Impact of Process Tampering on Variation

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Abstract

Variation is one of the four pillars of Deming's System of Profound Knowledge. The other three are Appreciation for a System, Theory of Knowledge, and Psychology. Lloyd S. Nelson was quoted saying that *the central problem in management and in leadership is failure to understand information in variation*.

This paper presents an educational tool that demonstrate the effects of process tampering on variation. It shows that reacting to common causes of variation as if they were special causes only leads to increase in variation and the likelihood of producing unacceptable output. To do so, an experiment was conducted by students (volunteers) in three stages. The first is the "control" stage, where the process operated as is. In the second stage, students were asked to make needed adjustments to achieve established target. The third stage represented taking the proper – process control – action then run the process. Finally, the three stages are compared next to each other on a statistical process control (SPC) chart.

Introduction

In his book, *The New Economics*, Deming introduced to the world the notion of seeing systems in what he coined as a System of Profound Knowledge (SoPK). It is comprised of four parts that must work together: appreciation of a system, variation, theory of knowledge, and psychology. These parts have been linked to much research work that has been done since then. This includes, but not limited to, transformational leadership [1], organizational transformation [2], learning organizations [3], [4], motivation [5]. In this paper, the concept of variation is examined with respect to process tampering.

"Life is Variation or Variation is Life" is how Deming described this concept [6]. He, of course, wanted to emphasize that variation impacts decisions at all levels. Difference in output may be observed in many products and services we experience on a regular basis. But there are also differences among people, whether they are members of the same team or students taking the same course at a university, which is tied to the *Psychology* part of Deming's SoPK. Another example for the interconnectivity between the parts of the SoPK is the fact that variation is a result of interactions between systems or processes. Therefore, understanding such variation requires us to appreciate the system [7]

Walter Shewhart worked on this concept at Bell Labs in the first half of the 20th century. He separated variation into two types: chance and assignable [8], [9]. This work was the foundation of statistical process control (SPC). Deming referred to the two types of variation as common-cause and special-cause [10]. Shewhart [9] used the term "Assignable" causes of variation before Deming popularized the term "Special" to refer to the same thing. In any case, common-cause variation (or un-assignable cause) is the natural type generally small in magnitude and follows random patterns and is inherent in the process. It is always there and can only be reduced through process improvements and through management beliefs and practices used in the organization [6]. On the other hand, special-cause (or assignable-cause) variation is an exceptional type of variation not based on chance; it is a signal of something unusual occurring in the process that needs immediate attention. It can be an indication that something was mismanaged or mishandled. It is typically treated or resolved at the process or local level by those immediately in charge.

Shewhart also determined that there are two types of mistakes that can be committed [6]. This comes from the misclassification of the types of variation:

- Mistake (error) 1: Reacting to the outcome as if it is the result of a special-cause variation when in fact it is a common-cause one.
- Mistake (error) 2: Not reacting to an actual special-cause variation (treating it as a common cause).

Ideally, losses from both types of mistakes should be eliminated. However, reducing one type of mistake has an adverse effect on the other leading to more losses. It was, therefore, necessary to design a tool that would keep both types at a reasonably low level. To do this, Shewhart developed a statistical tool called a control chart which can be used to distinguish between the two types of variation – common cause and special cause. This was designed economically to reduce both types of mistakes when rules for calculating the control limits are followed [6]. Since inception, the topic of economic design of control chart has been studied extensively by researchers with multitude of objectives [11-17]. However, Deming believed that no improvement had been made to Shewhart's original control charts [6].

Process tampering is essentially committing mistake 1 mentioned above. That is, reacting to random or common-cause variation as if it is a result of some assignable or special cause. Most of the tampering is committed by management through what is known as "management by results" [6]. Deming estimated that 94% of issues are the result of misinterpreting common cause variation, thus a management responsibility. With that percentage, more opportunities for such a mistake are created. Deming demonstrated the effects of management tampering using the funnel experiment [6]. In this experiment, rules were created to visually show how variation in outcome is impacted when the intention is to improve the performance.

