Light Metals 2004 ***Edited by A.T. Tabereaux*** *TMS (The Minerals, Metals & Materials Society), 2004*

GOING BEYOND SPC – WHY WE NEED STATISTICAL THINKING IN OPERATIONS SUCH AS CARBON PLANTS

Keith Sinclair[1], Barry Sadler[2]

[1]Sinclair Associates Inc.,
2006 Northwood Drive,
Maryville, Tennessee, 37803, USA
SincAssoc@AOL.com

[2]Net Carbon Consulting Pty Ltd,
P.O. Box 286, Kangaroo Ground,
Victoria, Australia, 3097
barry.sadler@bigpond.com.au

Keywords: Statistical thinking, Statistical methods, Process management, Process improvement

Abstract

Statistical *thinking* is based on the principles that all work occurs in interconnected processes, variation exists in all processes, and reducing this variation is the key to process improvement. The effective use of statistical *methods* such as Statistical Process Control requires that an implementation framework be established through statistical thinking. Several examples relevant to Carbon Plant operations are provided where the failure to apply statistical thinking to process monitoring and improvement has resulted in waste and lost opportunities. Some appropriate actions for Managers in applying statistical thinking are then outlined.

Introduction

Since the early 1980's, statistical *methods* and tools such as Statistical Process Control (SPC) have been widely applied in the process industries. Many practitioners found a powerful rationale for the use of these methods in an interpretation of Dr. W. Edwards Deming's contribution to the success of several Japanese companies. However, it was often overlooked that Deming's message had objectives that went well beyond the application of statistical *methods*. Deming was attempting to move the work of Managers from administrative oversight, managerial control, and an obsession with managing financial outcomes, to a focus on the means by which the organization provides products and services. In essence, he wanted Senior Management to take accountability for managing the processes within their organisations, not just the outcomes [1].

The application of statistical *methods* is a necessary element in the improvement pathway for many firms. Hence numerous organizations have devoted large amounts of effort and resources to statistical *methods* programs, usually with the objective of improving quality and productivity. The anticipated returns from these programs have often not been realized. Two primary reasons are proposed for this:

1. *There was a belief that the implementation of statistical methods in isolation would be sufficient to deliver the sought after organizational improvements.*

This belief is misguided. Statistical *methods* are a toolset. It is essential that these tools are applied to the most appropriate part of the business. They must be used where their context is defined, i.e. the connection is clear between the process improvements they are to deliver and the creation of business value. Statistical *thinking* is the means of providing this context.

2. *There was an overwhelming emphasis on training and then changing the work of Plant Operators, Supervisors, and Technicians.*

This focus on the Technician or Operator was often justified by the view that "this is where the process knowledge resides." Although the truth of this statement cannot be argued, it does not warrant the targeting of just this level of the organization. This focus on "front-line" employees could also be seen as the manifestation of the management view that their role in the implementation of statistical *methods* is one of support but not direct involvement. In reality, Management has the pivotal role of understanding and then using statistical *thinking* to provide the context and framework for the successful use of statistical *methods*. Part of any effort to implement statistical *methods* should include the training of management in statistical *thinking*. This training is most effective when it is experiential, with Managers directly experiencing the benefits of their use of statistical *thinking* [2].

In many cases, interventions such as Total Quality Management (TQM), SPC, or Six Sigma have resulted in superficial deployments of statistical *methods*. These efforts often overlooked the necessity for managerial change. As a result they did not produce the changes in managerial behaviour necessary to sustain the productive use of statistical *methods*. In order to deliver the potential benefits from statistical *methods*, it is necessary to first adopt statistical *thinking.*

Statistical Thinking & Statistical Methods.

Statistical *thinking* has been defined as [3]: "a philosophy of learning and action based on the following fundamental principles:

- All work occurs in a system of interconnected processes,
- Variation exists in all processes, and
- Understanding and reducing variation are keys to success."

In contrast to statistical *methods*, which are technical tools used for analysis, the focus with statistical *thinking* is to [4]: "better manage the organisation and produce better business results". The relationship between statistical *methods* and *thinking* is shown in Figure 1 [Adapted from 3]:

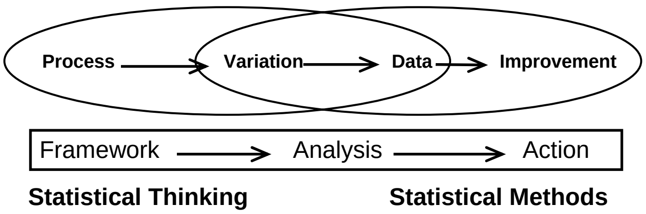

Figure 1. Relationship between statistical *thinking* and statistical *methods*.

