STRATEGIES FOR VARIABILITY REDUCTION

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Introduction

An important goal of quality improvement in manufacturing is the reduction of variability in product characteristics. Producing more consistent output improves product performance and can reduce manufacturing costs.

The problem can be simply demonstrated. Suppose a process produces output with an important quality characteristic Y (see Fig. 1). The current process performance, measured using an appropriate sampling scheme over a long enough period to capture most of the variation, is shown by the histogram. The goal is to reduce variability in Y while targeting the process at or near the nominal value. In this article, we focus on variation reduction and assume implicitly either that any reduction obtained does not move the process mean significantly away from its target or that we can retarget the process mean without affecting the process variability.

Processes are managed using a control plan that describes how the process should be operated and specifies the mechanisms through which the quality of a product will be monitored, controlled, and verified. In this context, reducing the process output variation requires either the modification of a current control plan or a change to the process itself. Changes to the method of operation correspond to the idea of a living control plan as discussed in the Automotive Industry Action Group (AIAG) reference manual, *Advanced Product Quality Planning and Control Plan* (1) referred to in the automotive industry quality standard, QS-9000. A living control plan is constantly modified and improved as more information and insight on the process becomes available.

Reduction in output variation can be accomplished by changing the way the process operates in a number of different ways. In our experience, however, all variation reduction approaches can be classified into one of the following five generic strategies:

1. Introducing or tightening output inspection
2. Introducing or improving feedback control
3. Reducing variation in process inputs
4. Introducing or improving feedforward control
5. Desensitizing the process to input variation

Each of these five strategies is currently used in industry. A sixth strategy, which we do not assess in detail, is to discard all or part of the existing process and start again with a new method or technology. In some situations, this

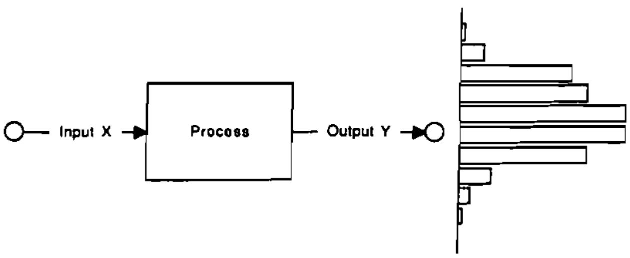

Figure 1. Process diagram.

sixth strategy of replacing the existing process (or part of it) may be the only viable option. For example, we may purchase a new gauge to improve the accuracy of our measurements or use a new supplier whose products are of higher quality. However, in the spirit of continuous improvement, we believe that it is cost-effective to consider strategies 1-5 first. In any case, strategy 6 could be considered an extreme example of strategy 5, where the process is desensitized by changing the process radically.

All variation reduction strategies are dependent on the ability to measure precisely the process output Y and possibly input(s) X. As a result, studies that examine the short-term variability [gauge repeatability and reproducibility (R&R)] and long-term stability of the measurement system should be carried out prior to any variation reduction exercise. In this article, we assume that the measurements obtained are reliable (i.e., that the measurement system itself is not the major source of variation).

The choice of an effective strategy depends critically on knowledge of the existing process. Key aspects of this knowledge include stability, predictability, ability to adjust, and identification of the causes of the variation. The availability and cost of attaining this knowledge provides an important input to a decision on which process variation reduction strategy is most applicable.

The goal of the article is to contrast and compare each of the variation reduction strategies, highlighting the required process knowledge, potential costs, benefits, and drawbacks of each method. We discuss each strategy in detail, providing information on how the strategy works and when it works. For each strategy, we give simple examples and discuss more complex extensions. This information is summarized in Table 2. The thought process required to choose judiciously is explored through a detailed example on a crankshaft machining process. We hope that this discussion will provide guidance to quality practitioners faced with a variation reduction problem.

Output Inspection

Output inspection is the simplest variation reduction strategy and is virtually always applicable. Assuming 100% effective 100% inspection, the variability is reduced by identifying and then scrapping or reworking all items that have values of Y beyond selected inspection limits. The more the limits are tightened, the greater the reduction in variation. The effect of tightened inspection is illustrated in Figure 2. Imagine inspecting and sorting units based on whether they fall between the dashed lines shown, where any units falling outside the limits are either scrapped or reworked (and then reinspected). Clearly, this selection of units reduces the overall variability in the product that is shipped subsequently.

Output inspection is very versatile. It can be used successfully in any situation where the output characteristic Y

