A Variation Reduction Algorithm

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Reducing the variation in process outputs is a key part of process improvement. For mass produced components and assemblies, reducing variation can simultaneously reduce overall cost, improve function and increase customer satisfaction with the product. Excess variation can have dire consequences, leading to scrap and rework, the need for added inspection, customer returns, impairment of function and a reduction in reliability and durability. Variation reduction efforts occur in a wide variety of engineering, scientific or management processes. Some examples are:

- reducing rework in due to brake rotor imbalance
- improving the reliability of a personal digital assistance
- increasing the average yield of a chemical process
- reducing variation in camshaft lobe geometry
- reducing the average number of errors made in the translation of technical documents

Variation reduction is best addressed using a step-by-step method. In Figure 1, we propose an algorithm (Steiner and MacKay, 2005) for reducing variation in high- to medium-volume manufacturing processes. It is designed to identify low cost changes such as improvements to the control plan or new process settings that reduce variation in process outputs.

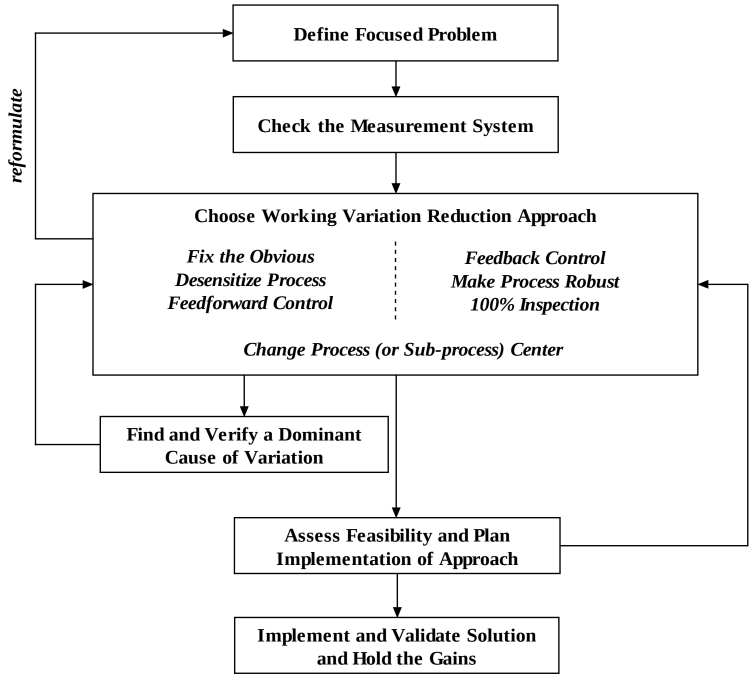

Figure 1: A Variation Reduction Algorithm

In most applications of the algorithm, we search for a dominant cause (Juran and Gryna, 1980). A dominant cause is a varying process input that is responsible for much of the variation in the output. If we apply the Pareto principle (80/20 rule) to causes of variation we expect that there will be a vital few that are dominant. Dominant causes may be special or common in the language of Statistical Process Control.

We illustrate the algorithm with a case study. An iron foundry produced veined brake rotors that were machined at a separate location. The machining plant 100% inspected the rotors for balance and welded a weight into the veins if the imbalance was too severe. We call a rotor needing added weight "a balance reject." The historic rate of balance rejects was approximately 25%. The foundry initiated the project because the reject rate jumped to 50%. This increase in rework coincided with a change from a four-cavity to a six-cavity core mold to increase productivity in the foundry. The cores were used to create the veins when the rotor was cast.

The foundry was convinced that the change to the six-cavity mold was not the cause of the increase in balance rejects. A dimensional analysis of the six-cavity mold and core-making process had shown all characteristics well within specification. The increased reject rate could not be explained by any other changes made at either the foundry or the machining operation. As it stood, each party blamed the other. To address the increased rework, the machining operation planned to add another rework station. The foundry formed a problem solving team with the goal of reducing the reject rate back to its historical level.

In the first stage of the algorithm, we select the particular output characteristics needed to specify the problem and carry out an investigation to quantify baseline performance.

In the brake rotor example, to determine imbalance, the machining plant measured the center of gravity (a distance and direction from the rotor center) that was then translated into a weight (gm) and orientation needed to balance the rotor. If needed, the weight was welded to the veins on the rim of the rotor. A balance reject was any rotor needing weight greater than 15g. To focus the problem, the team selected balance weight as the output. They knew that if they could reduce the weight, they could eliminate the rework, regardless of the orientation.

