PROCESS IMPROVEMENT

Ghosts in Your Process? Who Ya Gonna Call?

by **John Duncan**

We've all heard success stories in this magazine and across corporate America about Six Sigma programs and their positive bottom-line impacts. There is little doubt examples exist of engineers using tools to find and eliminate the root causes of poorly performing processes. And never is the success more satisfying than when the root cause or "critical x" was extremely difficult to find.

In 50 Words Or Less

- **Using Robert Traver's nine-step problem solving process in place of DMAIC uncovers hard-to-find root causes, or "ghosts."**
- **When you include data examination at the beginning of the improvement process, finding key variables can be data driven rather than intuitive.**

This is a story of how engineers uncovered very hard-to-find x's without using the usual Six Sigma methodology. Instead of the traditional define, measure, analyze, improve, control (DMAIC) process, they used Robert Traver's nine-step problem solving process.

Nine Steps vs. DMAIC

Traver proposes his nine-step process for finding root causes of manufacturing problems in his book, *Manufacturing Solutions for Consistent Quality and Reliability*.[1] As Table 1 shows, the process is very similar to the modern Six Sigma methodology. The one key difference is the point at which the multivariable study (step four) is conducted.

The multi-variable study may not even be included in your formal Six Sigma toolbox, yet this is the step when the process tells you where the root causes are located. Traver refers to these as key variables. This process differs from the traditional DMAIC steps because data are collected at the very beginning (step one) to locate the key variables, vs. the intuitive approach in DMAIC (cause and effect matrix or failure mode and effects analysis).

While DMAIC works on the measurement system, the Traver method simply forces you to quantify the data from the start. The finding of measurement problems can then be incorporated into

the multi-variable study (step four). Another difference is Traver's emphasis on validating the critical x's by turning the key variables on and off (step six). The following case is an example of a process improvement project made successful using this method.

Ghosts in the Process

My company was producing small plastic optics for a customer making barcode scanning machines, and we found our process was producing inconsistent results. The process consisted of injection molding the optical components in a two-cavity mold, degating the parts from the runner and loading them to a coater for an application of coating. The parts would then be packaged and shipped.

Two main critical-to-quality dimensions on the optics were the source of most rejects—the flatness of the optical area (measured in 10 different locations) and another optical measurement called tilt. Both measurements were done using an interferometer. Each time the mold was set to run, a different result would occur. Sometimes, one or more of these measurements would be out of specification at start-up. Other times the process would drift out of tolerance. Occasionally the process would produce a good yield on one or both cavities. The process problems that occurred from run to run or during a long production run seemed to come and go like ghosts with no apparent cause.

TABLE 1 Traver's Nine Steps vs. DMAIC

	Traver's nine steps	DMAIC phases	DMAIC tools
1	Provide focus (examine existing data).	Define	Project charter.
2	Get close to the problem.	Define	Process flowchart.
	n/a	Measure	Gage repeatability and reliability, cause and effect matrix, Pareto chart.
3	Quantify the output.	Measure	n/a
4	Run multi-variable studies.	Analyze	Failure modes and effects analysis, multi-variable study?
5	Design experiments.	Analyze	Design of experiments.
6	Turn the problem on and off.	n/a	n/a
7	Optimize.	Improve	Capability study.
8	Install process controls on key variables.	Control	Control plan.
9	Measure before and after results.	Control	Cost savings analysis.

We started a project to identify the root causes of the inconsistency and eliminate them. The following were some of the key variable hypotheses stated at the beginning of the project by the engineers and other process experts:

- Inconsistent mold cooling.
- Moving components within the mold.
- Ambient conditions, such as humidity.
- Measurement fixtures.

The engineers on the project were very familiar with the process because we were close to the problem and the output was already quantifiable (data were variable). So we began with the multi-variable study. This means we did nothing to the production process; we simply created a plan for part collection and measurement. The key was the plan must be strategically created to get the best possible picture of the process. The study was planned so all types of variation would be examined, including part-to-part, shift-to-shift, cavity-to-cavity, within piece variation (10 locations within each part for flatness) and measurement variation.

During a normal production run, we collected three parts from each cavity every four hours. This continued every day for seven days, producing 126 parts per cavity or 252 total parts for data collection. Two different inspectors measured the parts for flatness and tilt. After measurement, these same parts were coated and measured again by the same inspectors. This was very time consuming and rigorous, and, as with any Six Sigma initiative, support from management was critical. A lot of time and resources are required to do a multi-variable study at the start of a project—and to do it right.

