

# Reducing Process Variation With Statistical Engineering

## A Case Study

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### In 50 Words or Less:

- The statistical engineering algorithm is designed to reduce variation in manufacturing and assembly processes.
- The algorithm guides the user through a series of empirical investigations planned to accumulate the process knowledge needed for the selection and implementation of one of seven variation reduction approaches.

### Introduction

Chronic variation problems are best addressed using step-by-step methods. This is because these methods can be taught, learned and managed, they encourage teamwork, and they discourage leaping to solutions without sufficient process knowledge.

We propose using the statistical engineering (SE) algorithm<sup>1</sup> (see Figure 1) for reducing variation in high- to medium-volume manufacturing and assembly processes. The algorithm is designed to identify low-cost changes, such as an improvement to the control plan or a change of settings to reduce variation in process outputs. It is well suited for use in improvement systems like Six Sigma.

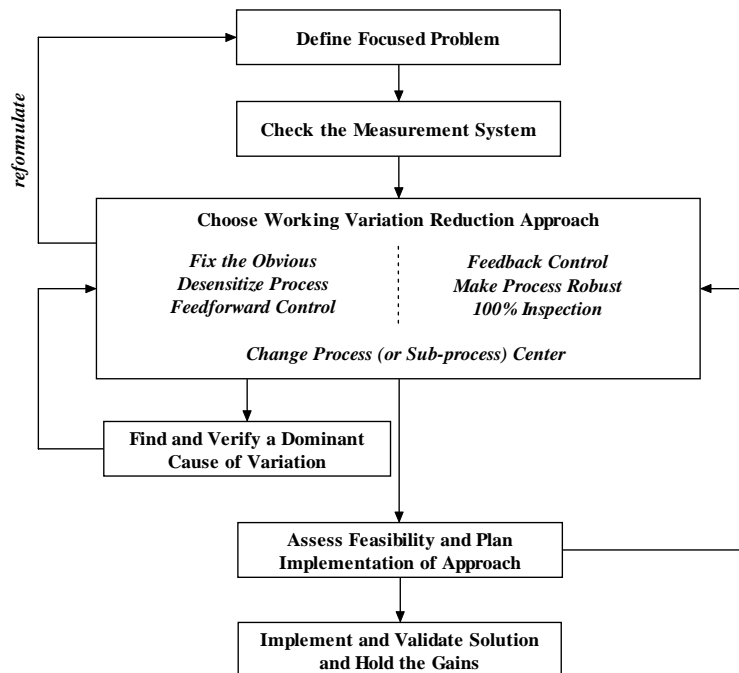


Figure 1: Statistical Engineering Algorithm

In many applications of the SE algorithm, the users may decide to identify a dominant cause of the variation.<sup>2</sup> A dominant cause is a varying process input that—if held fixed—would substantially reduce the variation in the output. We can, at least approximately, represent the total standard deviation as

$$\sigma(\text{total}) = \sqrt{\sigma^2(\text{due to the dominant cause}) + \sigma^2(\text{due to all other causes})}$$

For a dominant cause to be present, the standard deviation due to all other causes must be relatively small. Figure 2 shows the percentage reduction in the total standard deviation if we completely eliminate the contribution due to a specific cause. Little improvement is possible unless we reduce the contribution of a dominant cause. This is why the idea of a dominant cause plays such a large role in the SE algorithm.