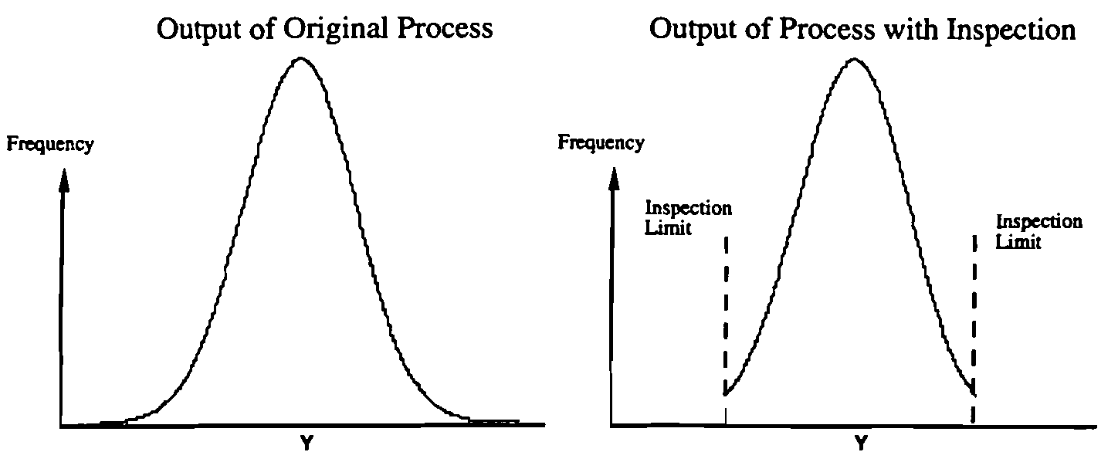

Figure 2. Output inspection example.

can be determined in advance of shipping the product to a customer. Output inspection is especially appropriate when the quality dimension is critical and the process produces only the occasional outlier or flier while all other units exhibit very little variation. For example, in the production of aluminum pistons, the diameter of each finished piston (as well as a number of other key characteristics) is measured by an automated gauge after the piston temperature is controlled. Pistons with large or small diameters are scrapped. In such a situation, the costs associated with 100% inspection, including installation and operation of the automated gauge, are warranted due to the high production volume and the critical nature of the product characteristic. Assuming no inspection error, the 100% inspection strategy has the advantage of being able to guarantee that no units with quality characteristic outside the inspection limits will be shipped to a customer.

Output inspection has a number of significant negative features. The cost of reducing variability by tightening the inspection limits may be very high due to increased rework and scrap costs and lost capability. Also, the cost of inspection itself may be large if new gauging or additional labor is required. In addition, measurement or inspection errors will result in increased variability. As a result, given the propensity of people to make inspection errors, most successful applications use automated inspection.

One common modification of this strategy is inspection sampling, where not every unit is measured. One approach is to define lots, where lots are accepted or rejected based on the quality of a sample taken from the lot. Accepted lots are shipped and rejected lots are 100% inspected or otherwise disposed. If we know that lot-to-lot variation is large and within-lot variation is small, then inspection sampling is effective. Thus, using inspection sampling, variation may be reduced by redefining a lot, changing the inspection limits, or changing the lot acceptance criteria. Compared to 100% inspection, inspection costs are reduced. However, overall variability will not be reduced to the same degree. Note that if the process is stable, then partial inspection is a poor strategy. Deming (2, Chap. 15) showed that in this case either no or complete 100% inspection is optimal.

Feedback Control

Feedback control is a simple concept that may lead to complex procedures. The idea is to monitor the current output characteristic Y and to make adjustments to the process based on the observed output. By making appropriate adjustments, we compensate for changes in unidentified process inputs, thus reducing the variability in future values of Y. The effect of a simple feedback control plan is illustrated in Figure 3. The panel on the left shows the output of the original process. The panel on the right shows the output of the same process when feedback control is applied. The feedback control mechanism involves retargeting the process to zero whenever the process output exceeds the adjustment limit. The amount of adjustment is based on the last observed process output. Figure 3 demonstrates the resulting reduction in variability of Y.

Feedback control can be successfully applied when three conditions are satisfied. First, the process must exhibit substantial structural variation (3). Examples of structural variation include drift due to tool wear and stratification due to batch-to-batch variation. Second, there must be an adjustment procedure to retarget the process. Finally, the time to measure the output and adjust the process must be small relative to the rate of change of the process.

A feedback control scheme is defined by its adjustment procedure that tells us when and how much to adjust, and its sampling frequency. Increased knowledge of the process behavior may be used to improve the feedback control scheme. For example, better knowledge of the nature of the structural variation can be used to change the sampling frequency or the adjustment rule.

As an example, feedback control is used to reduce variation in the concentration of silicon in molten iron in a foundry. Iron is sampled at a fixed frequency from the output stream and the concentration of silicon is determined in the sample. Based on the observed concentrations, adjustments are made (upstream) to the feed rate of silicon in the melting process. Another common example is the use of procedures based on first-off measurements, where, for example, a machining tool's setup may be changed based on measurements taken on the first few products in a batch. Once a good setup is achieved, no further process measurements are taken.

The major advantage of feedback control is that it requires little knowledge of the causes of variation. Like output inspection, it only uses information obtained from the final product.