To establish the baseline, the team selected 300 rotors spread out over the previous week's production at the machining plant. Figure 2 shows the extent of the problem. The team set the goal to reduce variation in the balance weight so that at least 75% of the rotors had weight less than 15g.

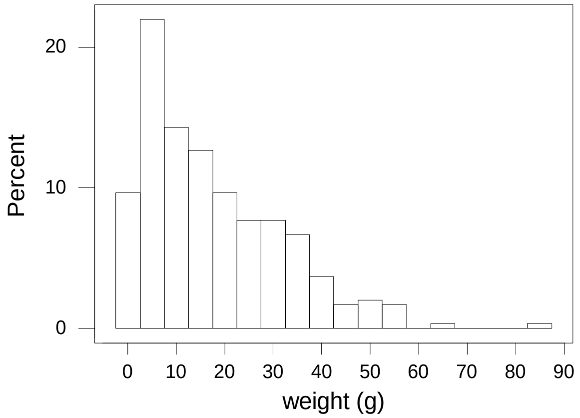

Figure 2: Balance Weights in the Baseline Investigation

In the second stage of the algorithm, we ensure that the measurement system for the output is not a dominant cause of variation and is adequate for use in later stages of the algorithm. We plan and execute an investigation to determine how much of the baseline variation can be attributed to the measurement system. If the we find the measurement system is inadequate, we reformulate the original problem to address the variation in the measurement system. With this new problem, we start the algorithm again. The process of interest becomes the measurement process. We have seen many failures because a team tried to reduce variation without an adequate measurement system.

In the case study, the team selected three rotors with initial measured weights of 3, 15 and 32g. They measured the three rotors six times each on three separate days. There was little operator effect since the gauges were automated. The results (not given) showed that the measurement system was highly repeatable relative to the variation seen in the baseline study.

At the next stage of the algorithm, we consider how we might reduce the output variation. This is a feature unique to this algorithm. We divide the variation reduction approaches into two groups. Approaches requiring the identification of a dominant cause are:

- Fix the Obvious: Use knowledge of a dominant cause to implement an obvious solution.
- Desensitize the process: Change the process settings to reduce the sensitivity of the output to changes in a dominant cause.
- Implement feedforward control: Predict the output based on measured values of a dominant cause and adjust the process appropriately to reduce variation.

Approaches not requiring the identification of a dominant cause are:

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

To choose a working approach, we consider the nature of the problem and process, our current state of knowledge, and for each of the seven approaches the:

- knowledge required to implement the approach
- likelihood and cost of obtaining this process knowledge
- likelihood of successful implementation
- probable cost of implementation

In the brake rotor case, the team first considered the non-cause based approaches. They ruled out 100% inspection since that was the current costly approach. They eliminated feedback control since there is no strong pattern in the variation over time in the baseline data and they did not know how to adjust the process. Robustness or move the process center (lower in this case) were possibilities but, without more process knowledge, were not likely to succeed. The team decided to proceed with a search for the dominant cause of variation in the balance weight.

To search for a dominant cause, we recommend the method of elimination (Shainin, 1993). We partition the causes of variation into families and use new or available data to rule out all but one family as the home of the dominant cause. We use elimination recursively to narrow down the potential dominant causes to one or a few suspects.

The brake rotor team first looked at available data to see what causes could be eliminated. They recorded the location of the welded rework weight for the 140 balance rejects from the baseline investigation on a concentration diagram shown in Figure 3. They saw that there was a non-symmetric pattern of balance weight locations. Since the machining process is rotationally symmetric and the casting process is oriented, the team eliminated all causes in the machining operation. With this simple investigation, the team made tremendous progress with little cost or time.

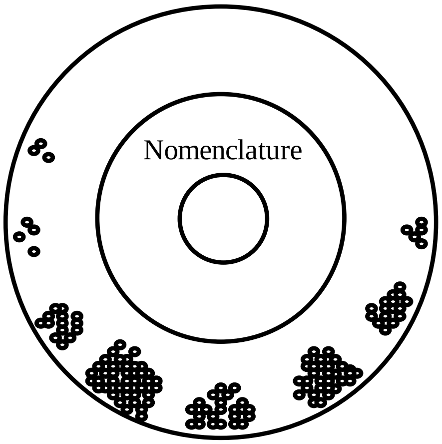

Figure 3: Concentration Diagram of Weight Locations

The team next compared 30 balance rejects and 30 balanced brake rotors. They measured 26 foundry-determined characteristics on each machined rotor. From this investigation the team identified two input characteristics, thickness variation and core position (offset) that were substantially different for balanced and unbalanced rotors. Both inputs were plausible dominant causes of imbalance.

