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Keywords

Common cause variation, Special cause variation, Control charts, Decision making, Simulation, Manufacturing system

Disciplines

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Comments

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Distinguishing between Common Cause Variation and Special Cause Variation in a Manufacturing System: A Simulation of Decision Making for Different Types of Variation

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Abstract: Controlling variation is an important aspect of quality improvement. Deming distinguishes between common cause variation and special cause variation and argues that both types of variation frequently result from people participating in the process. Confusing common cause and special cause variation can lead to incorrect decisions. This article analyzes the impact of an individual's ability to distinguish between common cause and special cause variation by simulating a manufacturing system with several human operators and a production manager. We use a recognition primed decision (RPD) model to simulate how human operators and the production manager would interpret the variation and make decisions to reduce the variation. A shared mental model with the RPD framework describes the interactions between different operators and the production manager. Results from this simulation demonstrate the

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importance of distinguishing between common cause and special cause variation, especially when problems occur at bottleneck points in the manufacturing system.

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1: introduction

Common cause variation and special cause variation are two types of variations common in any process. Common cause variation is a natural part of the process and is generally thought to be limited to three standard deviations of the mean. Special cause variation results from an assignable cause or external source to the process (Evans and Lindsay 2013). People may intuitively believe that any variation or problems in a process is attributable to specific causes or particular events. Deming (1986, 2000) argues that problems and variation often result from the system itself. He relates an anecdote where an insurance company warns a manufacturing firm about the number of fires the firm has experienced (Deming 1986). If the firm does not reduce the number of fires, the insurance company will cancel the firm's insurance. The firm's president immediately tries to identify the specific cause of the most recent fires. However, the historical data show that the number of fires is a stable process, and the number of fires is a system problem. If the president and his leadership view the fires as a special cause problem rather than as a system problem, they likely will identify incorrect solutions. Failing to distinguish between common cause variation and special cause variation may induce more variation in the system and lead to higher costs for firms.

Misinterpreting variation can occur in both inexperience and experienced individuals.

Individuals are bad at understanding how randomness appears within processes and rely on simple and often incorrect heuristics to predict uncertain events (Tversky and Kahneman 1974, Taleb 2005) An experienced person can misinterpret variation due to events that occur which he or she may have never seen before this time. An unexperienced person may misinterpret variation due to lack of experience and familiarity with the process or system (Gryna and Juran 2001, Kane 1989, Ishihara 1992).

Statistical process control (SPC) helps engineers and production managers interpret and understand variation in a process. The control limits in a Shewhart control chart can help distinguish between common cause variation and special cause variation. A data point that is greater than the upper control limit (UCL) or less than the lower control limit (LCL) generally indicates a special cause. If the data follow a pattern, such as continually increasing or continually decreasing, a specific cause might be inducing this pattern. If the data appear random and are contained within the control limits, the variation is likely common cause variation.

Even in the age of automation, human decision making is a crucial part of production systems and plays an important role in thinking about special versus common cause variation. People are part of the system and participate in the system process (Deming 1986). New operators or badly trained operators can make mistakes that could be a special cause in the system. Individual performances are naturally variable both within a single individual and across multiple individuals, and this variation is usually common cause variation. Humans are also responsible for identifying when problems exist in the process and developing solutions to fix those problems. Since people are often bad at understanding and interpreting variation, they may make mistakes when determining the cause of variation. Models of production systems and the variation in those systems should account for people within the system.

This article models and analyzes the differences between common cause variation and special cause variation and assesses the impacts of decision makers who correctly and incorrectly identify the causes. We simulate how experienced people could interpret variation or misinterpret variation. The article proposes different decision-making strategies based on a recognition-primed decision-making model (RPD) for reducing common cause or special cause variation (Klein 1993). The simulation quantifies the impacts of these different decision-making strategies and provides insight into how interpreting and misinterpreting variation can affect the quantity produced.

This article represents the first study, to our knowledge, that explicitly measures the impact of correctly and incorrectly distinguishing between common cause and special variation. The article compares system performance within four broad categories: (i) correctly identifying common cause variation as common cause variation; (ii) correctly identifying special cause variation as special cause variation; (iii) identifying common cause variation as special cause variation; and (iv) identifying special cause variation as common cause variation. Another unique element is the use of the RPD model to simulate how human experts make decisions within a manufacturing system. Shewhart control charts are used to represent the knowledge base of human experts in the simulation. The experts share a mental model and follow rule-based decision-making strategies for common cause and special cause variation. The innovation of this manuscript is the systematic analysis of common cause and special cause variation within a simulated manufacturing system that incorporates naturalistic decision-making strategies for identifying and resolving common cause and special cause variation.

The rest of this article is organized as follows: Section 2 reviews the literature in common cause and special cause variation and RPD. Section 3 introduces the simulation of a manufacturing system and describes the decision-making strategies. Section 4 presents the results of the simulation and analyzes the impact of correct and incorrect decision making. Concluding comments appear in Section 5.

2: literature review

Identifying, visualizing, and controlling variation are popular topics within the literature on SPC. SPC is widely used for quality improvement. A quality improvement strategy seeks to understand the reasons for process variation in order to properly address it. Traditional univariate SPC control methods, such as the Shewhart control chart, have been extended to multivariate SPC methods (MacGregor and Kourti 1995, Qiu 2008). Most applications of multivariate SPC methods are in industry process control (Mason and Young 2002, Kourti 2005). SPC can be used to do the structural health monitoring for transportation infrastructure (Chen, Corr, and Durango-Cohen 2014). Health care research is capitalizing on the benefits of using SPC for quality improvement (Berwick 1991, Perla, Provost, and Murray 2011, Benneyan, Lloyd, and Plsek 2003, Thor et al. 2007).

One feature of a process that often degrades quality is variation. Statistical tools, such as control charts, nested sampling studies, and graphical displays can be used to distinguish between the causes of variation (Snee 1990). SPC provides methods, such as control limits, to indicate when variation needs to be controlled or when the system is out of control. Some control charts can detect out-of-control signals in complex processes, such as auto-correlated processes. Some pattern recognition techniques can be combined with control charts to help people identify special cause variation (Du and Lv 2013, Du, Huang, and Lv 2013). SPC can also be used to provide useful insights into identifying and classifying variation (Marshall and Mohammed 2003, Du, Lv, and Xi 2012). Variation can be visualized by run charts or other graphs. Three-dimensional animation software is applied to help industrial practitioners visualize variation in complex manufacturing system (Wells et al. 2012). Other methodologies used for dealing with variation include the use of poka-yoke or mistake-proofing, Taguchi quality control methodology, a quality loss function, and signal-to-noise ratios to measure stability (Escalante 1999, Sauers 1999, Field and Sinha 2005).