Process thinking provides the framework for understanding the important sources of variation in the process; this sets the context for the application of appropriate tools for data collection and analysis. Good analysis then leads to actions that result in real process improvement.

Applying statistical *methods* without context from statistical *thinking* is analogous to "putting the cart before the horse". Managers need to take a different approach – they need to define how their process adds value to their customers and to the business. To do this they must understand the lateral relationships (Supplier – Customer) as well as the hierarchical ("Causal") relationships in their areas of the business. Then they must build process management systems that communicate this understanding, deploy these systems effectively, and inspect them regularly to ensure that are working.

Process thinking.

Statistical *thinking* begins with a *process orientation*, including recognition that all work occurs in a system of interdependent processes. The performance of a business is strongly affected by complex interactions between these processes. Supplier-Customer interfaces are the most critical of these interactions.

In Carbon Plants, internal Supplier-Customer relationships (Green Carbon - Carbon Baking Furnace - Rodding Room) result in strong interdependencies along the anode production process (We seek to moderate the impact of these dependencies by placing inventory at the interfaces). Other interdependencies in the Carbon Plant, such as the recycling of anode butts from the Rodding Room to Green Carbon, and the reprocessing of scrap products, further complicate Supplier-Customer relationships. Attempts to optimise individual parts of the Carbon Plant without understanding all these process interactions can often lead to sub-optimisation of the whole process and the loss of business value.

The process map is an essential tool for improving process thinking. These maps may be "lateral" showing a sequence of process steps, or "causal" showing the successive layers of sub-processes that make up the higher level processes.

<u>Lateral process maps.</u>

A SIPOC (Supplier Input Process Output Customer) diagram is the starting point of a lateral process map (Figure 2.).

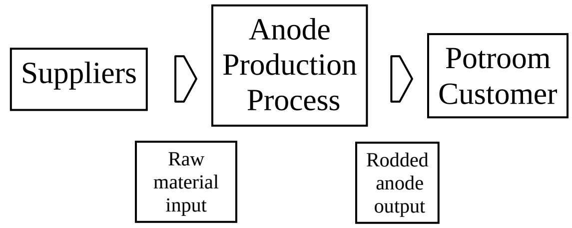

Figure 2. Carbon Plant SIPOC Process map.

In process operations such as Carbon Plants, the inherent interdependencies often mean that a reduction in variation at one point in the process (eg. Reduced baking temperature variation) creates value elsewhere in the business (eg. Lower anode dusting from the well-baked anodes increases current efficiency in the Potrooms). In the absence of process thinking, organizational structures and reward systems can inhibit this kind of "across organizational boundary" improvement. The converse can also happen; the Carbon Plant is rewarded for making an improvement (eg. reducing rod repair costs through dropping the standard for sending rods off for repair) while the net result at a business level is a loss of value (due to higher voltage drops in the Potrooms). Statistical *methods* are often applied in this way – with an *internal* perspective, aiming to improve operational efficiencies and costs within just one part of the process. This can result in lost opportunities to create real value through Carbon Plant process changes (at a local cost) that generate downstream business value.

Without process thinking, the interfaces at organizational boundaries can become a source of waste and emotional tension – it is not uncommon to hear exchanges between Potrooms and Carbon Plant staff such as – "*your anodes are no good, why don't you bake them properly"; "there's nothing wrong with the anodes – you just need to cover them properly in the pots."* This unproductive behaviour can be magnified by the setting of potentially conflicting targets for different parts of the business. This inhibits process thinking and drives sub-optimization.

A lack of process thinking can also lead to assigning accountability along organizational lines for improvement of critical performance measures without the explicit understanding of the interdependent nature of the outcome. An example of this might be assigning the full accountability for improving "Net Carbon ratio" to the Carbon Plant Manager. It is clear to all that are familiar with this measure that it can be highly impacted by processes outside the accountability of the Carbon Plant Manager.

