

Root Causes & Elusive Solutions

By Sheila Julien

THE ELUSIVE SOLUTION

A high end equipment manufacturer incurred large wastes in excess capacity to accommodate the quarter end spike in shipping requirements. It was widely, though erroneously, believed that the 'hockey stick' spike at quarter end was caused by the customers' preference to buy at end of quarter – perhaps motivated by the perception that the Sales Reps cut the best deals then. Because this driving factor was beyond the manufacturer's control, year after year, they incurred millions in excess costs without testing their assumption about the cause.

At a commercial print shop, the plant manager was very frustrated. He had chartered an improvement team to address excess paper waste and – unlike the high end equipment manufacturer described above – the team gathered facts and data. But here, too, the results ultimately disappointed. The improvement team discovered that print operators were setting the 'overage' percentage (that is the amount in excess of the ordered quantity to allow for some damage in the downstream production) at an amount that was *quadruple* the average needed to compensate for damage in the production process! The solution seemed obvious – tell the operators to reduce the overage percent to an amount more consistent with the expected amount of damage. After celebrating a 50% reduction in scrap last quarter, now material waste is rising again – almost to where it had been. Obviously, the team had not found and addressed the *root* cause.

At another company, an improvement team working on improving efficiency of a retirement community's housekeeping staff did not stop at the first level cause, but used the 'Five Whys' a method developed by Toyota founder, Sakichi Toyoda, to identify the *root* cause by asking 'why' five times. The retirement community required 25% more cleaning staff per square footage than their benchmark. Why? The housekeepers were unskilled in efficient cleaning techniques. Why? There was no formal training program for housekeepers. Why? There were no training personnel on staff. Why? There was no budget for that position. The team determined that the annual cost of the inefficiency against benchmark was almost three times the cost of a training position. The position was added, the training completed, and no improvements in efficiency appeared.



WHAT'S HAPPENING?

In each of these cases, people were convinced they understood what was causing the problem and what was needed to fix it. In each case, they were mistaken and left significant amounts of waste in their organizations.

Group think prevented the equipment plant manager from digging into the problem. Few things are more dangerous than common knowledge – when it is wrong. If they had charted customer requested ship date (as someone eventually did), they would have seen that it was level across the quarter – no ‘hockey stick’ spike at all. Digging deeper, they would have realized that the Order Management department had developed the practice of calling customers with equipment on order to ask if they would accept an early shipment. This allowed an earlier invoice date which improved the organization’s ability to make that quarter’s revenue plan (at the expense of the next quarter’s, of course), but caused a substantial hit to profits due to the overtime premiums and the excess capacity that had to be carried all quarter – costs of which the Order Management Department was unaware.

The printing team gathered data, but did not delve in to learn *why* the printer operators had raised the overage percent that high and what caused those situations that caused the operators to keep edging up the overage percentage. If they had, they would have learned that whenever a job had to be rerun, the printers would increase the overage another percent or two because setting up and running a job just for a few more copies was so costly and inefficient. If they had examined the details of the few jobs that required more copies, they might have discovered that only certain types of jobs were more likely to incur damage, so they could safely reduce the overage percent on almost all jobs. If they dug even deeper, they might have found that the Cutting and Binding equipment did not have jigs for these less common jobs so they were more prone to human error – actionable information that could solve the problem for good.

The Housekeeping staff may indeed have needed training to be more efficient cleaners, but the reason they required 25% more staff per square foot was that each resident had been given a schedule as to what day and time to expect their housekeeper, and that schedule allowed 25% more time per square foot. The housekeepers, never told otherwise, kept to the schedule even after the training, so no efficiencies showed up in their numbers. Not until the true root cause was found and addressed could any efficiencies be realized.

Root causes are tricky and elusive things, and even the Five Whys will not reliably find them. The most common culprit is an untested conclusion.



When brainstorming possible causes for the classic fishbone¹ diagram, it is wise to think quite broadly. If the real cause does not make the list, your chances of hitting on the right solution first time around are slim. Consider carefully every possible way that the people, technology, information, materials, environment, or methods might be contributing to the problem.

But when the brainstorming of possibilities is over, put on your skeptical hat and test each one – *before* you go to the next “why” to find the root cause. If you follow the Five Whys down the wrong path at any point in the process, it will lead you to the wrong conclusion.

USING LOGIC TO TEST CAUSES

One of the quickest ways to test a possible cause is to see if it is consistent with the data you already have.