Before variation can be controlled or reduced, an individual needs to identify the causes of variation in the process. Common cause variation stems from the design of the system, and an external source or unique feature is usually the root cause of special cause variation. Since identifying the root cause of variation is often challenging, several methods have been proposed to identify root causes. Root cause diagrams (cause-and-effect) diagrams investigate the causes and help to identify causes that have the greatest impact (Ishikawa 1982). Hypothesis testing or using a general linear mixed model can help identify the root causes in a multistate manufacturing processes (Zhou, Chen, and Shi 2004). Partitioning the variation to find the root cause in a metal stamping process enables the manufacturer to select proper countermeasures for reducing the variation (Majeske and Hammett 2003). People with different roles in a healthcare facility control variation differently in order to achieve their individual goals (Neuhauser, Provost, and Bergman 2011).

According to Shewhart's theory of variation, variation is classified according to the action taken to reduce it. Acting on the process can reduce common cause variation. To reduce assignable or special cause variation, people need to search for the exact cause and take actions to mitigate those causes (Nelson 1984, Wade and Woodall 1993). The existing literature on the causes of variation analyzes variation in a theoretical and mathematical way and seeks to describe it using probability distributions and control charts. The importance of understanding common cause variation and special cause variation is proposed by Deming (1986), and correctly understanding variation is a fundamental step to reduce variation. Data analysis and troubleshooting can detect problems and avoid problems. Run charts, tally sheets, control charts, and analyzing process means are commonly used to predict and troubleshoot problems (Ott, Schilling, and Neubauer 1990). Since reducing common cause variation can enhance system performance, eliminating problems can make processes more stable and more efficient. Changing the process mean, reducing variability, off-line and on-line quality control techniques, and process design can help reduce variation (Gryna and Juran 2001, Taguchi 1986).

SPC, by itself, cannot identify the causes of variations (Hodgson 1987). Identifying the causes of variation is usually done by people participating in the process. Unfortunately, people may make mistakes (Shingo 1986). They can misjudge the current state of the process and misidentify variations due to a lack of time or lack of familiarity with the situation (Shimbun 1989). Operators may misinterpret common cause and special cause variation, and exploring different decision-making strategies with respect to this variation remains an undeveloped field of research.

Decision making theories can be normative, descriptive, or prescriptive. A normative approach to decision making presents specific axioms that rational individuals should follow to make logically consistent decisions. A prescriptive approach focuses on helping people make a good decision. A descriptive approach analyzes how people actually make decisions (Bell 1988).

Several descriptive models have been proposed for decision making, such as prospect theory, satisficing, the garbage can model, image theory, conjunctive/disjunctive model, a lexicographic model, naturalistic decision making, and additive difference models (Dillon 1998). The RPD model is a type of naturalistic decision making that describes how experienced individuals make rapid decisions in everyday settings (Klein 1993). The RPD model consists of two parts: a situational assessment and a mental simulation. The RPD model finds the first workable solution for decision makers rather than the best alternative. When human teams are supported by an RPD-enabled decision support tool, the performance of team decision making can be improved in high pressure situations (Fan et al. 2005, Kaempf et al. 1996, Fan and Su 2010, Barnes and Hammell 2008). In addition to supporting human-agent collaboration, the RPD model has been applied to emergency decision making, such as clinical judgment and responding to natural disasters (Cioffi 2000, Elstein 2001, Norita 2004).

This article uses an RPD model to represent how an experienced individual makes decisions within a manufacturing setting. A simulation model helps us understand decision making and the impacts of individual decision making on different causes of variation. The individual's prior experience is represented by a control chart of previous simulations of a manufacturing system. During the production process, the experienced people work together to arrive at a final decision in order to control the production process and reduce variation. The team members share the current situation and problem among themselves, and a shared mental model exists among the expert team (Converse, Cannon-Bowers, and Salas 1993).

A shared mental model captures the manner in which different members within a team frame a decision problem among themselves. This article designs rule-based decision-making strategies for identifying and reducing common cause variation and special cause variation. The manufacturing system is simulated under several contexts: (i) with only common cause variation and with both common cause and special cause variation, (ii) with and without decision making, and (iii) with a correct interpretation of the variation and with an incorrect interpretation of the variation. The simulation results reveal and quantify the impact of correctly and incorrectly distinguishing between common cause variation and special cause variation. Section 3 provides details of the simulation and the decision-making strategies.

3: simulated experiment

3.1: manufacturing system

In our research, we use the manufacturing system adapted from Law (2007). As depicted in Fig 1, the manufacturing system has one shipping and receiving station and five work stations. Each work station has a different number of machines. Station 1 has four identical machines; station 2 has two identical machines; station 3 has five identical machines; station 4 has three identical machines; and station 5 has two identical machines.

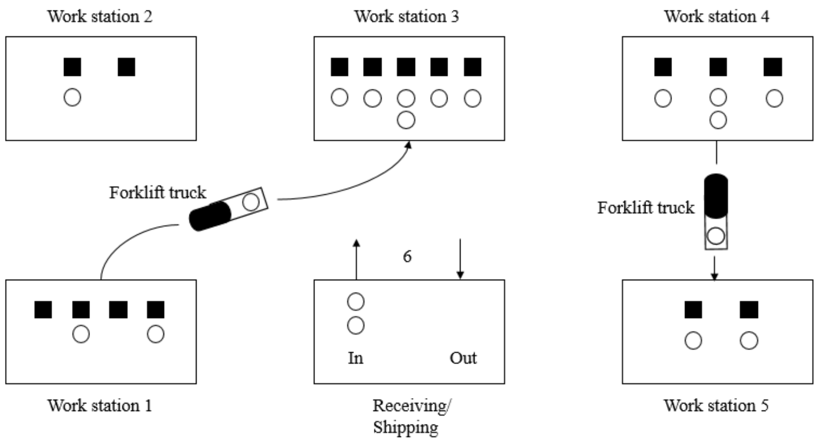


Figure 1. Manufacturing system layout, adapted from (Law 2007)

The arrival of jobs follows an exponential distribution with an average of 15 jobs arriving per hour. Three different types of jobs, type 1, 2, and 3, arrive at the manufacturing system with probabilities 0.5, 0.4, and 0.1, respectively. Two forklift trucks work in the manufacturing system to transport a job from one station to another station. The speed of a forklift truck is five feet per second. A forklift truck will search for the job that is closest to its current location. If there is no job request when the forklift truck arrives at a station, the forklift truck will stay at that station. The distances between five stations and the shipping and receiving station are shown in Table 1. If all of the machines are busy at a station when a job enters the station, the job follows a single first-in, first-out queue at that station. Table 2 displays the mean process time and routings of the different job types. The process time of a machine in each station follows a gamma distribution with a shape parameter of 2, which is a value assigned by Law (2007). The scale parameter of the gamma distribution is calculated so that the mean process time corresponds to Table 2. The mean process time depends on the type of job and the station in which the machine is located. When a machine finishes a job, the machine cannot begin another job until the forklift removes the finished job.