To embed process thinking in an organization, Managers must "work at the interfaces" and stop inappropriately assigning accountability for cross-functional measures to individual process owners. Managers can achieve this through a value stream mapping process that captures the interdependency of important business process outcomes [5]. Measures that drive the behaviour of Managers consistent with this understanding can then be developed.

<u>Causal process maps.</u>

Previously, it was stated that Managers must understand how their processes create value for customers and the business. Causal process maps (Figure 3) aid in this by "drilling down" to identify the layers of sub-processes that comprise a process. Causal maps are essential for efficient top down *diagnostics* ("What is the root cause of baked density going out of control?") and for bottom up *process control and variation reduction.* ("Which parameters must I focus on to ensure that we meet our Customer's requirements?").

Process Management systems are available [5] that include models for developing a hierarchy of measures that corresponds to the sub-process levels within a business:

- Customer or Business Value Measures (CVM) – the level where value is created or destroyed.
- End of Line (EOL) measures – a process capability or product characteristic that defines how the process creates value.
- End of Process (EOP) measures – product and process measures at the interfaces of steps in the production process.
- Critical Process Variables (CPV) – the key measures and activities that need to be "right" to ensure the output meets Customer requirements.

The measures at the various levels of this hierarchy can be linked to the levels of processes and sub-process shown in a causal process map (Figure 3.):

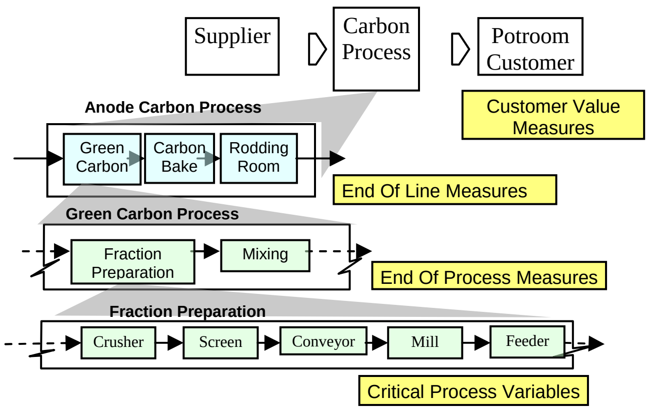

Figure 3. Partial causal process map for anode production.

In Figure 3, the CPV's for Fraction Preparation (e.g. Blaine Index of Fines fraction) impact the EOP's for Green Carbon (e.g. Green Anode Density), which in turn impact the EOL's for the Carbon Plant (e.g. Baked Anode Density). The EOL's influence the Customer Value Measures (i.e. Anode rota). This cascading linkage is shown in Figure 4.

Lateral and causal process maps help establish the pathway between process improvement and value creation. In the past this linkage has not always been clear.

If programs such as SPC don't deliver bottom line gains, they are rightly seen as failures. In the view of the Authors, such failures have less to do with the SPC tools, and more to do with a lack of statistical thinking to identify the target process steps that have the greatest impact on business value.

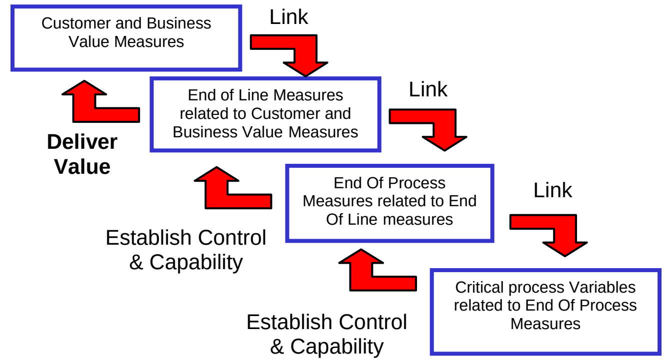

Figure 4. Cascade of measures with a causal process map structure.

Understanding variation

Understanding and reducing variation are keys to successful process improvement. Managers make decisions every day, often based on the interpretation of patterns (i.e. variation) in the data presented to them. Misinterpretation of the information, or the signals "nested" in the data, can lead to poor managerial judgements and loss associated with [6]:

- Assigning accountability for resolving a problem to people who don't have control of the problem.
- Spending money for new capital equipment that is not needed.
- Wasting time creating explanations for data points when questions should be asked about process design.
- Taking action when it would better to do nothing.