After collecting, measuring, coating and measuring the parts again, we compiled the data. We then conducted a multi-variable study on the current production process. The results from the initial study are displayed in Figures 1, 2 (p. 54) and 3 (p.55). The data were also put into control charts and were in statistical control over time. Higher flatness numbers were the goal.

As the main effects plot in Figure 1 shows, the greatest source of variation was within piece variation—that is, between the 10 different locations across the optical area where flatness was measured. Figure 2 is a multi-variable plot, with the averages for each variable designated by markers. Each circle represents the average of that particular inspector's measurements for each location, shift and cavity. Each gray square represents the average of both operators for each location, cavity and shift. Each blue square represents the overall average for each cavity at each shift.

From this graph, some other clues were apparent. Again, the greatest source of variation was within piece (between the 10 locations on the part), but the next source of variation was measurement. The important clue was that graphically you can see inspector two measuring consistently higher flatness readings than inspector one. This allowed the process to tell us where the key variables might be.

Figure 3 is a multi-variable plot for the tilt measurement. Lower tilt numbers were the goal. From the graph, it became obvious the investigation of tilt should focus on the difference between cavities. Measurement was the next biggest source of variation. Again, the data plotted over time were in statistical control. The coating of the parts was found to have no effect on tilt or flatness.

Now, instead of intuitively shooting for key factors that might or might not turn out to be root causes, we had data from the process in their natural state, isolating the location of the key variables. The multi-variable study had put the focus where it needed to be.

FIGURE 1 Main Effects Plot—Data Means for Flatness

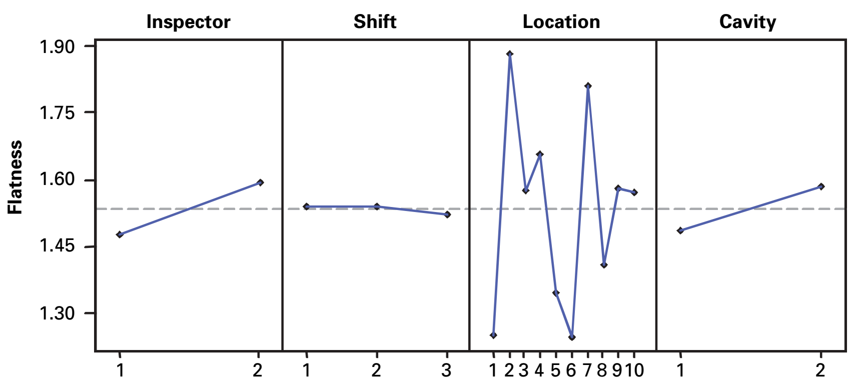
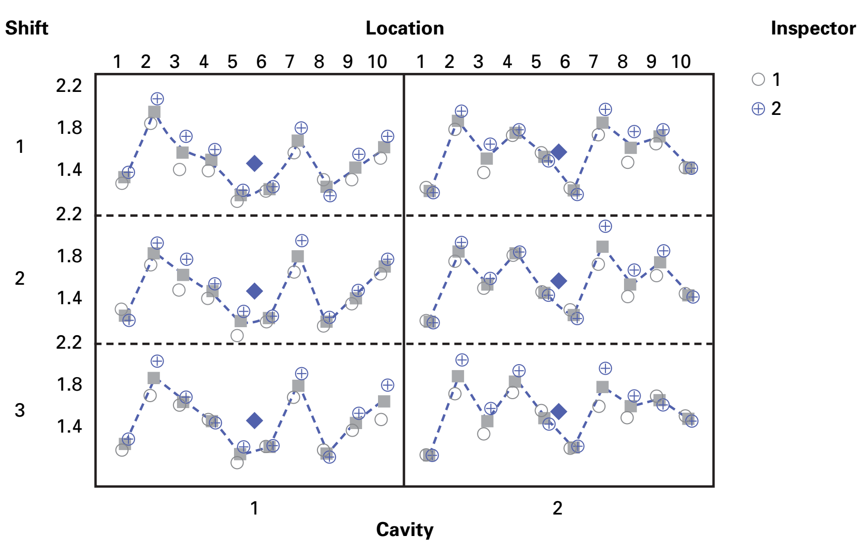


FIGURE 2 Multi-Vari Chart for Flatness by Inspector—Shift



Finding Key Variables

Following Traver's process, we were now ready to design experiments to find the key variables and, most important, turn them on and off to confirm we had identified them correctly.

The DMAIC method might have led us to focus on variation over time because of past experience. Looking for the wrong variables, we might have collected the wrong data and not seen the clues made evident by the multi-variable study.