There are a number of drawbacks to feedback control. A major danger is overadjustment (tampering). If the process is stable (i.e., it does not exhibit structural variation), then adjusting on the basis of the output will lead to increased variability. This is illustrated in the famous funnel experiment; see Ref. 2, pp. 327–328. Another drawback is that the process measurements and adjustments may be expensive. Finally, due to the feedback nature of the control, there is an inherent time delay. To identify when an

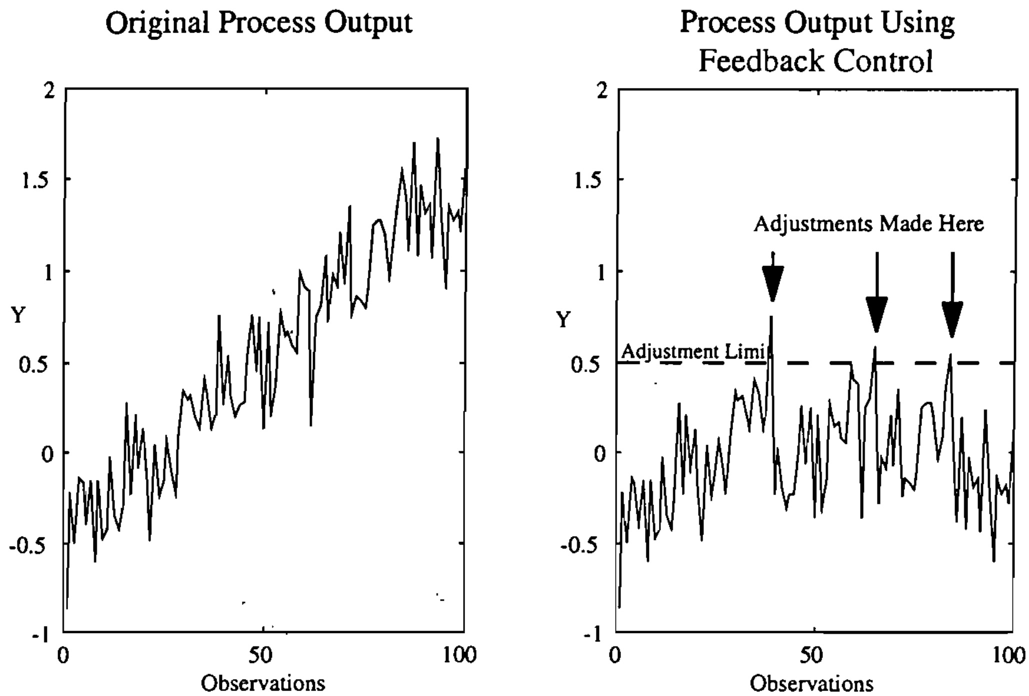

Figure 3. Feedback control example.

adjustment is required, we must first observe some output values that are significantly different from the target value. Thus, feedback control is always reactive.

There are many variations of feedback control; see Ref. 4 for further details. Specific examples include acceptance control charts (5) and Pre-control (6,7). Most feedback control systems use a function of recent output values, not just the last value, to determine if an adjustment is necessary. If the drift in Y is as regular as shown in Figure 3, we could also base adjustments simply on the time or the number of units processed (or any other cheaply measured variable highly correlated with the output dimension Y).

Reduction of Variation in Process Inputs

As the saying goes "garbage in, garbage out." If there is a large amount of variation in process inputs, then it is difficult to produce consistent output. One improvement approach in this environment is to reduce the variability in one or more inputs. For ease of discussion, we assume, for the moment, a single important input X. See Figure 1. The input X may be a characteristic of raw materials or component parts, a changing environmental factor such as heat, or any other process input that changes over time. From the point of view of the process that produces X, the problem of reducing variability in X is analogous to reducing variation in Y and we have created a recursion in the problem definition.

The effect of reducing the variability in an input is illustrated by the variance transmission plots shown in Figure 4. In this example, most of the variation in Y is due to variation in the input X. As a result, if we reduce the variability in the input X as shown, the variability in the output Y will also be reduced substantially.

There are three basic conditions necessary for this strategy to work. First, we must be able to identify an input X that has a causal influence on the output Y. Second, we must identify an X that is a major source of the variation in Y. Third, we must be able to reduce the variation in X.

There are many tools for discovering the identity of such an X. We may use observational studies such as control charts, multivari studies (7), and regression, or we may use designed experiments which require an intervention in the process. It is important that the identified factor X is a significant factor influencing the variation in the output.

This approach is proactive. The control of the process is moved upstream, which may reduce cost and complexity, and less effort may be needed to monitor the process

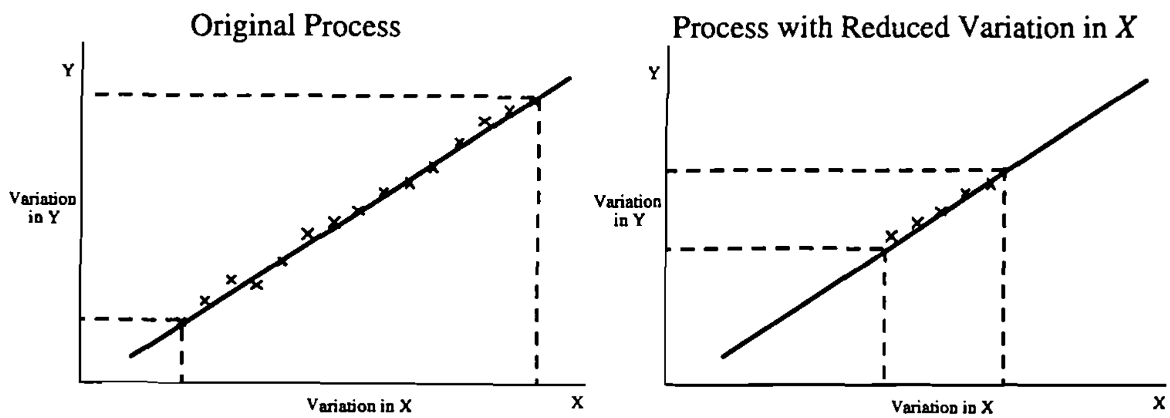

Figure 4. Variance transmission between input X and output Y.