To be able to better interpret and respond to data, Managers must be able to understand the difference between *common cause* and *special cause* variation. This is important, as the improvement strategies and accountability for action are different for each type.

Achieving a stable and predictable process focuses on identifying and eliminating special (assignable) cause variation - *external factors* affecting the process. This is primarily the accountability of people that work ***in*** the process (assuming they have appropriate systems and know how to use them).

Improving the capability (i.e. ability to meet specified requirements) of a process focuses on reducing common cause variation, which is *inherent in the process* design. This is the work of the people accountable for system and process design - Management. People who work in the process are often unable to affect common cause variation; however, they are a source of improvement ideas.

Understanding the sources of variation in a process is critical to process improvement. By outlining a common scenario we will show how the absence of statistical thinking can lead to the inappropriate use of statistical methods, resulting in false comfort for a supplier and quality problems for the downstream processes.

<u>A problem with Blaine Index………</u>

With Figure 3, it was shown how Blaine Index (a Critical Process Variable) is one of the factors that impacts Baked Anode Density (the process outcome). Because of the perceived importance of this causal relationship, Blaine Index has been selected as a key measure for monthly reporting at a Smelter:-

The Green Carbon (GC) Superintendent enlisted the assistance of a Development Engineer (DE) to define the appropriate target and specifications for Blaine Index (BI) and set up a sampling plan. After establishing the suitability of the measurement process (through gauge repeatability and reproducibility analysis), the DE conducted optimization experiments (involving the Carbon Plant and Potrooms) and established a BI target of 3000 +/- 120. The Carbon Plant Manager asked that Blaine Index be reported for his monthly Manager process review. The GC Superintendent receives a Blaine Index value on a daily basis.

The Monthly Meeting

In a monthly Smelter process meeting, the Potroom Manager wrapped up his review of key performance measures. “This past month was on plan with all key measures coming in right around target. Overall, a good month in spite of the fact that we are observing a bit more variation in butt size in the last couple of weeks which has caused higher than normal levels of stub flux wash”.

The Carbon Manager was about to start reviewing the Carbon measures when the Plant General Manager (GM) jumped in. “Tell me more about this butt size variation and flux wash change you have observed… do you have any data?”

The Potroom Manager responded that these types of “fluctuations” are not unusual; they often come and go without any significant impact. Knowing a bit about the process, the GM asked if there had been any changes in anode properties.

Putting a table up on the screen (Table I), the Carbon Manager stated that Baked Anode Density (BAD) had shifted a bit in recent weeks - but not enough to go out of specification.

Table I. Carbon Monthly Performance Report

Measure	Target	Actual	Variance
BAD (g/cm3) Min. 1.55	1.58	1.56	-0.02
GAD (g/cm3) Min. 1.59	1.62	1.60	-0.02
Blaine Index	3000	2988	-12

A quick look at the BAD data supported the Carbon Manager’s statement; the number for last month looked a bit low. Being familiar with the recent Blaine Index studies, the Technical Manager asked if the Blaine Index data showed anything unusual.

Quickly the Carbon Manager flicked to a histogram of Blaine Index data for the last month (Figure 5.).

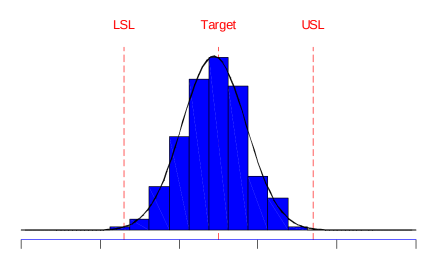

Figure 5. Histogram of Blaine Index results for the past month.

The histogram showed a mean of 2988 (as reported) with all data appearing to fall within specification (+/- 120). The Technical Manager, however, was not satisfied - “Before we move off this, can you tell me about this data? How is it sampled and reported?”

Unsure how to respond, the Carbon Manager called upon the DE who was able to explain that each Crew in the Green Carbon Plant (The plant operates a 2 Crew, 12 hour shift operation, 4 days on, 4 days off) was instructed to try to achieve the 3000 BI target within a range of +/- 120. The BI of the Ball Mill product is tested every 2 hours (i.e. 6 tests/shift with the 6 results averaged to give the shift result). The two shift averages are averaged and reported daily to the GC Superintendent. At the end of the month, the 30 or so daily averages are averaged and the standard deviation of the 30 data points determined. These were reported in the monthly report and are shown in the histogram (Figure 5.).