Table 1. Distances between different stations (feet)

Station	1	2	3	4	5	Shipping / receiving
1	0	150	213	336	300	150
2	150	0	150	300	336	213
3	213	150	0	150	213	150
4	336	300	150	0	150	213
5	300	336	213	150	0	150
Shipping / receiving	150	213	150	213	150	0

Table 2. Mean process time and routings of different type jobs

Job type	Mean process time of successive operations (hours)	Work stations in routing
1	0.25, 0.15, 0.10, 0.30	3, 1, 2, 5
2	0.15, 0.20, 0.30	4, 1, 3
3	0.15, 0.10, 0.35, 0.20, 0.20	2, 5, 1, 4, 3

3.2: shared mental RPD model

Common cause variation in a manufacturing system results from variation in the machine processing times, the arrival of different jobs to the system, the routes of jobs, and the layout of the system. Special cause variation in this system could occur if a machine fails, the truck used to transfer jobs moves more slowly, or an unexperienced operator works in this system. Human operators will try to make decisions and take actions to increase throughput, reduce variation, and identify problems in the system. Their decisions will likely depend on their previous experiences. It may be difficult to distinguish between common cause variation and special cause variation. If an individual decision maker fails to correctly distinguish between the two, his or her decision could negatively impact the performance of the whole system. Including a simulation of how human operators may make decisions to reduce variation with the simulated manufacturing system can help us to understand why people may interpret and misinterpret the variation and to analyze the impact of that interpretation and misinterpretation.

A team consisting of five station operators and one production manager control the manufacturing system described earlier. Each station operator—one operator for each station—gathers production information such as the queue length for each station. Each station operator compares the information to the control chart and may make a recommendation to the production manager. After receiving the report and advice from each of the station's operators, the production manager also uses the throughput of the system to make a final decision about changing production.

Both the station operators and production manager mentally follow their own naturalistic decision-making procedures. The RPD model is used to capture how an experienced individual makes rapid decisions in natural settings. Fig 2 captures how the RPD model is embedded in the manufacturing system simulation model. The station operators and the production manager classify the situation based on different experience knowledge bases. During the manufacturing process, station operators observe the stations' queue lengths. If the queue length of a station is in control, the station operator will share the queue length information with the production manager and not recommend the production manager take any action. If the queue length of a station is out of control, the station operator will recommend the production manager to take actions to control the queue length.

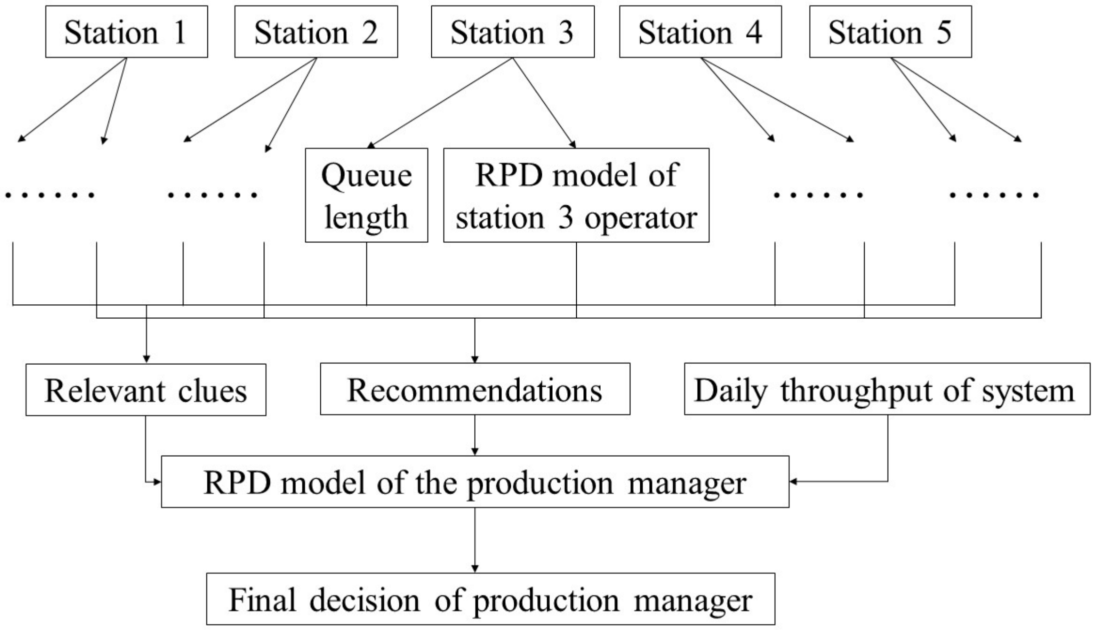


Figure 2. Shared mental RPD model

The production manager seeks to ensure that the throughput of the system achieves the production goals. The production manager relies on a control chart for the daily throughput of the manufacturing system. The daily throughput control chart—an individual observation control chart—represents the knowledge base of the production manager. The production manager makes a preliminary judgement about the manufacturing system by comparing the current daily throughput to his or her experience as depicted by the control chart. In this article, we mainly assume that decisions are based on the center line and the control limits of the control chart. Other decision rules may also be appropriate. For example, the production manager may make decisions if the daily throughput decreases for several days or if the daily throughput is less the average daily throughout for several consecutive days. Future research could explore the effect of alternative decision rules on the system variation.

The production manager also relies on relevant cues when making decisions. These relevant cues are the recommendations from the station managers and the queue lengths at each station. For instance, if the production manager observes that the daily throughput is out of control, he then evaluates reports from each station operator. If one of the stations' queue lengths is out of control, the production manager will decide to implement some actions to control the queue length of a station and improve the daily throughput of the manufacturing system. If all of the stations' queue lengths are in control, the production manager may not make any decisions on that day and wait for more information on the second day.

3.3: decision-making strategies

The shared mental RPD model only provides a framework for the production team's decision-making processes within a manufacturing system. This section details the rule-based decision-making strategies for the different members of the production team. Different decision-making strategies are proposed based on whether the production team is trying to control common cause variation or special cause variation.

3.3.1: decision-making strategies for common cause variation

When common cause variation exists in the manufacturing system, we consider three potential actions the production manager could use to control the variation in production. The actions are: (i) changing the mix of arriving jobs, (ii) reducing the variance in the process time of a machine, and (iii) reallocating resources from one station to another station. Changing the mix of arriving jobs means altering the probabilities that a job is one of the three types when it arrives. Different types of jobs require different routes through different stations. Changing the mix of arriving jobs can more effectively utilize the system's machines. Reducing the variance in the machine's process time means altering the gamma distribution so that it is less variable but the mean remains the same. Several reasons may explain why the variance but not the mean process time is reduced in a real manufacturing system. Reducing the mean process time may require purchasing new equipment, but the variance of the process time could be reduced through better scheduling, eliminating set-up times, and other lean manufacturing methods (Taylor and Heragu 1999). These types of continuous improvement strategies could be mathematically modeled by decreasing the shape parameter in the gamma distribution so that the variance is smaller but increasing the scale parameter so that the mean remains constant. If the production manager decides to reallocate the resources for each station and a station receives more resources, that station will process jobs more quickly. If a station loses resources, that station will process jobs more slowly.

All three decision-making strategies require the production manager to collect reports from each station operator at the end of the day. The station operator may recommend to take action to reduce the queue length of his or her station. The operator makes a recommendation based on the station's average queue length during the day and his or her previous experience (as represented by control chart of queue length). Three lines exist in the control chart: the UCL, the central line, and the LCL (Fig 3). If the average queue length is greater than the UCL (area A), the station operator will recommend taking action to reduce the queue length. Otherwise, the station operator will not recommend anything to the production manager. After the production manager receives reports from all of the stations, he or she will check the system's daily throughput to make decisions about managing production.