An example of incorrectly reacting to the type of variation might be making decisions on sales figures. Lower monthly sales figures produced by a salesperson may be followed by a quick decision on what to do next without examining the type of variation over time or as plotted against other salespeople. In other words, process parameters connected with other systems could be manipulated to gain advantage. This can have negative effects on the system, like other units, product quality, or other salespeople, that would be realized immediately or at some point in time. For this, employees are often blamed for not achieving certain performance targets when the problem is more systemic and beyond their control. When this is the case, no worker is better than any other - all the differences between them are due to random (common-cause) variation.

Understanding variation comes with separating common-cause variation from special cause. Without properly studying the process using the right tools, management will almost always react to process random variation. This is known as tampering. This can be put into perspective by using a statistical process control (SPC) charts

Experiment with Control Charts

The aim of this experiment was to teach students taking a quality improvement course about variation. In other words, what is the likely impact on process variation when different scenarios for running a process are introduced? The learning outcomes expected are identifying the type of variation correctly so that correct decisions can be made.

In this experiment, we asked teams of three student volunteers to run the catapult (process) without prior knowledge about any learning outcomes. As is the case for any process, the catapult has controllable factors that can be set to increase or decrease the distance reached. There can also be some variability coming from noise such as slight movements while launching, inspector's position when reading the distance, among others. To summarize, the experiment involves the following three scenarios:

(1) Run the process as is – no adjustments are allowed
(2) Hit the target distance – adjustments to the process are allowed
(3) Run the process as is after making simple improvements.

A team of three volunteers was asked to run the process according to the given instructions. The volunteers were unware of the aim of the experiment. The work was divided among the volunteers as follows:

- Launcher
- Inspector
- Recorder

The catapult was set on a table top and a measuring tape was laid out on the floor with about 120 inches of range. Initially, the process was set to achieve an average of about 80 inches.

<u>Scenario 1: Run the process as is</u>
After a brief introduction on how to operate the catapult with a few practice launches, the volunteers were asked to operate the process as is and record results without worrying about the distance reached. Figure 1 below displays the results.

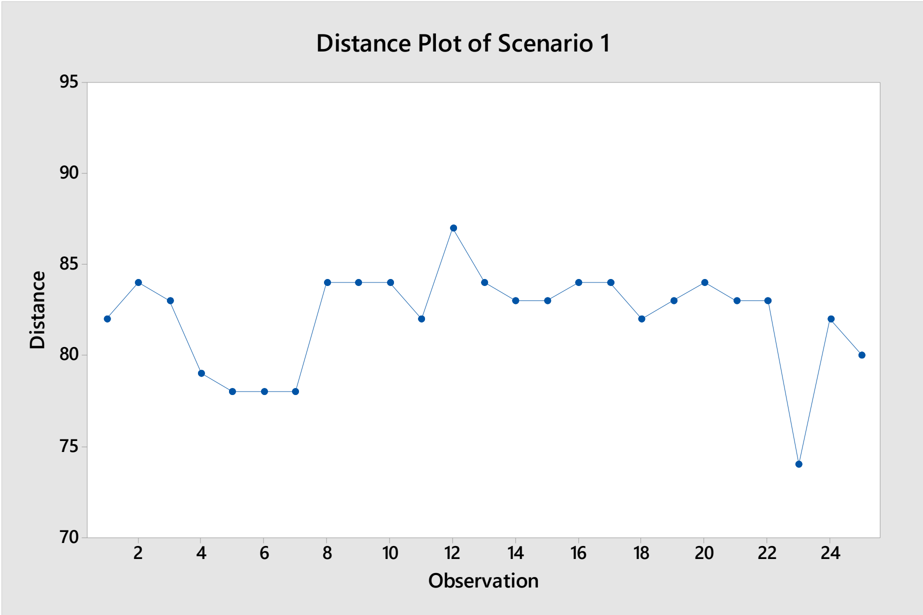

Figure 1: Run Chart for Scenario 1

Figure 1 is a run chart in the order or launches made. To evaluate the process variation, control limits need to be calculated using Shewhart control chart rules. Since we collected one data point (x_i) at a time, let $\bar{X}$ be the average of all launches, the upper and lower control limits (UCL and LCL) can be calculated as follows [18]:

$$UCL = \bar{X} + 3\,\frac{\overline{MR}}{d_2}$$

$$LCL = \bar{X} - 3\,\frac{\overline{MR}}{d_2}$$

Where $\overline{MR}$ is the average of the moving ranges. That is, the average of the ranges determined from each pair (two consecutive data points.)