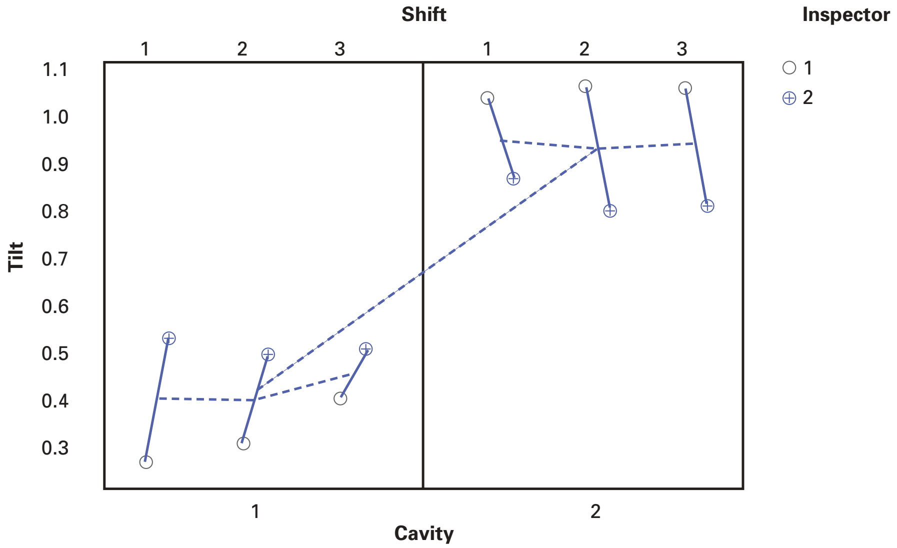
Even if DMAIC had provided the key variables, we would not have gotten the answer as efficiently as from the nine-step method. This is because a well-planned and executed multi-variable study at the start can tell you definitively where to focus in the process. This helps foster quicker

breakthroughs at the beginning of the project.

We started designed experiments with a fishbone diagram (Figure 4, p. 56). This exercise concentrated on identifying all the possible causes for cavity-to-cavity variation in tilt, variation of flatness within each part and measurement variation. We planned small experiments to attack each bone on the diagram. Whenever possible, we tested more than one item per experiment.

For this article, four of the tests will be discussed. The first quick experiment was to swap components from one cavity to the other and rerun the mold. This produced the same result—cavity two still measured higher in optical tilt—thus revealing more clues. The components in each cavity did not create the cavity-to-cavity difference. More tests revealed there was a difference between the cavities during the mold open stage of the molding process. The amount of movement in the mold while the two halves separated might have caused one cavity to distort while the other cavity was cleared and not distorted.

FIGURE 3 Multi-Vari Chart for Tilt by Inspector—Cavity



After we changed the method by which the mold was aligned from standard taper locks to a new locking method during mold open and close, the tilt difference between cavities disappeared. Was a key variable or root cause discovered? Not yet. The key variable must be validated by demonstrating it could be turned on and off. So the mold was pulled, the locking method removed and the old taper locks installed.

After we reran the test, the difference in tilt between cavities returned, and cavity two was again higher. The mold was pulled and the locking method reinstalled. After the test, the tilt difference between cavities disappeared again. These differences between runs were statistically validated using two-sample t-tests. The results are shown in Table 2 (p. 56). We had discovered a key variable.

Because the multi-variable study provided the focus where it was needed, the team was able to concentrate efforts on improving the uniformity of flatness across the optical area. This led to a new method for fabricating the actual optic pin that produced the flatness. The new method created a surface that was more uniform in the direction of optical axis. This not only improved the uniformity, but it also produced such a flat pin that all locations within the molded part significantly increased in flatness.

Again, each experimental run used the two-sample t-test with a sample size of 20 at a 95% confidence interval. The old pins were then replaced in the mold, and the flatness results dropped to previous levels. The new pin design was used again with the same good results. We had identified a key variable for flatness variation.

We saw the importance of being able to confirm key variables when we thought we had found another one. In the multi-variable chart, the pattern of flatness over the 10 locations seemed to follow the thickness of the part, which was not uniform. A new insert, which would change the part's thickness to be uniform through the entire cross section, was made for one cavity. During the next run, the cavity with the uniform thickness produced a molded optic with uniform flatness across all 10 locations. However, when the old design was reinstalled, the uniform flatness was still present. Turning the variable on and off did not seem to affect it.

That check prevented the team from making some false assumptions. Upon further investigation, it became apparent the fit between two inserts (that formed the part on one half of the mold) had a greater effect on flatness uniformity. Insert pairs that were fabricated with a better fit between them produced better and more uniform flatness than older inserts with a looser fit. This was confirmed by measuring the fit and running samples from both good and bad inserts. The variable had been turned on and off, confirming another key variable.