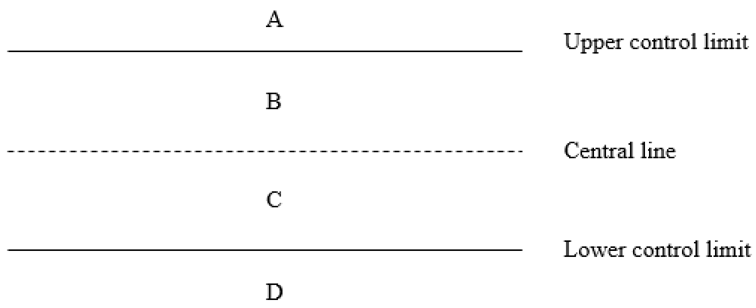


Figure 3. The areas in the control chart

The production manager uses a control chart of the system's daily throughput. If the daily throughput is greater than the center line (area A or area B), the production manager will not make any change in production even if a station operator recommends making a decision. For the purposes of this study, we assume that if the daily throughput is greater than the UCL (area A), that is acceptable because the manufacturing system is performing better than average. Future research can explore whether a production manager should also be concerned about daily throughput exceeding the UCL. If the production manager has changed the setting of the manufacturing system in the previous day, he or she will not change it again at the end of the current day. If the daily throughput is less than the center line but greater than the LCL (area C), the production manager will be inclined to take action to improve the throughput.

If the daily throughput is less than the LCL (area D), the production manager will take action to improve production. If the throughput is less than the LCL (area D), the production manager will take actions on each station for which the operator has made a recommendation.

If the production manager is inclined to take action (area C) but receives no reports from the station operators recommending action, then the production manager will do nothing. All settings of the manufacturing system will stay the same. If the daily throughput is in area C and only one report from the station operator recommends taking actions, then the production manager will take action for that station. If multiple reports from the station operators recommend taking action, then the production manager will choose one station to address. There are several steps used to decide which station should be chosen. Step 1: For each station for which the station operator recommends action, a station is qualified if that station was not chosen to modify the previous day. Step 2: If there is only one qualified station, the production manager will choose that station. Step 3: If more than one qualified station exists, the production manager will choose a station based on a prioritization scheme related to how many jobs require that station and the average queue length of the station.

Once the production manager decides to take action on one station or multiple stations, the specific decision strategy used by the production manager depends on which action is taken. If the production manager chooses the strategy to reduce a machine’s variance, the production manager will choose a station to reduce the variance of each machine at that station. Reducing the variance of a station is modeled by increasing the gamma distribution’s shape parameter by 20% while adjusting the scale parameter so that the mean process time of the machine remains the same as in Table 2. If the shape parameter was increased by 20% in the previous day, the shape parameter will not be increased any more. Twenty percent is chosen as a simple assumption to demonstrate how the variance could be reduced. In a real situation, the manufacturing system could be analyzed to assess how much the variance might change if actions are taken to stabilize the system.

Changing the job mix requires understanding how each station is impacted by the current job mix. If station 1 is selected, that means the queue length at station 1 is long and a lot of jobs are waiting at that station. According to Table 1, station 1 is the second station in the routing for job types 1 and 2 and the third station in the routing of job type 3. Intuitively, increasing the proportion of type 3 arriving at the manufacturing system can postpone new jobs entering station 1. The proportion of job type 1 arriving at the system is decreased by 10%, and the proportion of job type 2 arriving at the system is decreased by 10%. The proportion of job type 3 arriving at the system is increased by 20%. For other selected stations, the production manager will use a similar way to take actions. Table 3 shows the details of changing the job mix for each station. If the proportion of a job type is already greater than the initial setting, the simulation assumes that the job type's proportion cannot be increased further. But it could decrease.

The third strategy to reduce common cause variation is to reallocate resources from one station to another station. This action will increase the overall processing time at the former station and decrease the overall processing time at the latter station. If station 1 is selected, it means the queue length of station 1 is too long. In order to reduce the queue length of station 1, more resources should be used to decrease the processing time of station 1. From Table 1, all jobs entering station 1 come from station 3, 4, or 5. Fewer jobs entering station 1 can reduce the queue at station 1. Therefore, the production manager can reallocate some resources from stations 3, 4, and 5 to station 1 to reduce the queue at station 1. The process time of station 1 is decreased, and the process times of stations 3, 4, and 5 are increased. The production manager uses a similar reallocation strategy. Table 4 shows how the process time of each station is changed for the other stations. If the average process time for a station is already greater (less) than its initial average, the station's process time will not be increased (decreased) further.

Table 3. The change of arriving job mix

Selected station	Proportion of job type 1	Proportion of job type 2	Proportion of job type 3
1	decreased by 10%	decreased by 10%	increased by 20%
2	decreased by 10%	increased by 20%	decreased by 10%
3	decreased by 20%	increased by 10%	increased by 10%
4	increased by 20%	decreased by 10%	decreased by 10%
5	decreased by 10%	increased by 20%	decreased by 10%

Table 4. The change of process time for different stations

Selected station	Station 1	Station 2	Station 3	Station 4	Station 5
1	decreased	×	increased	increased	increased
2	increased	decreased	×	×	×
3	increased	×	decreased	increased	×
4	increased	×	×	decreased	×
5	×	increased	×	×	decreased

3.3.2: decision-making strategies for special cause variation

Special cause variation indicates that a problem has occurred in the manufacturing system. The production team will try to identify and fix the problem. We simulate a decision-making process and strategy to identify and fix the special cause. The special cause problems that exist in this simulation consist of a machine failure at one of the five stations and the forklift trucks moving more slowly.

We develop two types of decision-making strategies for controlling the special cause variation: strategy I and strategy II. The difference between these two decision-making strategies is how the production manager uses daily throughput to identify the existence of a problem in the manufacturing system. At the end of each day, the production manager observes the daily throughput and receives reports of the average queue length for each station. First, the production manager checks the daily throughput. If the daily throughput is greater than the LCL in the daily throughput control chart, the production manager will think there is no problem in the system during that day. Otherwise, the production manager will compare the current daily throughput with the previous days. In strategy I, if the daily throughput is less than the previous day's daily throughput by more than 15, the production manager will check the queue length of each station. In strategy II, if the daily throughput is less than the LCL at least two out of the three most recent days, the production manager will inspect the average queue length of each station.

Once the production manager decides to check the average queue length, it means that the production manager has received an initial alert of special cause variation from the change in the daily throughput. After checking the average queue length of each station, the production manager could know which station's average queue length is out of control (greater than the UCL). The production manager also considers the average queue length of previous days. If the average queue length over the three previous days is increasing and the current day's average queue length of a station is out of control, then the production manager will send people to inspect all machines at that station and the two forklift trucks. If the problem of machines or forklift trucks can be found, we assume the problem can be fixed immediately.