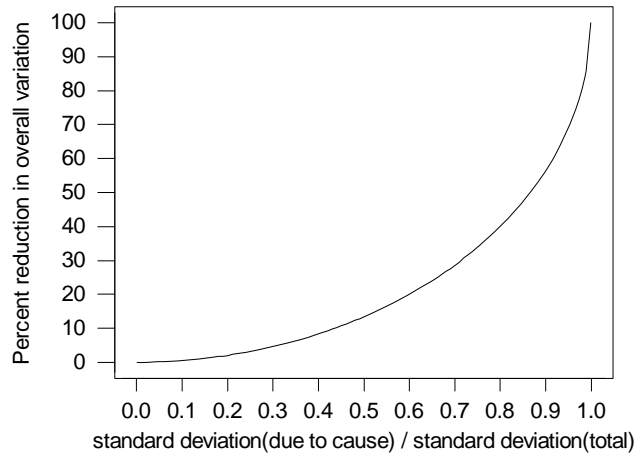


Figure 2: Effect of Individual Cause on Overall Variation

A team used the SE algorithm to reduce variation in the manufacture of a molded base for an assembly. In this case, the length of a key crossbar—measured as the difference from a nominal value—was a good surrogate for the overall geometry of the base. If the crossbar was too long, then components pressure fitted into the base tended to move or fall out. If the crossbar was too short, then there was breakage during insertion.

### Define Focused Problem

In the first stage of the SE algorithm, we narrow the process boundaries and select the particular output characteristic or characteristics needed to specify the problem. We conduct a baseline investigation to estimate the full extent of variation in the output and understand how the process changes over time.

One defining feature of the SE algorithm is the explicit and frequent use of the information discovered in this baseline investigation to help:

- Set the goal in terms of a process performance measure.
- Plan and analyze investigations in the search for a dominant cause.
- Assess the selected variation reduction approach.
- Validate the solution.

In the example, the team decided to concentrate on reducing variation in crossbar length. To quantify the problem, they planned and executed a baseline investigation in which six consecutive parts were systematically sampled from the process each hour for five days. Note the team did not use random selection because they were interested in how the process varied over time. The histogram in Figure 3 shows the full extent of variation in crossbar dimension is -0.25 to 2.1, indicated by the dashed lines on all plots. The multi-vari chart shows the dominant cause acts hour to hour with some evidence of day-to-day differences. The overall standard deviation is 0.45. The team set a goal to reduce this to less than 0.25.

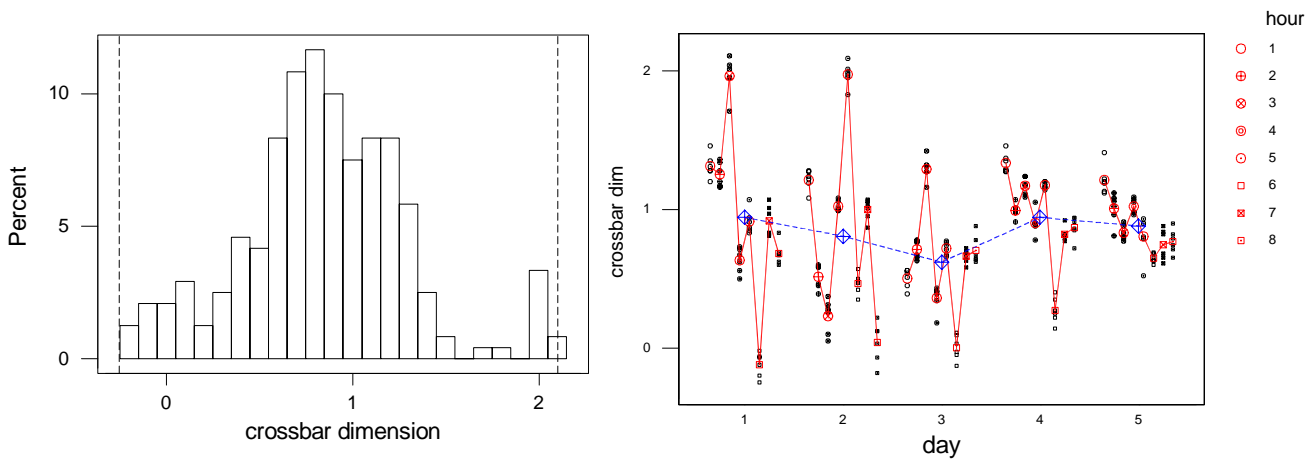


Figure 3: Baseline Histogram and Multi-vari Chart

### Check the Measurement System

In the second stage of the algorithm, we ensure the measurement system for the output is not home to a dominant cause and is adequate for use in later stages of the algorithm. Hence, we carry out an investigation to determine how much of the baseline variation can be attributed to the measurement system.