The team decided to verify these suspects hoping they could then reformulate the problem into one with an output measured in foundry. This would save time and effort in future investigations since they would no longer needed to trace rotors between the foundry and the machining operation. They planned and conducted a verification experiment to confirm that core thickness variation and core position were substantive causes of the balance weight variation and that the six-cavity mold was not. They used two levels for each input and a 2^3 factorial design. For core position and thickness variation the two levels were the nominal value and a second level selected at the high end of their normal range of variation.

From the interaction plot given in Figure 4, the team concluded that low thickness variation using the four-cavity mold produced the optimal results (the weights required were so small that balance

specification was met without rework). Thus, the dominant cause of the imbalance problem was in the core molding process.

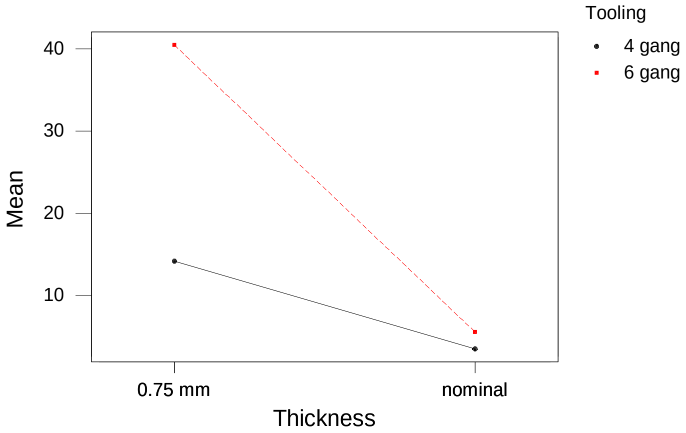

Figure 4: Interaction Plot from Verification Experiment

In general, after we verify a particular input as the dominant cause, we consider the feasibility of the cause-based approaches. If we rule out the cause-based approaches, we have three options:

- reformulate the problem in terms of the dominant cause
- reconsider the non-caused based approaches
- search for a more specific dominant cause

If the we decide to reformulate the problem, we restart the algorithm with the goal of reducing variation in the dominant cause. We sometimes reformulate a problem several times. Eventually, we must select one of the variation reduction approaches.

Having chosen a variation reduction approach, in the next stage of the algorithm, we look in detail at the feasibility of the selected 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 the knowledge
- determine the solution, i.e. 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 is feasible, we validate and implement the solution. Otherwise, we must reconsider the other variation reduction approaches.

In the brake rotor case, the team made the “obvious fix” and recommended that the foundry go back to the original four-cavity core mold. When this change was implemented, the rate of balance rejects dropped to its historic levels. The team had met the project goal. Alternatively the team could have considered trying to compensate for the variation in core thickness. In theory this could be accomplished either by making a one time change to the process (desensitization) or measuring core thickness variation for each rotor and adjusting the process as needed for each rotor to compensate for the measured thickness variation (feedforward control). Both these suggestions were rejected in favour of the more direct obvious solution.

The major lesson learned was the effect of the thickness variation on the balance weight. The verification experiment showed that thickness variation in the cores was a dominant cause of balance weight variation in the original process using the four-cavity mold. Knowledge of the dominant cause provided the opportunity to improve the process further. A new core making process was already available in the plant but not in use. The team knew that this cold box process was stable dimensionally and they expected much less thickness variation with this process.

In the final stages of the algorithm, we reassess the baseline performance after the process change to ensure that the project goal has been met. We also examine other process outputs to check for negative side effects. Finally we implement and lock the change into the process or its control plan. We recommend monitoring the process output and auditing the process change until we are certain that the solution is effective and permanent.

With the implementation of the cold box method, the process was greatly improved. The rate of balance rejects dropped to 0.2%, a large reduction from the 50% at the start of the project. The machining plant eliminated the expensive rework stations and scrapped the few remaining balance rejects in the new process.

In summary, we believe the proposed algorithm is well suited to reducing variation in manufacturing processes. The unique features are the search for a dominant cause using the method of elimination and the demarcation of the variation reduction approaches. To be successful, the algorithm should be embedded in a global improvement system such as Six Sigma.

References

Juran J.M. and Gryna F.M. (1980), *Quality Planning and Analysis*, 2nd edition, McGraw-Hill, New York.
Shainin, R.D. (1993), Strategies for Technical Problem Solving, *Quality Engineering* 5, 433-448
Steiner, S.H. and MacKay R.J. (2005), *Statistical Engineering: An Algorithm for Reducing Variation in Manufacturing Processes*, Quality Press, American Society for Quality, Milwaukee, WI, ISBN 0-87389-646-7