The simulation also allows for more reactive decision-making strategies to identify special cause variation. In more reactive decision-making strategies, the production manager will follow the steps for strategies I or II if the daily throughput is less than center line instead of the LCL.

4: simulation results

Based on the manufacturing system, decision models, and decision-making rules introduced in last section, we run the simulation to analyze the system performance under the different types of variation when the production manager correctly interprets the variation and when he or she wrongly interprets the variation. Four scenarios are considered: (i) correctly interpreting common cause variation; (ii) correctly interpreting special cause variation; (iii) misinterpreting common cause variation as special cause variation; and (iv) misinterpreting special cause variation as common cause variation.

We assume there are 40 days for one experiment or replication, and each day consists of eight hours. We run 20 replications for each simulation scenario. Each replication has an eight-day warm-up period and a 40-day operation period where each day is eight hours. The system performance metrics, such as daily throughput and average queue length, are tracked during each replication. The simulation results are the average performances over 20 replications.

4.1: interpreting variation

4.1.1: common cause variation

Without any decision making, the daily throughput of the manufacturing system during 40 days of one replication is shown in Fig 4. The variation depicted in the control chart is common cause variation. The Shewhart individual control chart is used to monitor daily throughput. Fig 4 includes the center line and control limits, which are calculated from simulating the manufacturing system with no decision making or problems. The system in

Fig 4 is stable, and no external sources are causing problems in the manufacturing system.

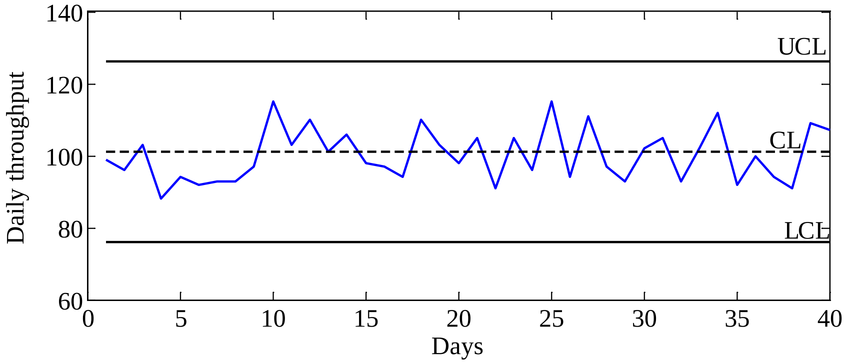


Figure 4. Daily throughput under common cause variation of no decision making

As discussed in Section 3, three decision-making strategies to reduce common cause variation are simulated. Fig 5 depicts the results of the simulation, including the average and standard deviation for the daily throughput and the average and standard deviation for the queue length of each station. The x-axis represents different decision making for common cause variation. The average value is shown by the bar, and the standard deviation value is shown by error bar.

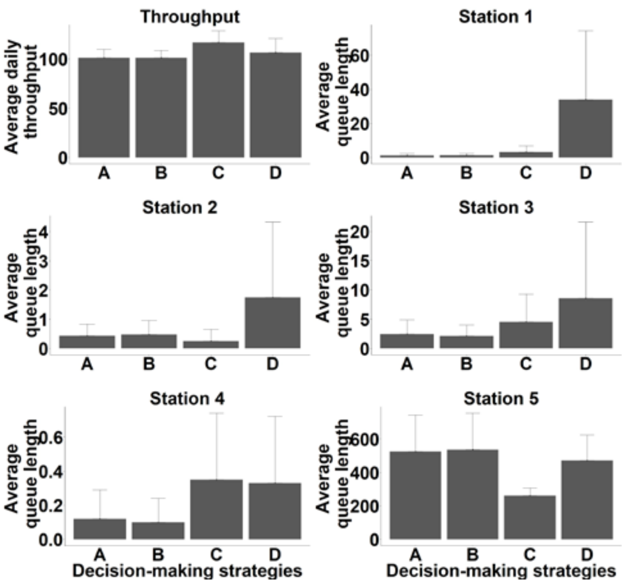


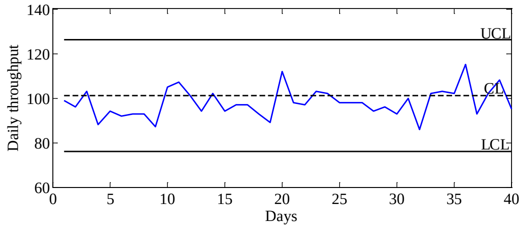
Figure 5. Simulated system performance for common cause variation (A: no decision making, B: reduce variance of each machine, C: change job mix, D: divert resources from one station to another)

The simulation results provide insights into the effect of interpreting common cause variation correctly. First, when the production manager decides to reduce the variance of each machine, the average daily throughput and average queue lengths are close to the values when there is no decision making. Daily throughput becomes less variable, however, because the processing times are less variable. Second, when the production manager chooses the other two decision-making strategies, the average daily throughput increases and the average queue length of station 5, which has the longest queue, decreases. However, the daily throughput becomes more variable than if no decisions are made. Third, the average queue lengths of the stations other than station 5 increase and become more variable. The daily throughput is at its greatest when the production manager changes the mix of the arriving job types. Station 5 has the shortest average queue length and the smallest variance if the mix of arriving job types are altered.

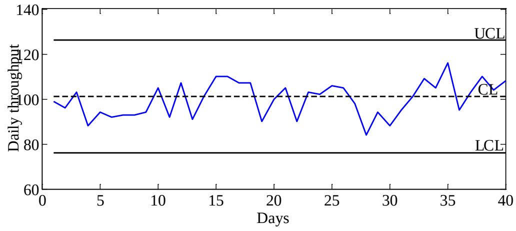
Not all actions which improve the initial settings of the manufacturing system reduce the variation in the system. In this example, decreasing the variability in the processing time for each station reduces the overall variance but does not improve the daily throughput. Changing the arriving job mix and diverting resources from one station to another station improve the daily throughput but increases the variability. This increase in variation may be due to the fact that the system is changing for short periods of time and then returning to its original state.

4.1.2.: special cause variation

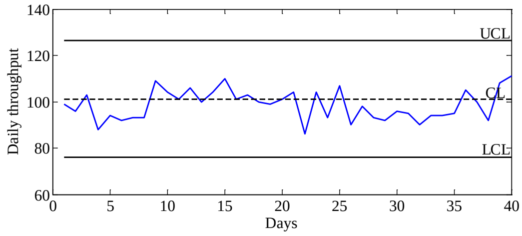
Special cause variation is caused by specific events or external sources. Our research considers two different types of special causes. First, special cause variation occurs because machines fail. Second, the forklift trucks move more slowly. Fig 6 depicts the simulated daily throughput for a machine failure at each one of the five stations. In each simulation, the machine fails on the eighth day. Fig 6(f) depicts the daily throughput if the forklift trucks move more slowly beginning on the eighth day.