The Technical Manager responded, “So what I am looking at is the average of daily averages and you calculate the standard deviation of daily averages. I am concerned that this may be masking important variation.” The DE agreed. From spending time in the workplace getting a good understanding of the Ball Mill operation, she knew that one of the key sources of variation in the BI results was the different ways the Crews operate the mill circuit. These differences were within the ranges allowed in the current Standard Operating Procedure (SOP) and each Crew believed that their settings give the best results. She volunteered that she could easily stratify the data by Crew on a shift by shift basis, although the actual 6 samples every shift would be very difficult to retrieve.

She quickly punched a few keys and the following results were presented for the Management team to analyse (Table II.)

Table II. Blaine Index data stratified by crew.

Crew	Average of shift BI results	Standard Deviation of shift BI results
1	2939	58
2	3037	61

All present could see that the two Crews, although operating with roughly the same amount of variability within their shifts, were producing results that are consistently different by about 100. This is clear in the histograms of the BI results from each Crew (Figure 6.).

The discussion concluded and all agreed that measures such as Blaine Index (and many others) need to be reviewed to ensure that they were properly operationally defined and accurately reflected the critical sources of variation in the process. These steps will help to avoid the problem demonstrated in Figure 7, which shows the difference in BI between what was being reported and what was actually being sent to the downstream processes.

The GC Superintendent worked with his DE to set up an action plan based on statistical thinking to improve the process and correctly report performance:

- Understand what the process is doing, and confirm the connection to value through a causal map.
- Using the map, identify the most likely sources of variation, i.e. Crew-to-Crew operating differences.
- Set up data collection, analysis and reporting to highlight process improvement opportunities, i.e. Crew-to-Crew variation.
- Implement an action plan to standardize the operating procedures of the two Crews to reduce the variation in BI results and hence improve anode quality. Until the Crews are delivering the same BI results, data analysis and reporting will incorporate Crew-by-Crew differences.

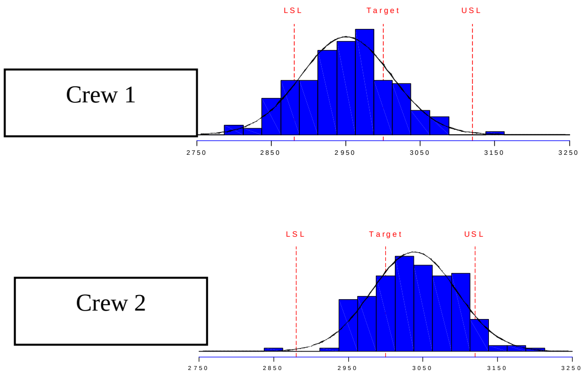

Figure 6. Blaine Index data stratified by Crew

Figure 7. The problem with averages – what is reported is not what the downstream processes see.

Important lessons can be learned from this scenario:

- Ask questions to understand the data - averages mask variation, which may make the numbers look good but won't help the Plant run better.
- Hiding variation with averages means critical questions may not get asked and opportunities to learn and improve are lost.
- Always use a measure of data dispersion together with averages - averages don't tell the whole story.
- Stratify data and analysis to reflect known critical sources of variation.
- Don't use averages to report conformance to specifications.

Data collection and analysis

The absence of statistical thinking in the interpretation of data is evident in routine reports that contain copious quantities of tabular data. The traditional Plan – Actual – Variance table structure obscures opportunities for improvement and can lead to poor decision-making. Action may be taken when it shouldn't (*tampering*), or action not taken when it should be. Tables of data can result in Managers trying to explain all variances from plan targets. This ignores the nature of the variation inherent in the data, which can be analyzed by presenting and interpreting the data as time ordered graphs, preferably control charts [7].

To look at this further – what conclusions could be drawn from this table from a monthly report?

Table III. Typical summary Plant production report.