Using the typical moving range for sample of two consecutive points, d_2 is replaced by 1.128 (constant for variable control charts), the above formulas are simplified into:

$$UCL = \bar{X} + 2.66\,\overline{MR}$$

$$LCL = \bar{X} - 2.66\,\overline{MR}$$

For our experiment, the UCL and LCL are determined and drawn on the chart in Figure 2

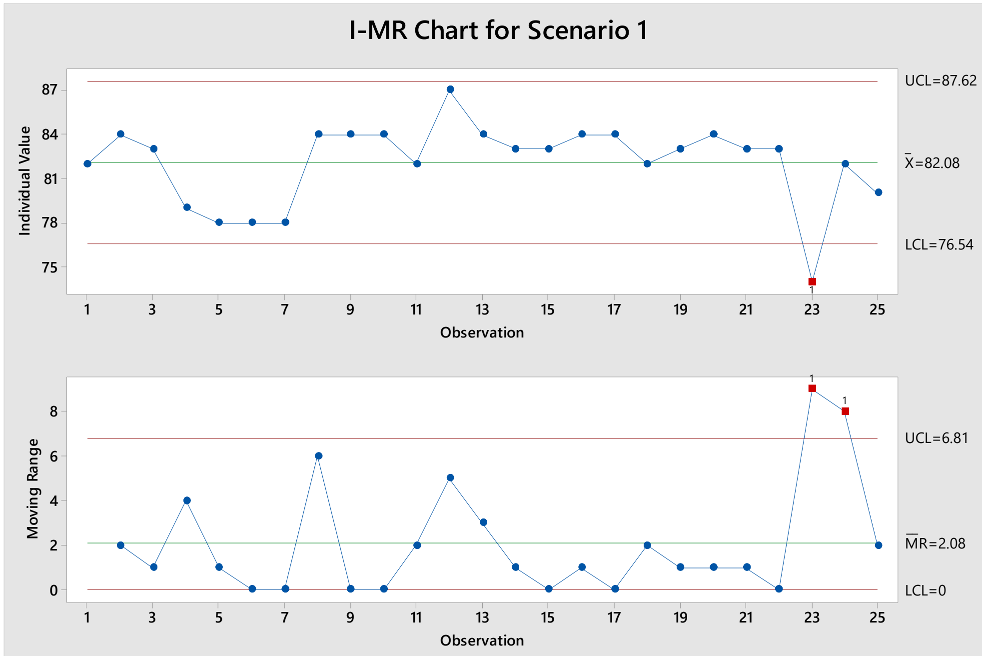

Figure 2: I & MR Control Chart for Scenario 1

It should be mentioned here that data point 23 (distance of 74) is plotting below the control limit (causing 2 points in the Moving Range chart to also be out of control). This was attributed to slippage when attempting to launch at the time.

<u>Scenario 2: Aiming at Target</u>

In this scenario, the team of volunteers is asked to launch the ball and hit the target of 80 inches. Here, the volunteers could adjust the catapult to achieve target. For example, they could change the rubber band extension, elevation, ball seat, among other factors. The aim for this scenario was to achieve a target of 80 inches.

After making many launches, the data was plotted on a control chart and compared to the Scenario 1 (Figure 3).