output Y. An example of this strategy occurred in the machining of the aluminum pistons described previously. A variation transmission study identified the piston diameter after an intermediate operation (X) as the major source of variation in final piston diameter. The variation of X was reduced by instituting improved operator instructions and training at the intermediate operation.

One difficulty with this strategy is that first we must identify an X, which is both an important contributor to the variation in Y and which is causally related. This may prove arduous and involve significant study costs. Second, reducing variability in X may be very difficult and/or costly. Third, tightened specifications on X moves the responsibility for control of the process upstream, and possibly outside the influence of local management.

Figure 4 shows a continuously varying input X. However, in many cases, X is discrete. For example, X could represent multiple suppliers or multiple machines in parallel processing operations. In this case, reducing variation in X could be accomplished by reducing the number of suppliers or establishing procedures to reduce differences among the suppliers. Also, in general, the situation where a number of important X variables can be identified should be considered because in typical applications, there are many inputs that are sources of variation. With any input factor that satisfies the three given conditions, reducing the variation in that input is a viable output variation reduction strategy. However, the resulting reduction in variation of the output Y depends on how strong a source of variation X is and how successfully we can reduce its variability. Fortunately, based on the Pareto principle, we can usually focus on only the one or two most important X factors because they typically contribute the majority of variation in Y.

Feedforward Control

Using feed-forward control, we adjust the process in response to measurements made on an input X, anticipating the effect on the output Y. If the measured value of X provides a good prediction of the corresponding output Y, feed-forward control can reduce variation in Y by adjusting the process to compensate for different X values. Figure 5 demonstrates the effect of adjusting Y based on knowledge of X and the relationship between X and Y.

Feed-forward control works under restrictive conditions. First, we must identify an X that is an important source of variation in Y. Second, the relationship between X and Y must be well known and stable over time. Third, we must be able to measure X in a timely way. Finally, there must be a way to adjust the process to compensate for the changes in X.

Feed-forward control can be very effective if the above conditions are satisfied. A simple example is the use of setup procedures based on the properties of the raw materials. Feed-forward control is an attractive alternative because it is proactive and because it is not necessary to measure the output Y.

There are substantial costs and risks associated with feed-forward control. Costs arise because we need to determine the relationship between X and Y, measure X, and adjust the process repeatedly when appropriate. As with feedback control, there is a danger of overadjustment if there is a measurement problem with X or if the relationship between X and Y is not well understood and stable. In addition, repeated process adjustment may be impractical or costly and may introduce undesired side effects.

Applications of feed-forward control are not always easily identified. Consider selective fitting, the technique

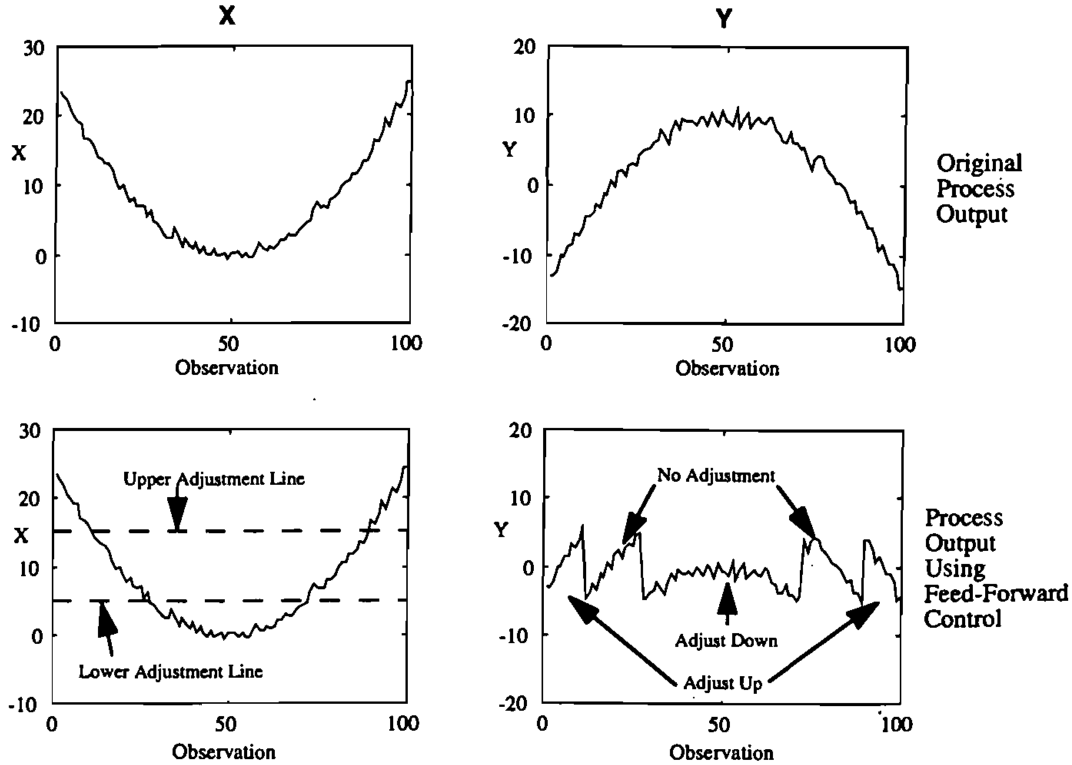

Figure 5. Feed-forward control example.