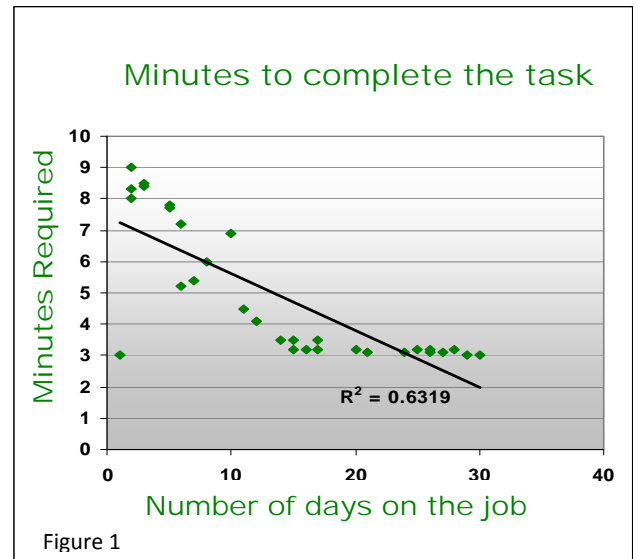
- ❖ Did the proposed cause *precede* the effect? If not, it is probably not the real cause. If poor call response rate is being blamed on the new answering system, was the call response rate better before the system was installed? If not, the new system cannot be the culprit.
- ❖ Does the data indicate the problem is trending or cyclical? If so, you can probably rule out ideas about causes that would produce steady effects. For example, to test the possibility that shipping errors are on the rise due to poor technology, ask whether the technology has changed. If there have been no changes in the technology, any changes in the results must be caused by something else.
- ❖ What other effects would you see if the proposed cause were true? Are you seeing them? If not, look elsewhere for the cause. For example, to test whether ‘poor morale’ is causing a high number of defects, ask where else would signs of poor morale show up. Are you seeing them there?
- ❖ If the proposed cause were not true, could the effect have happened? Could the product weight be dropping if a blockage had *not* developed in the dispensing line? If the answer is ‘no’, you know you must find the blockage.
- ❖ If the cause had been X, would it always produce this effect? If the answer is ‘yes’, then in order to test this, you simply need to check whether the supposed

¹ See The Conway Charting Solutions Cause & Effect Tutorial for more information about the Fishbone Diagram.

cause actually occurred. For example, if my car will not start, a possible cause is that I left the lights on. (I drive one of those old fashioned cars that require operator involvement to turn off the lights.) If I check and find the lights are in the 'on' position, I can confirm my theory. Otherwise, I must keep looking for the cause.

USING CHARTS TO TEST CAUSES

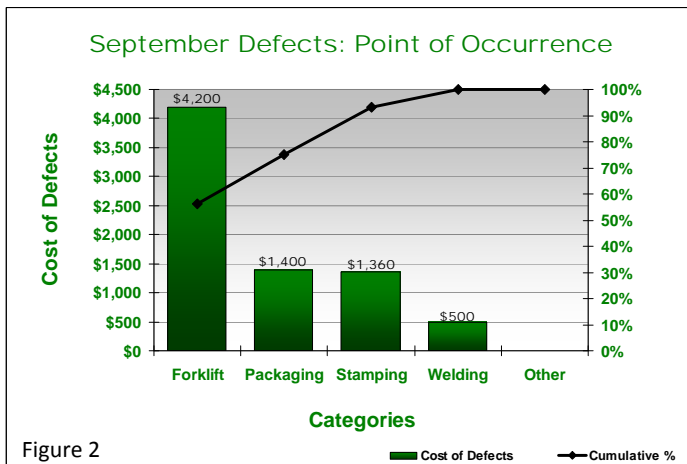
Some possible causes cannot be refuted or confirmed with logic, so you will need to gather and analyze data. If you believe the cause may be 'variable data' (that is it varies quantitatively, such as temperature, number of hours of training, number of days of use, weight, etc.), a correlation chart can help you evaluate a possible cause. Figure 1 displays a correlation chart of the relationship between the time required to complete the work and the number of days of experience.



Visually, you can see solid evidence that the number of days on the job significantly reduces speed – to a point. After about three

weeks, the relationship no longer holds. The *linear* trend line doesn't quite fit, does it? So the R^2 will be understated. In a case like this, you might want to apply a *logarithmic* trend line. (See our Correlation Tutorial for more information about how to make and interpret correlation charts, including non-linear trend lines.) Correlation charts can support or undermine a theory about a possible cause by showing you if the effect

seems to vary depending on the suspected cause.