If we find the measurement system is not adequate, we reformulate the original problem to address the variation in the measurement system. We have seen many failures because a team tried to solve a problem without an adequate measurement system. Less often, we have seen teams become bogged down trying to improve a measurement system that is not home to a dominant cause and is perfectly adequate for use in further investigations.

In the example, the team selected three parts with initial measured crossbar dimensions that cover the full extent of variation seen in the baseline. From the baseline, they expected the process to exhibit its full extent of crossbar dimension variation within one day. Accordingly, they measured each part three times an hour for six hours on one day. The team concluded the measurement system is highly capable (see Figure 4).

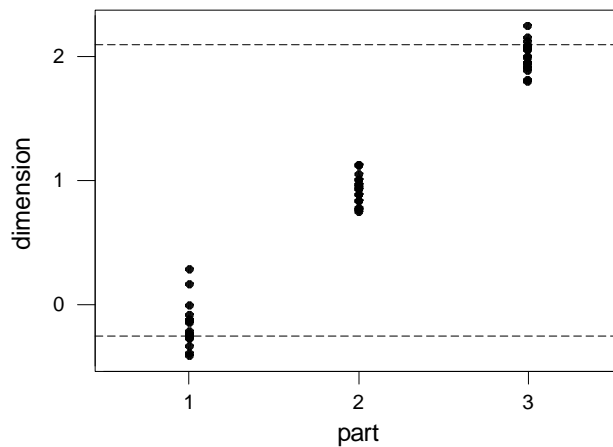


Figure 4: Repeated Measurements on a Set of Three Parts

### Choose a Working Variation Reduction Approach

At the next stage of the algorithm, we look ahead to a possible approach to reduce the variation. We choose an approach from seven classes of process changes, divided into two groups.

If we know the dominant cause, possible approaches are:

1. Fix the obvious: Use knowledge of a dominant cause to implement an obvious solution.
2. Desensitize the process: Change process settings to reduce the sensitivity of the output to variation in a dominant cause.
3. Implement feed-forward control: Predict the output based on measured values of a dominant cause, and adjust the process to compensate for its effect.

If we do not know the dominant cause, possible approaches are:

4. Implement feedback control: Predict the output using current and past output values, and adjust the process to reduce the output variation.
5. Make the process robust: Change process settings to reduce the output variation.
6. Use 100% inspection: Use an inspection scheme to select units with less variation in the output.
7. Move the process center closer to the target.

Although this classification is somewhat arbitrary, it is useful at this stage of the algorithm to consider each approach. This is a difficult step, but without some decision, it is unclear how to proceed. Using available knowledge and likelihood of success, we choose an approach, then determine whether it is feasible. If so, we proceed to the implementation stage; if not, we consider a different approach. In most applications, we search for a dominant cause because experience suggests knowledge of a dominant cause usually leads to a more effective and efficient solution. Choosing a working variation reduction approach is one feature that distinguishes the SE algorithm from many others that have a similar intent.

In the example, Figure 3 shows approach four, feedback control, is promising because the process varies relatively slowly from hour to hour. Despite this, the team decided to search for a dominant cause.

### **Find and Verify a Dominant Cause**

We recommend the method of elimination to identify the dominant cause.<sup>3</sup> In elimination, we partition all the varying inputs into families (groups of inputs that act in the same time frame or location) and use available data to rule out all families but one as the home of the dominant cause. We use elimination recursively to quickly narrow down the potential dominant causes to one or a few suspects. Then we use an experiment to verify a particular cause is dominant. In some problems, there may be no dominant cause, and this step will fail. Then we must consider using the non-cause based approaches or abandoning the project.