of sorting and matching component parts to get good assemblies. Selective fitting has been used to reduce variation in clearance between pistons and cylinder block bore walls by matching piston and bore diameters. This is feed-forward control because we measure the dimensions (X) of the pistons and bores and use that knowledge to adapt the matching process. Note that this adds complexity to the assembly process.

Process Desensitization

Desensitization of the process aims to reduce variability by making the process more robust to the variability in process inputs. This is also called parameter design as discussed by Taguchi and Wu (8) and Nair (9). Desensitizing the process works by identifying and exploiting interactions between important varying inputs X and other normally fixed process parameters such as machine settings. In this context, Taguchi calls X a noise factor or variable. Figure 6 demonstrates how modifying the relationship between Y and X by changing other process parameters results in less variation in Y over the same range of variability in X.

Typically, the settings of the control parameters that yield a more robust process are identified through a designed experiment which uses both X and selected process parameters (called control parameters) in the experiment. The experiment must be designed so that interactions between X and the control parameters can be identified.

Process desensitization is a desirable strategy because once it is complete, no further action is required. Taguchi and Wu (8) cite several examples, including the famous Ina tile case. Another example involved the reduction of variation of the sulfur concentration (Y) in molten iron, where X was the uncontrollable amount of sulfur in the scrap iron being melted. It was known that Y was highly dependent on the amount of sulfur (X) in the scrap iron. An experiment identified a new way to run the desulfurization process that reduced this dependency and, hence, reduced the variability of Y.

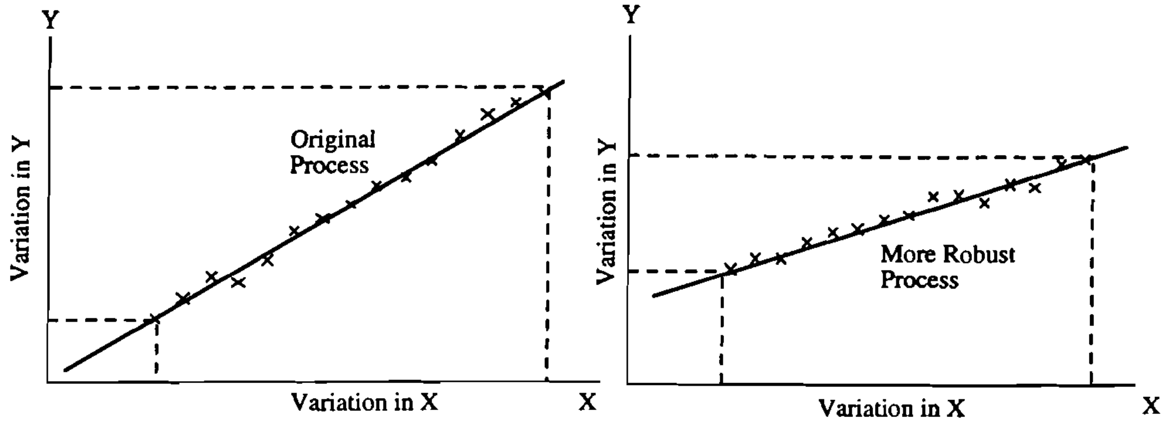

Figure 6. Desensitizing the process example.

It is difficult to predict when desensitizing the process will work. This is one of its great weaknesses. Also, making a process more robust requires a great deal of process knowledge. Determining appropriate settings of the control parameters usually requires expensive designed experiments that may fail to determine process settings that lead to improvement. Also, the new process settings may lead to extra costs.

In theory, making a process more robust can be accomplished without any knowledge of the factor X, even its identity. Taguchi recommends identifying X (the noise factor) and then conducting an inner–outer array experiment in which X is controlled. An alternative is to define an experimental run as the operation of the process over a period of time sufficiently long to allow the unknown X to vary substantially. The process variability is measured over each run and is then used as the response in the analysis of the experiment. However, without knowing X, we run a significant risk of determining a more robust setting that is only better under the limited operating conditions used in the experiment. It is also more difficult to identify process parameters that may be used to reduce the variation when X is not identified. Process desensitization without knowledge of X is illustrated by the speedometer cable example (11, p. 367). The goal was the manufacture of speedometer cables that had very little variation in the shrinkage along the length of the cable. An experiment was designed that varied process factors. Based on the results of the designed experiment, new process settings were determined that resulted in less shrinkage variation; however, the identity of a cause for variation was not reported.