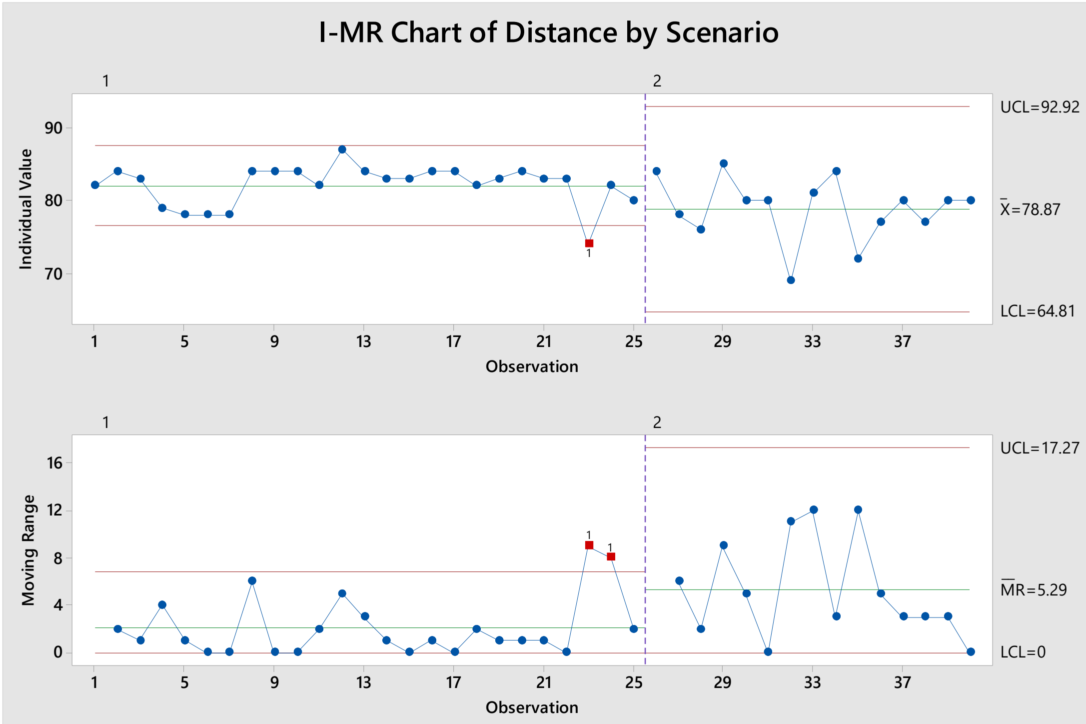

Figure 3: I & MR Control Chart for Scenarios 1 and 2

<u>Scenario 3: Run process as is - after slight improvements:</u>
The team of volunteers was asked to make simple improvements to the process to achieve consistency. Those improvements included holding the catapult steady when launching, using the same release method, and locating and watching the region of ball landing before each launch is made. Launches were then made without any specified target. Although a learning curve might be a contributing factor in reducing variation here, students were running the process per instructions given. If this was significant, then variation could have been reduced from Scenario 1 to Scenario 2 above. Results of Scenario 3, along with Scenarios 1 and 2 are plotted on the control chart in Figure 4.