In the example, the team knew from the baseline investigation the dominant cause must vary from hour to hour, not part to part. They eliminated all inputs that varied from one part to the next. There was only a small number of inputs that changed from hour to hour that matched the pattern on the multi-vari chart. The team planned an investigation in which 40 parts were selected systematically, four per hour over a two-day period. For each part, the team measured the crossbar dimension and recorded five inputs: die temperature, nozzle temperature, barrel temperature, hydraulic pressure and cavity pressure.

The left panel of Figure 5 shows a strong relationship between barrel temperature and crossbar dimension. There was little evidence of a relationship between crossbar dimension and the other inputs as illustrated for hydraulic pressure in the right panel of Figure 5. Since the range of the crossbar dimension matched that seen in the baseline, the team was confident the dominant cause had acted. Hence, barrel temperature was a suspected dominant cause.

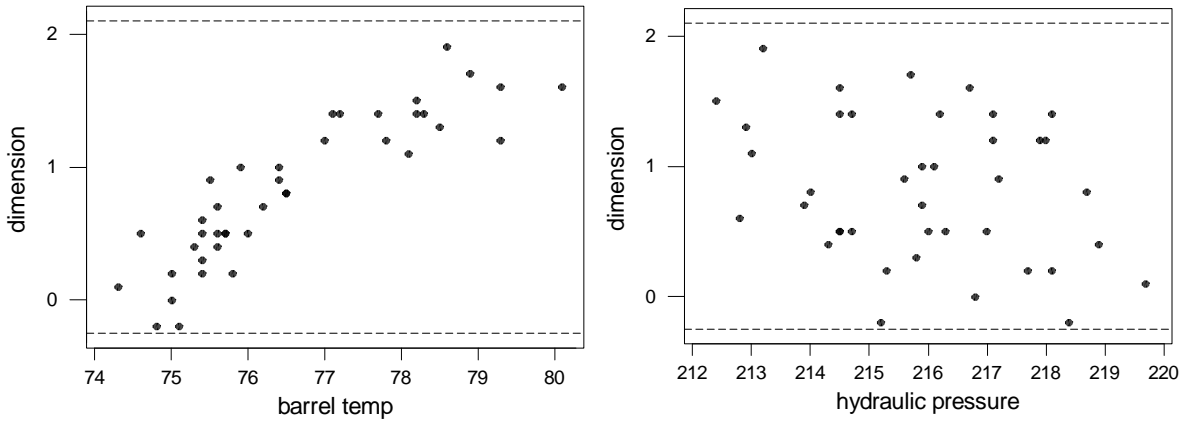


Figure 5: Crossbar Dimension versus Barrel Temperature and Hydraulic Pressure

To verify barrel temperature as the dominant cause, the team planned a simple two-level experiment. They chose the low level for barrel temperature as 75° and the high level as 80° to cover the full range of barrel temperatures seen in the previous investigation. Barrel temperature was difficult to hold fixed in normal production but could be controlled for an experiment. The team set the barrel temperature, made 25 parts to ensure the temperature had stabilized and selected and measured the next 10 parts. Then they changed the barrel temperature as quickly as possible for the second run. There were two runs, with 10 repeats per run and no replication.

Figure 6 shows barrel temperature has a large effect on crossbar dimension relative to the baseline variation (given by the dashed lines). The team concluded they had verified barrel temperature as the dominant cause of crossbar dimension variation.