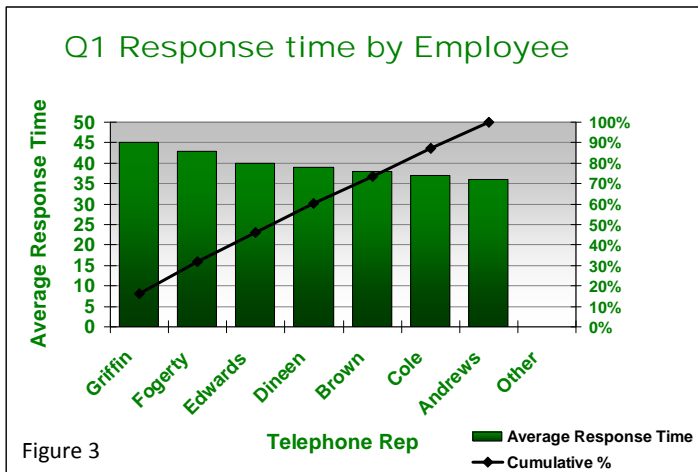
the primary cause of damage, and Figure 3, which shows the average response time

But many times your ideas about causes are of a different nature, such as: or 'Second shift produces more defects', or 'Some people are not motivated to do a good job and are slow to respond to incoming calls,' or 'The forklifts are the major cause of damaged product.' A Pareto chart can test these possible causes. Figure 2 supports the idea that forklifts are



by employee, refutes the idea that some people lack proper motivation and this is what is causing the error rate.

If the problem lies with one or two individuals, this would show up in a Pareto chart with substantially worse performance by the employees with 'poor motivation'. But if the Pareto chart is low and gradual as in Figure 3, you can conclude that the problem is common across all operators. The difference between the different employees is purely random. Whatever the cause is, Figure 3 indicates that it lies in the system, tools,



environment, materials or some other aspect of the work that is common to everyone.

A commercial laundry used a Pareto Chart to test possible causes of a spike in lost clothing claims. One theory was that the clothes were slipping through small holes in the net bags, although each bag was inspected by the operators (who were measured and compensated by their speed) before they were filled with clothing. To test

the "hole theory", the facility created a Pareto chart of locations where loose clothing was found. They found that 80% of loose, unidentified laundry was found in the large washers that cleaned a number of net bags at once, strongly supporting the theory that undetected holes in the bags were leading to the increase in lost clothing claims.

BUT WHERE IS THE ROOT CAUSE?

In the examples described so far, only the first level cause – a superficial level—was tested. The paper scrap team had verified with solid data that the cause of scrap was an 'overage' percentage that was quite high. But fixing that did not get at the root. Why was the 'overage' percent so high? The commercial laundry confirmed that undetected holes in some of the bags resulted in high lost clothing claims, but what caused the holes and why were they not detected in the inspection process?



The Five Whys is a classic tool to drill down to find the underlying cause of the first-level cause and further down three more levels until you can claim to have reached the 'root cause'. But the housekeeping team used the Five Whys and *still* arrived at the wrong solution!

There are several caveats to keep in mind when using the Five Whys. First and most critical is to realize that it is not “repeatable” – if you ask different people to apply the Five Why’s to a situation, you will get different results. Unless you verify the suspected cause at each step, you are more likely to arrive at a wrong conclusion than a right one. For Five Whys to be effective, you must use logic and data tests such as those described above before moving on to the next causal level.

A second caveat is that the Five Whys model follows a ‘single cause’ paradigm, when many problems have two or more causes. There may be factors that only produce the problem in certain circumstances or in combination with another condition. For example, excess inventory will result from poor demand forecasting, but only if the poor forecasting is within the time frame when production plans are fixed. If *either* demand forecasts were excellent *or* if production were more nimble (i.e. ‘lean’ enough) so as to respond to *actual* demand, neither excess inventory nor shortages would result. When you identify a cause, ask “Will this produce the effect in *every* circumstance or are there some conditions when this will not produce the cause?” This question will help unearth the combination-causes and open up new possible solutions. If two or more conditions are necessary for the bad effect to result, you can evaluate ways to eliminate either one of them. For example, it may be easier to increase the agility of the production process, or to shorten the timeframe in which production must be fixed, than to improve the forecasting accuracy.

Expansive brainstorming of possible causes, careful testing of each of them, and drilling down to unearth the underlying causes are necessary to arrive at lasting solutions. But you only know for sure when you have studied the results over time. You need to evaluate whether the problem is fixed and stays fixed. There’s the ultimate proof that you have gotten the ‘root cause.’

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Conway Management Company provides consulting, education and training to enable people at all levels to work more effectively. Established in 1983 by Bill Conway, former CEO of a Fortune 500 Company, Conway Management has worked with hundreds of organizations in diverse industries such as nuclear power, supermarkets, oil and gas, local, state and federal government, food manufacturing, distribution, and more. Clients learn to eliminate waste, improve all processes and increase their organization’s competitiveness, sales and profits.

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