Choosing a Strategy—An Example

In any application, a decision must be made as to which strategy or combination of strategies should be used. To demonstrate the thought process required, we consider an example from the machining of crankshafts.

Journal diameter is a key product characteristic on machined crankshafts. To keep the discussion simple, we consider only one diameter of the several that are measured. Y is the diameter of the shipped product. The machining process at the start of the variation reduction effort with respect to the diameter (called the initial process) is illustrated in Figure 7.

The raw castings, identified by hour, date of casting, and mold number, were processed by one of four grinders and subsequently automatically 100% inspected. All crankshafts that did not conform to the after-grinder specification were either scrapped or reworked. All in-specification parts were subsequently lapped to improve the surface finish. After the lapping operation, all output was again automatically 100% inspected at the final gauge, with parts not conforming to the final product specifications yielding scrap or rework. At any time, if an operator noticed a significant number of rejects due to small or large journal diameters at either gauge, he or she asked for an adjustment of all the grinders. Also, periodically, if the final output quality was deemed poor, the inspection limits at the intermediate gauge were changed. Thus, initially, the process was controlled using a combination of inspection and feedback control.

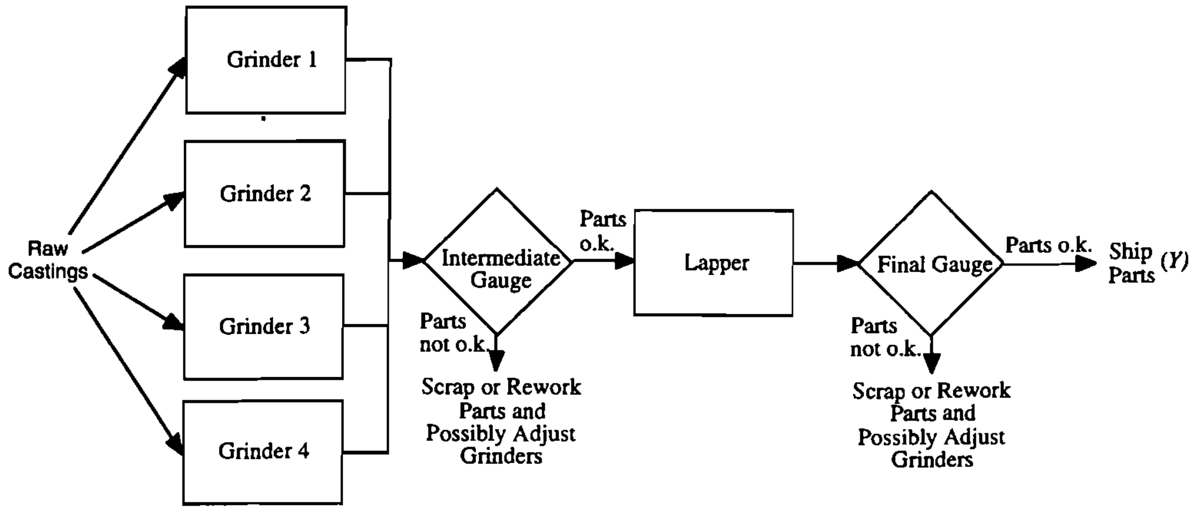

Figure 7. Crankshaft production process.

The initial process had a process capability $C_{pk} \approx 1$, which was considered too low. As well, there was an unacceptably high level of scrap/rework. The objective was to reduce long-term variation in the journal diameters of finished crankshafts and decrease costs. The question of interest was how to select an appropriate variation reduction strategy.

A required preliminary step in our investigation was studying the measurement systems utilized. This is fundamental because we base much of our process knowledge and control decisions on measurements, and, indeed, the whole impetus for conducting this variation reduction exercise is based on the measurements. To determine the quality of the measurement systems, both the short-term variability and the stability of both gauge measurements were examined. A gauge R&R study (10) showed that both gauges were capable in the short term; in other words, the amount of the variation introduced by the measurement system was small compared with the typical process variation. A stability study of the gauges where a master part was measured every 2 h, however, showed that the intermediate gauge was unstable. This was fixed by performing extensive maintenance on the intermediate gauge. The measurements on the master part also identified a calibration problem because there was a systematic difference between the measurements obtained with the two gauges. This problem was alleviated by retargeting the intermediate gauge. Based on these studies, an ongoing program was established to ensure the measurement systems remain stable, capable, and calibrated. Once confidence in the measurement system was established, we turned to the goal of variation reduction.

The simplest approach, because it does not require any additional process information, was tightening the inspection limits at the final gauge. This approach could be easily implemented because inspection was already performed. The consequence would be not only reduced variation in Y but also an increase in scrap and rework and lost capacity, which, in this case, was considered too expensive.

Determining whether any of the other strategies were feasible required more information about the process. The first step was to determine current process performance in terms of stability and structural variation of the output measurement. This required monitoring process performance at the final gauge. To gain as much process information as possible, we used measurements from all units, even those that were rejected by the inspection scheme. $\overline{X}$ and R control charts based on five consecutive parts measured every 2 h at the final gauge are shown in Figure 8. The control charts show that the process was stable and did not appear to exhibit structural variation over time. As a result, feedback control did not appear to be a viable strategy. At this point, a more extensive study (e.g., one that tracks output from every crankshaft) could be considered, as additional study may show that exploitable structural variation does exist. However, this analysis was postponed to pursue more promising avenues.