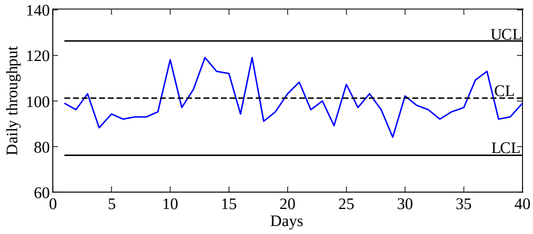
(a) Station 1



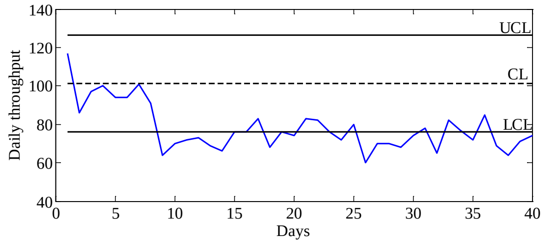
(b) Station 2



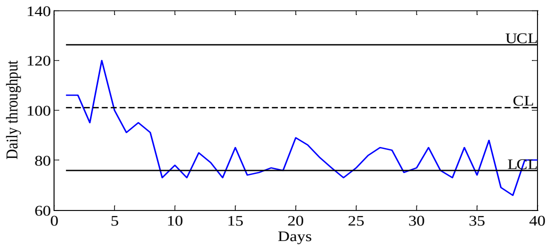
(b) Station 3



(d) Station 4



(e) Station 5



(f) Trucks move slowly

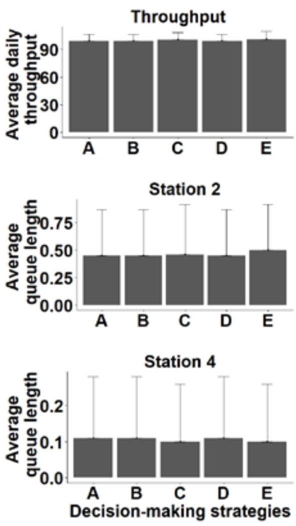
Figure 6. Daily throughput of the system having special cause variation of no decision making

The daily throughput clearly decreases if the machine at station 5 fails or the forklift trucks move more slowly. However, if a machine at stations 1 through 4 fail, the daily throughput is very similar to the daily throughput in Fig 4 when common cause variation exists. A bottleneck exists at station 5, and the queue length at station 5 is much longer than the other stations' queue lengths. The bottleneck explains why a failure in a machine at station 5 impacts the daily throughput more than the other four stations. Since the daily throughput does not change when a machine fails in stations 1 through 4, the production manager may have trouble distinguishing between special cause variation and common cause variation.

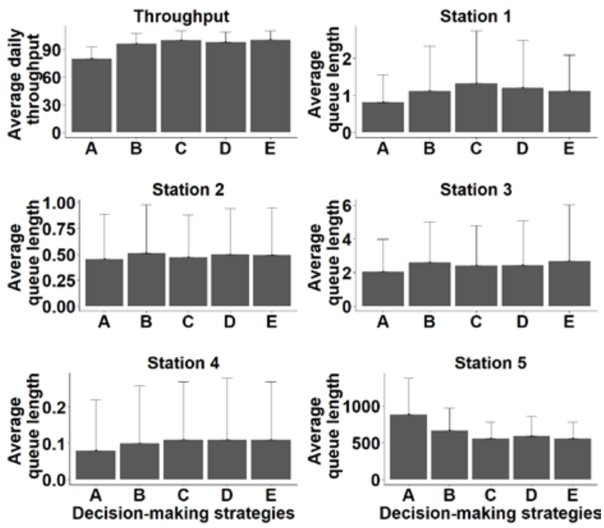
The simulation analyzes two different decision-making strategies for special cause variation, strategy I and strategy II, as described in the previous section. The more reactive strategy means that the production manager makes decision more frequently. Once the daily throughput is less than the center line in the control chart, the production manager is inclined to make decisions. The simulation results, as shown in Fig 7, assume the production manager interprets the special cause variation correctly. When a machine fails in station 1, 2, 3, or 4, the simulation results are very similar, so only the simulation results for station 1 is shown in Fig 7. If a machine at station 1 fails, the less reactive decision-making strategies do not recognize that a problem exists. There is no difference between the less reactive decision-making strategies and no decision making. The more reactive strategies have some effect on the queue length and increases the daily throughput slightly at station 1. The more reactive strategies can identify the problem during the simulation. However, the more reactive strategies often do not identify the problem immediately after machines fail in station 1, 2, 3 or 4. If a machine at station 5 fails or the trucks move more slowly, all four decision-making strategies can fix the problem, improve daily throughput, and reduce the queue length. The more reactive strategies identify the problem more quickly and result in better performance.

If the production manager wants to control the special cause variation, he or she should identify and fix the problem as soon as possible. The total time of the simulation is 40 days, and the problem (i.e., machine failure or trucks moving more slowly) always occurs at the beginning of the eighth day. Table 5 shows the average time when the problem is identified and fixed. The results in Table 5 can explain why the less reactive strategies do not perform as well as the more reactive strategies. If the machine at station 5 fails or the trucks move more slowly, all four decision-making strategies can detect and fix the problem. The problem is detected the most quickly if the trucks move more slowly. This explains why all four decision-making strategies improve the daily throughput and reduce the queue length if the special cause is a failure in machine 5 or the trucks move more slowly. For the other four stations, the less reactive strategies usually do not detect the problem. The more reactive decision-making strategies detect the problem, and the more reactive strategy II only takes a couple of days to detect the problem. However, since a machine failure at stations 1 through 4 do not negatively impact daily throughput to a large extent (Fig 6), fixing a machine at those stations only increases daily throughput by a little bit.

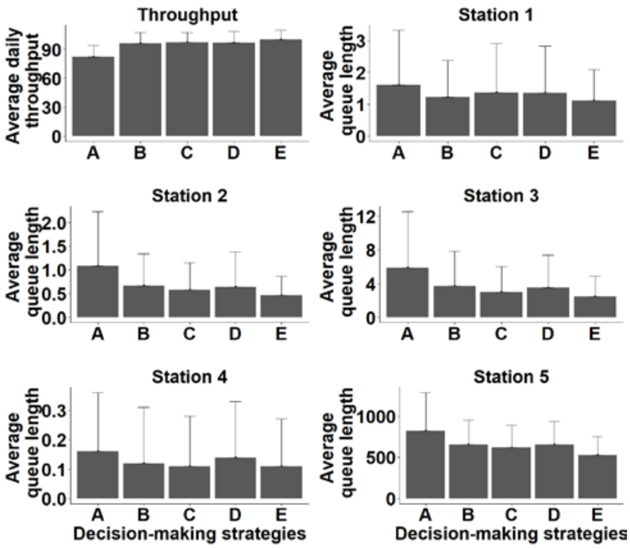
If a machine fails at any station, the queue length at that station increases considerably. For example, if no machine fails in station 1, the average queue length is 1.15. If a machine fails in station 1, the average queue length increases to 48.11, which is much greater than the UCL of the average queue length control chart for station 1. Table 6 shows that the average queue length at a station that experiences a machine failure exceeds the UCL one or two days after the machine fails. The third column in Table 6 shows the percentage of time the average queue length exceeds the UCL after the machine fails on the eighth day. The average queue length continues to exceed the UCL at least 60% of the time.