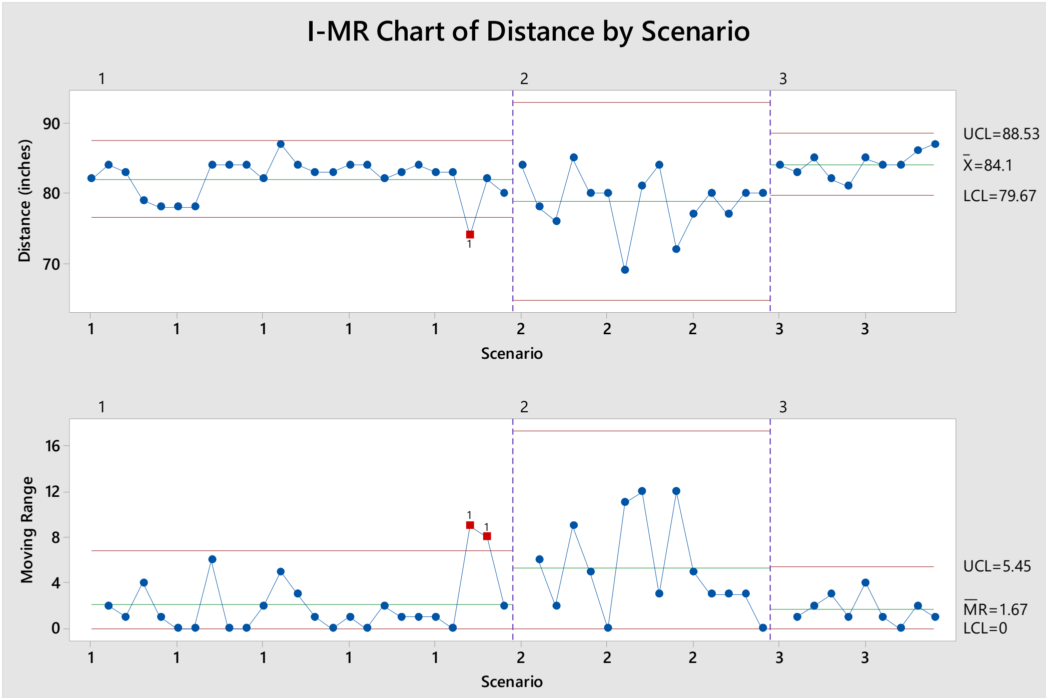

Figure 4: Comparing Process Spread among Scenarios

Discussion of Results

It can be seen from the above figures that process tampering (Scenario 2) resulted in more variation in the process as target was being chased through making adjustments to the process (system manipulation). Table 1 below shows the process spread for each of the three scenarios:

Table 1: Comparison of Process Spread among Scenarios

Scenario	Process Spread (UCL-LCL)	Comparison
(1) Run Process as Is	11.1 inches	Baseline
(2) Achieve Established Target	28.1 inches	Variation increased by 2.5 folds (250%)
(3) Run Process as Is – after making slight improvements	8.9 inches	Variation decreased slightly from phase one with simple instructions

As mentioned above, the aim of this paper is to demonstrate through a hands-on experiment the impact of process tampering on variation. When management does not understand variation, it typically treats common-cause variation as special-cause. The results of this behavior by management ultimately leads to blaming and ranking employees based on perceived performance. This can have devastating effects on employee morale and engagement. It also encourages some employees to be "creative" in meeting objectives and goals.

Understanding variation comes with separating common-cause variation from special cause. Without properly studying the process using the right tools, management will almost always react to process random variation. This is known as tampering. This can be put into perspective by using a statistical process control (SPC) charts.

To reduce the damaging costs of reacting wrongly to common-cause variation, the actions to be taken need to be of a systemic nature, which usually means they cannot be achieved overnight. It is a longer-term investment by management to reduce variation and optimize the process (or the system as a whole). Continuous improvement projects, such as Six Sigma types, can be carried out when only this type of variation is present - that is, common cause variation. On the other hand, if special cause conditions materialize, we should act quickly, and usually locally to bring the process back into stability or statistical control before long-term improvements can begin.

Concluding Remarks

This paper demonstrated, with examples, how a simple experiment with an inexpensive process such as the catapult and SPC control charts can be used as educational tools to demonstrate the concept of variation. Specifically, how the types of mistakes (errors) can be made when misclassifying common-cause and special cause variation. Additionally, this experiment can be linked to many management decisions that are made because of this misclassification. Management ends up pressuring employees to work harder to compensate for system issues. One reason for this is short-term thinking where no long-term improvement initiatives to address common causes of variation

Future work in this area may focus on ways to promote understanding of variation by management in business, government entities, and educational institutions. Other work may be directed at causes of short-term thinking (or short-term profits) and other diseases of management and obstacles [10]. They include lack of constancy of purpose, performance appraisals, mobility of management, and management by figures, among others.

Additionally, future experiment may involve using a larger group of students with surveys about their perception and beliefs of hypothetical scenarios of misclassification. These surveys can be conducted before and after the experiment to determine differences.

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