The remaining variation reduction strategies require the identification of an input X that is an important source of variability in the final journal diameters. A study was con-

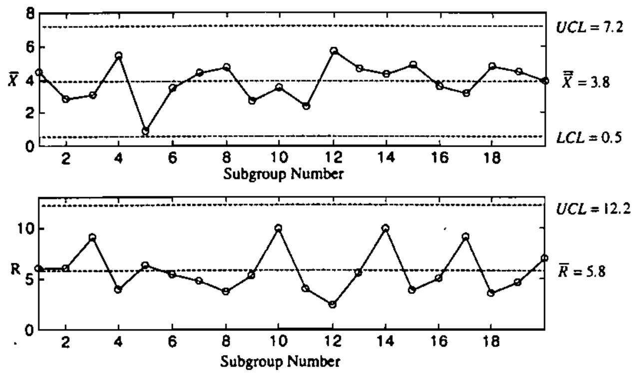

Figure 8. $\bar{X}$ and R control charts of final crankshaft data.

ducted where parts were sampled from each grinder and followed through the lapper step to see how the grinders and measurements at the intermediate gauge were related to the final journal diameters. In the study, six sample parts were taken from each of the four grinders. Figure 9 shows a scatterplot of all 24 pairs of before- and after-lapper journal diameter measurements. Clearly, there was a very strong relationship between before-lapper diameter and the final diameter (Y). Thus, we concluded that the before-lapper journal diameter is an X, as the variability in the before-lapper diameter appeared to cause the majority of the variability in final journal diameter. Note that we also determined that the variability caused by the lapper itself is relatively small even though it transmits the variability in X. Thus, reducing the variation added by the lapping operation was not considered a priority.

The remaining three strategies were then considered. A version of feed-forward control would be the use of a "smart" lapper that would measure the incoming journal diameter for each crankshaft and change the lapping time accordingly. Note, however, that the major purpose of the

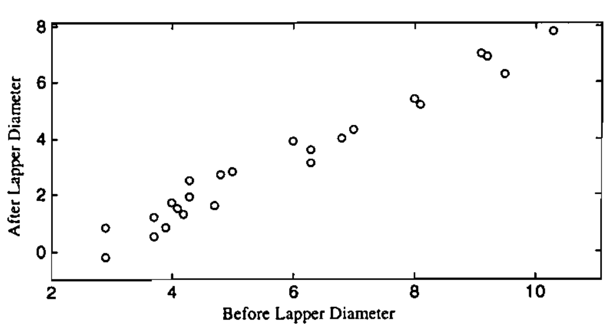

Figure 9. Scatterplot of before-lapper versus after-lapper journal diameters.

lapper is to improve surface finish, so this scheme would involve a change in function for the lapper. Also, this strategy would likely require greater lapping times and result in a bottleneck at the lapping operation. Thus, feed-forward control was rejected due to high cost. The strategy of desensitizing the process to the variation in after-grind diameter was considered briefly and also rejected because there were no process parameters in the lapping operation that could feasibly be changed to yield a process more robust to variation in incoming journal diameters. This elimination process left reduction in the variation of journal diameters prior to lapping (reducing variation in X) as the only feasible strategy.

To reduce the variation in X, we again considered each of the five generic strategies. Tightening the inspection criterion, this time at the intermediate gauge, was the first strategy considered. This would yield reduced variability in parts sent to the lapper. However, tighter inspection on X was rejected because the increase in scrap and reduced yield was deemed too expensive.

Feedback control was also a possibility, but informal monitoring of X at the intermediate gauge failed to show any structural variation due to time, and further study at this point was again unwarranted because more promising approaches were present.

At this stage, we needed further information about what was causing the variation in X. Our previous study that sampled parts from different grinders and followed them through the process provided some valuable information. Using the results of that study, we investigated the influence of the different grinders. Table 1 shows the results of an analysis of variance (ANOVA) to study the effect of different grinders on the final diameter. The average value of the after-grinder diameters were 6.4, 2.1, 1.0, and 3.2, respectively, with a standard error of 0.41. Clearly, between-grinder variation was a significant contributor to the variation in X. As a result, an input factor that caused a significant amount of the variation in X was the grinder number. We denoted this factor by $X2$. Notice that $X2$ was discrete with four different realizations.