(a) Machine fails at station 1



(b) Machine fails at station 5



(c) Trucks move slowly

Figure 7. Simulated system performance for special cause variation (A: no decision making, B: strategy I, C: more reactive strategy I, D: strategy II, E: more reactive strategy II)

If the production manager checks the average queue length of each station first instead of the daily throughput of the manufacturing system, the problem can be identified much more quickly. What a production team is measuring is crucial to a proper understanding and analysis of a manufacturing system. In this simulation, if a production team is only observing daily throughput, the production team may fail to detect problems at many stations since many of those stations have extra capacity. If the production team also considers the queue length in its decision-making processes, they may realize that a problem exists sooner. Knowing ahead of time if the daily throughput or the queue length will be out of control first may be challenging, but these types of simulations can provide clues about which one is more susceptible to special cause variation.

Table 5. Average time when the problem is fixed

	Machine fails at station 1	Machine fails at station 2	Machine fails at station 3	Machine fails at station 4	Machine fails at station 5	Trucks move slowly
Strategy I	Never fixed	Never fixed	37th day	Never fixed	25th day	17th day
More reactive strategy I	26th day	16th day	19th day	25th day	21th day	14th day
Strategy II	Never fixed	Never fixed	Never fixed	Never fixed	15th day	15th day
More reactive strategy II	10th day	10th day	10th day	11th day	14th day	9th day

Table 6. Average queue length changes for special cause variation

	When the average queue length of the station having problem reaches the UCL after 8th day	Percentage of time that the average queue length of the station with a failed machine is greater than the UCL after the 8th day
Machine breaks in station 1	9th day	100%
Machine breaks in station 2	9th day	100%
Machine breaks in station 3	10th day	97.81%
Machine breaks in station 4	10th day	61.25%
Machine breaks in station 5	14th day	68.50%

If the special cause degrades the performance significantly, it will be much easier for the production manager to detect the special cause and control it. For example, in the simulated manufacturing system, if a machine fails in station 1, 2, 3, or 4, the daily throughput does not decrease much. It is difficult for the production manager to detect the problem if he or she uses the basic decision-making strategies. The more reactive strategies can find the problem. If a machine at station 5 fails or if the forklift trucks move more slowly, the daily throughput decreases a lot. All four decision-making strategies can detect the problem. Although the more reactive decision making may detect the problem in the system sooner than the basic decision making, the more reactive decision making may raise more false alarms and be more costly.

4.2: misinterpreting variation

4.2.1.: common cause variation

A production team may misinterpret common cause variation as special cause variation. This section explores the impacts of misinterpreting common cause variation within the manufacturing system. In the simulation, if the daily throughput is less than a certain value, the production manager may believe that is due to special causes. If the production manager misinterprets the common cause variation, he or she will follow procedures to identify a problem that does not really exist. The misinterpretation of common cause variation will guide the production manager to check the average queue lengths of the station, check the status of the machines, and make sure the forklift trucks are not moving more slowly. Checking these machines and the forklift trucks could waste time, energy, and money. Table 7 shows the average number of times the production manager inspects the machines and forklifts over a span of 40 days if he or she is following the decision-making strategies for special cause variation even though only common cause variation exists.

Table 7. Times of inspection when the common cause variation is misinterpreted

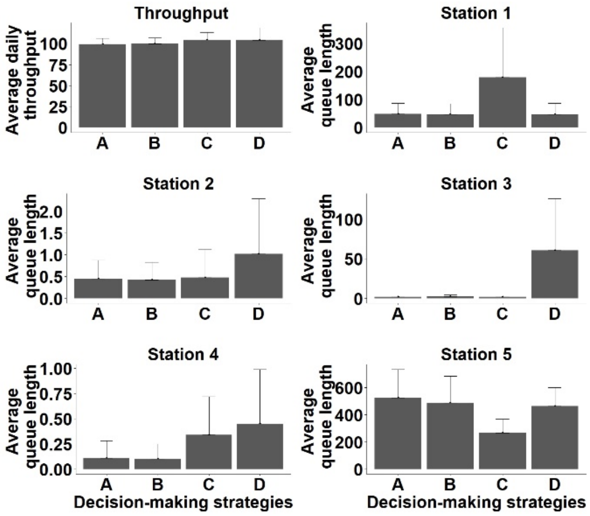
	Average days of checking machine and trucks status during 40 days
Strategy I	0
More reactive strategy I	3
Strategy II	0
More reactive strategy II	14

The simulation results demonstrate that if the production manager only follows the basic decision-making strategies for special cause variation when common cause variation exists, the production manager will not waste his or her time looking for problems that do not exist. The more reactive decision-making strategies lead to more inspections. The more reactive strategy II results in many more inspections than the more reactive strategy I. The more reactive strategy I uses the difference between two consecutive days' daily throughput to identify special cause variation. If the difference specified in the more reactive strategy I is greater than 15 units, the production manager will be less likely to misinterpret common cause variation as special cause variation. The more reactive strategy II focuses on the value of the daily throughput. If several days' daily throughputs are less than the average daily throughput, the production manager may misinterpret the common cause variation as special cause variation. Although the more reactive strategies can more quickly identify special cause problems that may exist, they also result in more false alarms.

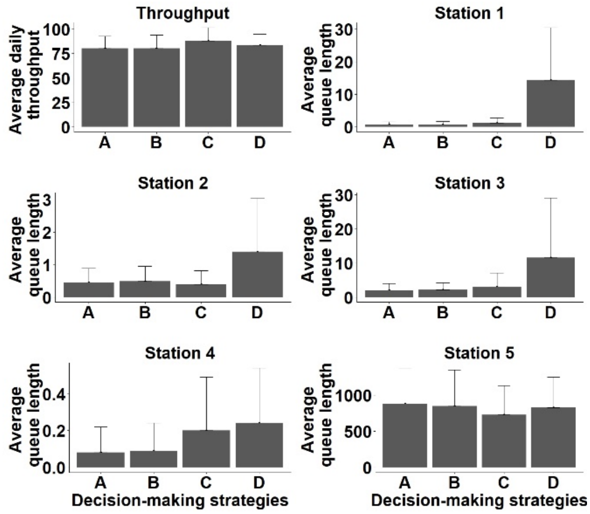
4.2.2: special cause variation

Just as common cause variation can be misinterpreted as special cause variation, so can special cause variation be misinterpreted as common cause variation. This section explores the system's performance when special cause variation is treated as common cause variation. The simulation assumes that if the production manager misinterprets the special cause variation, he or she will use the three strategies for common cause variation: reducing the variance of each machine, changing the job mix, or diverting resources from one station to another station. The simulation results are shown in Fig 8. When a machine fails in station 1, 2, 3, or 4, the simulation results are very similar, and only the simulation results for a machine failing in station 1 is depicted.