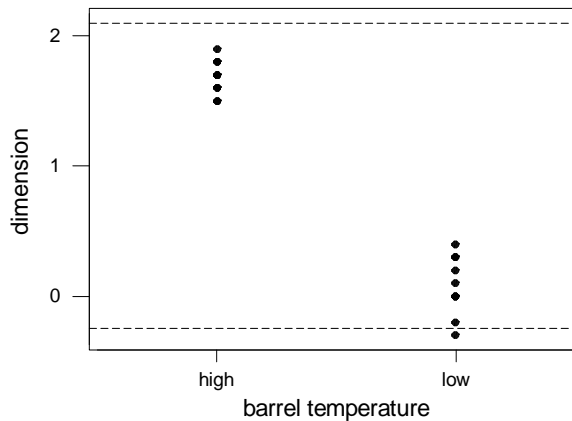


Figure 6: Crossbar Dimension versus Barrel Temperature

The team was somewhat concerned about the small number of runs because previous investigations had shown the dominant cause acted in the hour-to-hour family. Over the 30 minutes needed to conduct the verification experiment, the team decided it was unlikely they would see the full extent of variation in the crossbar dimension unless barrel temperature was a dominant cause. They assumed there was insufficient time for other causes in the hour-to-hour family to change substantially. There was some risk in this assumption, and it was possible some unidentified varying input, not barrel temperature, could explain the experimental results. The team accepted this risk and proceeded.

## **Return to the Choice of Variation Reduction Approach**

After we identify an input as the dominant cause, we consider the feasibility of the cause based approaches. If we rule out these approaches, we have three options:

- Reconsider the non-cause based approaches.
- Reformulate the problem in terms of the dominant cause.
- Search for a more specific dominant cause.

If we decide to reformulate the problem, we restart the algorithm with the goal of reducing variation in the dominant cause. Reformulation corresponds to moving the problem upstream or searching for the root cause. We sometimes reformulate a problem several times.

A dominant cause may be described generally or specifically. For example, we may have identified a particular component as the dominant cause of variation in the function of an assembly but then ask what specific characteristic of the component is the dominant cause.

No matter how often we reformulate or decide to look for a more specific cause, eventually, we must select one of the variation reduction approaches to meet the goal of the overall project.

In the example, the team first considered reformulating the problem. Reducing variation in barrel temperature would result in reduced variation in crossbar dimension, but the team suspected this was an expensive proposition. Instead, they noticed in Figure 5 a nonlinear relationship between barrel temperature and crossbar dimension. The variation in crossbar dimension was greater when barrel temperature varied from 74° to 77° than when the barrel temperature ranged from 77° to 80°. The team tried to desensitize the process to barrel temperature variation by increasing the target barrel temperature. Note that while the variation in barrel temperature was found to be a dominant cause, the target barrel temperature was fixed.

## **Assess Feasibility and Plan Implementation of Approach**

At the next stage of the algorithm, we look in detail at the feasibility of the working approach. We:

- Examine the process to see if it meets the conditions for the approach to be effective.
- Determine what further knowledge is required.
- Plan and conduct investigations to acquire this knowledge.
- Determine the solution (how the process will be changed).
- Estimate the benefits and costs of the proposed change.
- Look for possible negative side effects.

If the working approach proves feasible, we validate and implement the solution. Otherwise, we must reconsider alternative approaches.

In the example, to see whether it was feasible to desensitize the process to barrel temperature variation, the team planned a half fraction factorial experiment with three fixed inputs: target barrel temperature, target injection pressure and a material property, each at two levels. The current target for injection pressure was 1,000 pounds per square inch. The four treatments were run in random order (see Table 1). The team repeated each treatment in the experiment at two levels of the barrel temperature (target temperature  $\pm 3^\circ$  C). Five parts were produced in each run.

Table1: Results of the Half Fraction Desensitization Experiment

Treatment	target barrel temperature	Injection pressure	Material property	Dimension at barrel temperature -3°C	Dimension at barrel temperature +3°C
1	75	1000	old	0, -0.1, -0.1, -0.1, -0.1	0.5, 1.1, 0.5, 0.6, 0.5
2	75	1200	new	1.1, 0.6, 1.1, 1.4, 1.1	1.5, 1.5, 1.5, 1.4, 1.3
3	79	1000	new	1.1, 1.0, 1.1, 0.9, 1.0	1.0, 1.0, 0.8, 0.9, 1.0
4	79	1200	old	1.2, 1.8, 1.8, 1.7, 1.9	1.5, 2.1, 2.4, 2.1, 1.9

Figure 7 shows treatment three looks most promising, since it has much smaller variation in crossbar dimension than the current conditions (treatment one). Changing to the higher target barrel temperature, using the new material and keeping the target injection pressure the same is expected to make the process less sensitive to variation in the barrel temperature.