Having identified $X2$, one possible variation reduction strategy was to use feed-forward control. In the initial process, feed-forward based on $X2$ was not possible because the grinder used was not recorded. However, a simple process change would make it feasible. For example, we could have changed the transfer process between the grinders and the lappers so that the lapper worked sequentially on a batch of crankshafts from a single grinder. Then feed-forward control would be possible because the lapper could be set to remove more material from batches

Table 1. Analysis of Variance Table for Crankshaft Example

SOURCE	DEGREES OF FREEDOM	SUM OF SQUARES	MEAN SQUARE	F	p
Grinder	3	98.38	32.79	32.56	0.000
Error	20	20.14	1.01		
Total	23	118.52			

ground by a grinder that typically yielded larger incoming diameters. For this feed-forward control scheme, an estimate of the average diameters that would result from each grinder would be needed. A potential problem with this approach was that to ensure the lapper was compensating correctly, each grinder's average output diameter must either stay constant over time or, occasionally, be reestimated. This feed-foward strategy was similar to the one discussed previously and was also rejected because it would lead to a bottleneck at the lapping operation. Desensitizing the process to the variation in grinder targets was also rejected because, as mentioned previously, there were no process parameters in the lapping operation that could feasibly be changed.

This left reducing the differences between the grinders (reducing variation in $X2$) as the logical alternative. Based on Table 1, we anticipated that removing the between-grinder variation would reduce the variation in the before-lapper diameter from approximately 5.2 to 1.0. This was accomplished by realigning the four grinders so that their output was targeted to the same nominal mean value. The results of implementing these changes in the process showed a decrease in the variation of the final diameters and a substantial reduction in the amount of scrap and rework generated by the process at both the intermediate and final inspections. The intermediate and final inspections were retained to monitor the success of the new control plan and to protect against poor quality.

This example presents a successful application of variation reduction and illustrates the thought process followed. However, reduction in variation itself should be an ongoing process. For example, based on our experience with grinders, we suspect that the average output value of each grinder will drift over time. This implies that the implemented variation reduction strategy will only be effective in the short term. This anticipated structural variation in X was not evident previously because when measuring X, the output from the different grinders was mixed together and the drift is probably fairly slow. This suggests that by plotting the after-grinder diameter for each of the grinders separately, over a longer time, structural variation may become evident. These plots can be obtained by either changing the intermediate gauge into four separate gauges, one for each grinder, or keeping track of which grinder was used for each part. If this structural variation exists, we anticipate that keeping the grinders aligned can be accomplished using feed-back control on the diameter after grinding. Identifying the exact nature of this feed-back control requires more information and is currently the object of further study. Determining the best feedback control scheme will require an understanding of the costs associated with retargeting, grinder maintenance, downtime, and so forth and an understanding of the variability caused by the grinder itself.

In this example, there are also many other process changes that could lead potentially to variation reduction. At each iteration of our analysis, we tried to focus on the major source of variability because it provides the greatest potential for improvement. However, in subsequent variation reduction exercises, different sources of variation will be most important, and different strategies will likely be most appropriate.

Summary and Conclusions

This article compares and contrasts five variation reduction techniques. We believe these five techniques, either singly or in combination, encompass all possible variation reduction methods. The goal of the article is to describe and explain the various methods and to aid the practitioner in making a judicious choice of technique. The process knowledge requirements and potential risks of the different variation reduction methods are summarized in Table 2. By keeping in mind the various strategies and their strengths and weaknesses, a practitioner will be able to make better decisions regarding process information that should be obtained and how best to improve the process.

Choosing an appropriate variation reduction strategy is not a linear process. At each stage, there are many options and there is no recipe. In each variation reduction exercise, we try to learn enough about our process so that the feasible strategies are determined. However, it is often the

Table 2. Summary of Information and Process Requirements of the Five Generic Variability Reduction Strategies

VARIABILITY REDUCTION STRATEGY	INFORMATION AND PROCESS REQUIREMENTS	POTENTIAL RISKS
Introducing or improving output inspection	Measurement on Y	Scrap/rework/inspection costs Inspection errors Loss of capacity
Introducing or improving feedback control	Measurement on Y Process targeting procedure Stable structural variation in Y	Measurement time lag Overadjustment
Reducing variation in X	Identity of X Measurement on X	Not true X Increased cost of inputs
Introducing or improving feed-forward control	Identity of X Measurement on X Process retargeting procedure Stable $Y = f(X)$ relationship	Not true X Overadjustment $Y = f(X)$ relationship unstable
Desensitizing the process	Identify robust process settings Feasible robust process settings Identity of X useful	May work only in experiment New process settings may be more expensive

quality of our study that determines how much useful process knowledge we obtain. A study can fail to identify a process characteristic, such as structural variation, either because the characteristic is not present or because the study is flawed. For example, in the crankshaft example, based on the current data no structural pattern in the after grinding diameters is apparent, but structural variation may be evident if we look at the output of each grinder separately. This means that as we obtain more process knowledge, we may be led to designing different studies. Also, variation reduction is an ongoing process, with each subsequent iteration attempting to reduce the variation further.

Another potential problem, in practice, is that the current process control strategy, such as feedback or feedforward control, masks the operation of the actual process and may make it difficult to determine an appropriate variation reduction strategy. For more information on overcoming this difficulty and a good review of process control strategies, see Ref. 12.

For ease of discussion, this article has focused on the applications with only a single quality characteristic Y. In most practical applications, a product would have multiple critical characteristics that must all be controlled simultaneously. In that case, reducing the variation in the output is a more difficult problem, as we do not want to reduce the variation in one characteristic only to see the variation in some other characteristic increase. The complications introduced by considering multiple quality characteristics simultaneously is worthy of further study.

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