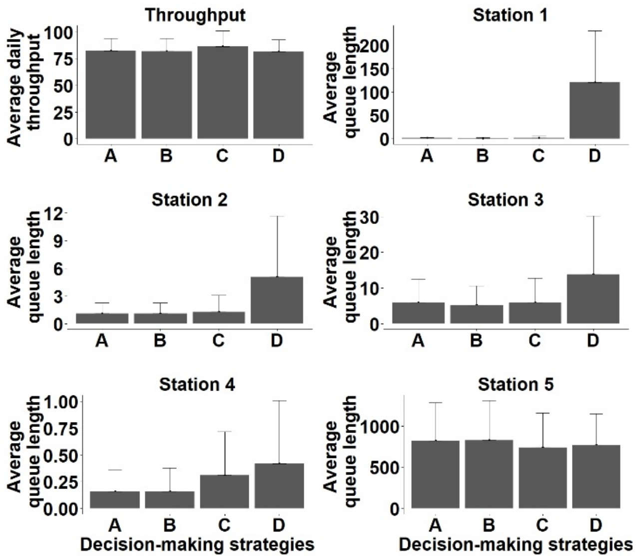
When a machine in station 1 fails, the average daily throughput with no decision making is 99. If the machine's failure is detected, the average daily throughput can be increased to 100 or 101, depending on how quickly the failure is discovered (Fig 7(a)). However, if the machine is never fixed but strategies for common cause variation are selected, the average daily throughput can be increased to 104 or 105 (Fig 8(a)). Changing the arriving job mix or diverting resources from one station to another station can alleviate the system's bottleneck by reducing the queue at station 5. The decision-making strategies used for the special cause variation fix the machine failure at station 1 instead of alleviating the bottleneck at station 5. Although these strategies improve the daily throughput of the manufacturing of system, the average daily throughput is still less than the average daily throughput when those strategies are implemented and there is no machine failure (see Fig 5). The average daily throughput in those scenarios are 107 and 117. Changing the arriving job mix increases the average queue length at station 1 significantly.



(a) Machine fails at station 1



(b) Machine fails at station 5



(c) Trucks move slowly

Figure 8. Simulated system performance when special cause variation is misinterpreted as common cause variation (A: no decision making, B: reduce variance of each machine, C: change job mix, D: divert resources from one station to another)

When a machine fails in station 5, changing the job mix or diverting resources from one station to another station increases the average daily throughput from 80 to 87 or 83, respectively. This daily throughput is much less than the daily throughput when the special cause variation is correctly identified. Fixing machine 5 increases the average daily throughput to 96-101 (Fig 7(b)). The average queue length of station 5 continues to be very large (between 731 and 848) when the special cause variation is misinterpreted as common cause variation.

When the trucks move more slowly, the results are similar to the results if a machine at station 5 fails. The queue length at station 5 is very long when the decisions for common cause variation are implemented. The average daily throughput can be increased due to these decisions, but the average daily throughputs depicted in Fig 8(c) are much less than the average daily throughput when the production team correctly detects that the trucks are moving more slowly (Fig 7(c)). Long queue lengths also result for stations 1 through 4 when the incorrect decisions are made. In the manufacturing system, the finished job will block the machine if it is not moved by a truck. If the problem of trucks is not detected, the trucks will still move slowly, and the finished job cannot be picked up by trucks immediately. Once the finished job blocks the machine, more unfinished jobs are waiting at stations. The queue length of a station grows longer.

When special cause variation is misinterpreted as common cause variation, incorrect decision making can degrade the manufacturing system’s performance for some scenarios. Often, the incorrect decision making does not make things worse and can improve the daily throughput. However, this improvement in daily throughput may be much less than if the production team correctly detects and fixes the problem. If the special cause occurs at a bottleneck in the system (such as at station 5), the difference between correctly and incorrectly identifying the special cause is significant.

5: conclusion

This article studies and analyzes the impact of decision making when common cause variation and special cause variation exist in a manufacturing system. A discrete-event simulation is used to produce different scenarios for a manufacturing system. The RPD model is used to represent how an experienced individual makes decisions. Shewhart control charts represent the individual's experience and enable the individual to distinguish between common cause and special cause variation. A decision team consists of a production manager and station operators. Different rules are established for interpreting and reducing common cause variation and special cause variation.

Analyzing the simulation results reveals several important insights and recommendations for practitioners even if the manufacturing system is more complex than what is presented in this article. Correctly distinguishing between common cause variation and special cause variation can have important implications for production. Simple strategies such as better planning, moving resources from one station to another, and changing the job mix can increase the average daily throughput by 5-10%. If standard procedures are implemented that reduce the variability at each machine or station, the average throughput might not change, but the variability in the daily throughput can be reduced. If a production manager mistakes common cause variation for special cause variation, the simulation results indicate that the production manager may waste time checking for special causes. However, whether or not there is wasted effort looking for causes that do not exist depends on the aggressiveness of the production team in trying to identify special causes.

If special cause variation exists in the manufacturing system, a production manager may have different types of data or control charts to consider in order to identify if special cause variation exists. If the problem occurs at point that is not a bottleneck in the production system, the production manager may not identify a problem has occurred by observing control charts for the daily throughput. The queue lengths of jobs at different stations may provide an earlier indication of special cause variation in the manufacturing system, but relying on the queue lengths may also generate more false alarms. A production team may still succeed in improving throughput if it misinterprets special cause variation for common cause variation, but the improvement in daily throughput will be less than what could have been achieved if the special cause were identified and fixed before making the improvements to reduce common cause variation. A production manager should ensure that there are no special causes impacting system performance before taking steps to reduce common cause variation.

One limitation of this research is that the decision-making rules were relatively simple and assumed that individuals were relying on control charts. Future research could conduct empirical studies to determine the extent to which people correctly interpret common cause and special cause variation. Modifying the decision rules to reflect such an empirical study could lend more credence to the conclusions. Integrating the results of such a study into the manufacturing simulation could provide additional insights into the impact of misinterpreting common cause and special cause variation. Applying this analysis of distinguishing between common cause and special cause variation could be extended to other systems such as healthcare, criminal justice, transportation, and sports. If the system involves many different people who are making their own decisions, an agent-based simulation that allows for more complex interactions could also be considered.

Despite these limitations and avenues for future research, this article represents one of the first detailed studies that analyzes the impact of interpreting between common cause variation and special cause variation. The innovative aspects of this article include the use of a discrete-event simulation of a manufacturing system with several human operators and a production manager in order to understand the impacts of decision making to address common cause and special cause variation. An RPD model describes how human operators and a production manager interpret variation and make decisions. Each operator and the production manager use a control chart that reflects their knowledge basis. Decision rules based on these control charts and whether the focus is common cause or special cause variation enable us to quantitatively assess the impacts of proper and improper decision making. Believing that common cause variation is special cause variation can lead decision makers to waste resources trying to identify a specific problem and fail to consider solutions that address the entire system. Believing that special cause variation is common cause variation can lead decision makers to ignore a specific cause that degrades system performance. Understanding the differences between the two types of variation can lead to more effective processes and higher-quality production systems. The methods proposed in this research can also be applied to more complex manufacturing systems with more stations or more machines.

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