



Four perspectives proposed by Hitoshi Kume have proven quite useful for this purpose:[5]

1. **Time:** When do problems happen? Is one day each week, one shift or one week per month better or worse than others?
2. **Place:** Where do problems occur? Is one production line, plant or operator better or worse than others?
3. **Type:** What types of products or services are problematic? Do problems seem to occur more in one product line or service process than in others?
4. **Symptom:** What makes the product or service defective? Are there more blemishes? Dents? Gouges?

Of course, this is not root cause analysis. The activity of stratification occurs before root cause analysis and helps focus root cause analysis on likely strata within the data. This is a valuable activity because focusing helps shed light on real potential avenues for achieving the project goals. It's not uncommon to have team members who might have been somewhat resistant and unenthusiastic up to this point begin to gain energy and enthusiasm as they see real progress toward a path to the end.

Another advantage to this approach is that the team members now have measures—direct components of the primary progress measure—they can track at a more local level. Teams can more clearly focus root cause analysis and experimentation. A roadmap for a project might now look something like Figure 4.

This method is not an untried idea. Colleagues and I have used this model with great success in more than 200 DMAIC projects across a variety of industries (see Table 1 for a summary of some of these projects). Although it can add time to the define phase, all other phases benefit from the superior start offered by this approach. In organizations with a solid foundation of SPC for vital operational measures, it accelerates every phase of the project.

This modest change to the DMAIC method enhances the rational, scientific approach Six Sigma brings to process improvement projects. It offers a more useful operational definition for a baseline project progress measure: a solid foundation that starts with an understanding of a process's current potential helps establish the existence and boundaries of a problem and provides coherent knowledge on which to base improvement experiments. QP

REFERENCES

1. Donald J. Wheeler, *The Six Sigma Practitioner's Guide to Data Analysis*, SPC Press, 2005.
2. Ibid.
3. *AT&T Technical Journal,* March-April 1986, cited in Louis E. Schultz, Profiles in Quality, Quality Resources, 1994.
4. Donald J. Wheeler and David S. Chambers, *Understanding Statistical Process Control*, SPC Press, 1992.
5. Hitoshi Kume, *Statistical Methods for Quality Improvement*, the Association for Overseas Technical Scholarship, 1992.

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