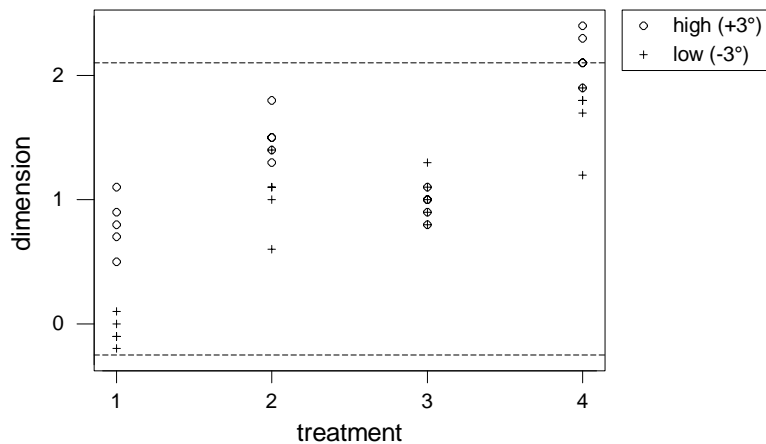


Figure 4: Crossbar dimension versus Treatment Number

“o” and “x” correspond to the high level and low level of the dominant cause respectively

### Implement and Validate a Solution

In the final stage of the algorithm, after changing the process, we reassess the baseline performance to ensure the project goal has been met. We also examine other process outputs to check for negative side effects. Finally, assuming success, we implement and lock the change into the process or its control plan. We monitor the process output and audit the process change until we are certain the solution is effective and permanent. We should also document what we have learned and identify opportunities to further reduce variation.

In the example, the team recommended raising the target barrel temperature and using the new material to make the crossbar dimension less sensitive to variation in barrel temperature. In a preliminary validation investigation, the team found that while crossbar dimension variation was substantially reduced, the new process settings resulted in an unacceptable increase in the frequency of a defect called burn. They decided to attack the burn defect as a new problem.

Once the burn defect problem had been solved, the team proceeded to a validation investigation with the proposed new process settings. They selected 300 parts systematically over five days, as in the baseline investigation. They measured the crossbar dimension and inspected each part for the burn defect. The standard deviation in the crossbar dimension was reduced to 0.23, and the burn defect occurred on only two of the 300 parts. With the new settings, the process performance met the project goal. It is important to note the solution did not involve the improved control of barrel temperature—instead, the process was made less sensitive to this variation.

## **Conclusions and Recommendations**

The SE algorithm and its associated strategies—such as the use of elimination to find a dominant cause and the early consideration of a variation reduction approach—is ideal for improving processes in medium- to high-volume manufacturing.

While we have no experience in applying the algorithm to nonmanufacturing processes, we see no reason why it would not be effective in these settings. If the process has frequent outputs and it is feasible to measure both input and output characteristics, the SE algorithm should work. Overall, to be successful, the algorithm must be embedded in a universal improvement system, such as Six Sigma, to manage the selection of projects and the provision of resources and training.

## **References**

1. Stefan H. Steiner and R. Jock MacKay, *Statistical Engineering: An Algorithm for Reducing Variation in Manufacturing Processes*, ASQ Quality Press, 2005.
2. Joseph M. Juran and Frank M. Gryna, *Quality Planning and Analysis*, second edition, McGraw-Hill, 1980.
3. Dorian Shainin, “Strategies for Technical Problem Solving,” *Quality Engineering* Vol. 5, 1993, pp. 433-448.

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