Again, a weakness in the typical DMAIC process is that this is not a formal part of the method. As that example showed, you can end up with a wrong conclusion without this extra validation step of turning the problem on and off.

Another improvement area was measurement, and the multi-variable study would provide the clues needed to solve the problem. The data graphed by the multi-variable chart revealed one inspector consistently measured higher flatness values than the other. We then focused on understanding why this happened.

The interferometric measurement was done by each inspector manually, setting a drawing of a mask over each area of the 10 locations on the part seen on the computer screen. There was no way to guarantee each inspector would put the mask in the same exact location; therefore, we started a project to create an automated method by which the computer would place the mask on each location. At the same time, a new leveling technique was developed for the measurement of tilt. This was a more accurate way to measure tilt and also limit the inspector's influence.

Method Proved

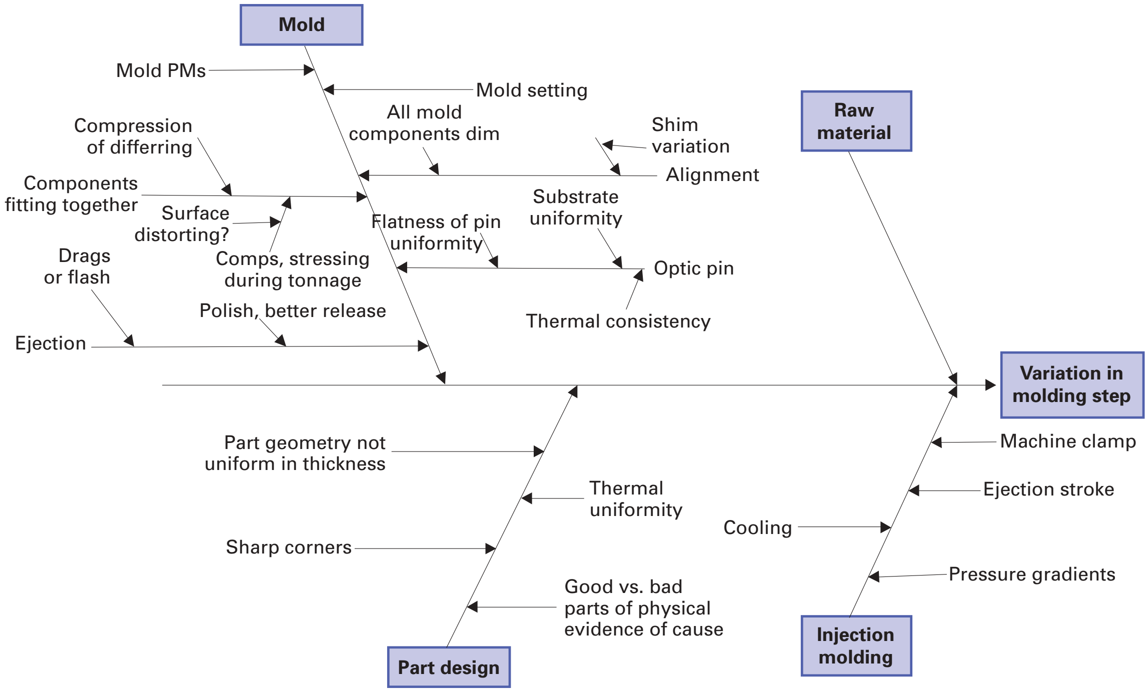
The key variables we identified and confirmed were alignment method, optic pin fabrication, cavity insert fit and measurement. We wrote a report that

TABLE 2 Results of T-Tests—Tilt

Pin used	N	Mean	Standard deviation	Standard error mean
Taper locks	20	1.262	0.297	0.066
Locking pins	20	0.561	0.307	0.069

Difference = (1) - mu (2)
Estimate for difference: 0.7005
95% confidence interval for difference: (0.5071, 0.8939)
T-test of difference = 0 (vs. not =): **T-value** = 7.34, **P-value** = 0.00, **Data field** = 37

FIGURE 4 Fishbone for Identifying Possible Causes of Variation



completed the final three steps of Traver's process—optimize, install controls on key variables and measure before and after results. We put a control plan in place to document new measurement procedures and the type of mold alignment and optic fabrication methods used to ensure certification of cavity inserts for fit. We measured the results over the next year to capture the improvements.

We had successfully demonstrated the advantage and power of using the multi-variable study during the earliest stages of Six Sigma projects. Deciding which variables to attack can be data based rather than speculative. Traver's nine steps are clearly useful to anyone trying to find the annoying ghosts in any process.

REFERENCE

1. Robert W. Traver, *Manufacturing Solutions for Consistent Quality and Reliability*, Amacom, 1995.

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