	Plan	Actual for month	Variance
Production (Anodes per month)	**4950**	**4720**	**-230**
Cost ($/tonne)	**535**	**525**	**-10**
Safety (# LTI's)	0	0	0
Environmental (Spills)	1	0	- 1
Quality (% Green Scrap)	**5.5**	**5.4**	**- 0.1**

Tables of data drive *binary thinking.* Information is analyzed and classified as either <u>acceptable</u> (on plan or desirable variance) or <u>unacceptable</u> (undesirable variance). Unacceptable results are implicitly assumed to be due to "special cause" variation and an explanation is required. (In many cases this can be a futile task as there may not be a specific explanation for the data point – it may be the result of common cause variation.) Action plans are then developed, reported and implemented to try to avoid having to explain more undesirable variances next month. At best this process is a waste of managerial time; at worst precious resources are expended to fix the wrong problem.

Looking at Table III, in the absence of statistical thinking the comments attached to this Plant report would explain why production was low for this month (e.g. unexpected downtime, lack of raw materials, etc) and how each of these reasons will be addressed to avoid a recurrence. If we now look at the production data as a time ordered trend (e.g. as a control chart, Figure 8), we can see the folly of this.

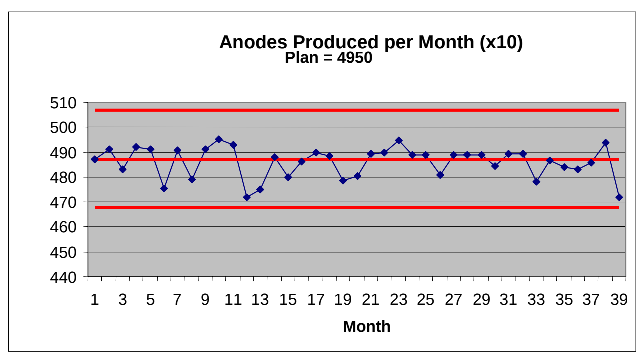

Figure 8. Control chart - monthly anode production (last 40 months).

It can be seen from Figure 8 that while anode production for the last month looks to be a bit low, it is within the expected month to month variation. Searching for an assignable cause to explain the result will probably be a witch hunt, and subsequent actions are likely to increase variation – this is tampering. We can also see that the production rate is stable and predictable with a monthly mean of 4880 anodes, 120 a month less than target. This prediction for future production suggests that we can expect the mean to continue below plan and put our safety stocks at risk (unless we *artificially* work around the problem by steps such as overtime and reducing maintenance time). Action on individual data points (treating low points within the limits as special causes) will not solve this problem.

Statistical thinking tells us that we cannot expect to achieve the target production rate without fundamentally changing the process. The appropriate comment for the monthly report is not the explanation of the last point, but to outline the action plan to change the anode production process to increase monthly production to the target through appropriate action on sources of common cause variation (e.g. reduce cycle time variation in the bottleneck process step.).

Trying to explain results that do not have an explanation is one problem stemming from the binary interpretation of tabular data. There will also be occasions where the data contains *signals* that something has changed that will be missed without statistical thinking. These signals are valuable as they can be used to trigger corrective action before significant losses are incurred (or explanations are required in the monthly report). We can see this by looking at the control chart for anode cost (Figure 9.).

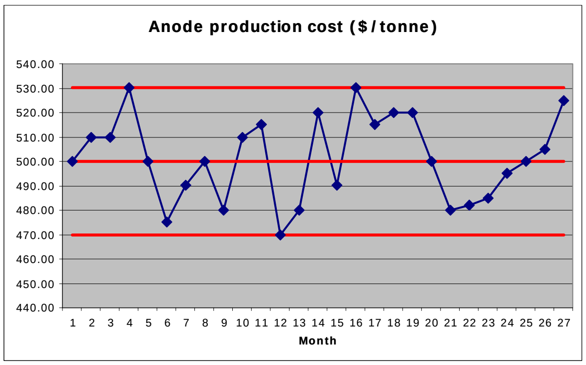

Figure 9. Control chart of anode production costs.

The last data point in Figure 9 is within plan (Table III); binary thinking would suggest that it is *acceptable*. No comment is required on the monthly report and no corrective action expected. However, interpretation of Figure 9 gives a different outcome. The increasing trend would not be expected from only common cause variation, hence there is likely to be an assignable cause present (even though the last point is still within the control limits). Finding and removing this special cause will avoid incurring costs (and may remove the need for an explanation in the next monthly report). The Green Scrap data (Figure 10.) also includes a signal that would be missed with binary thinking.

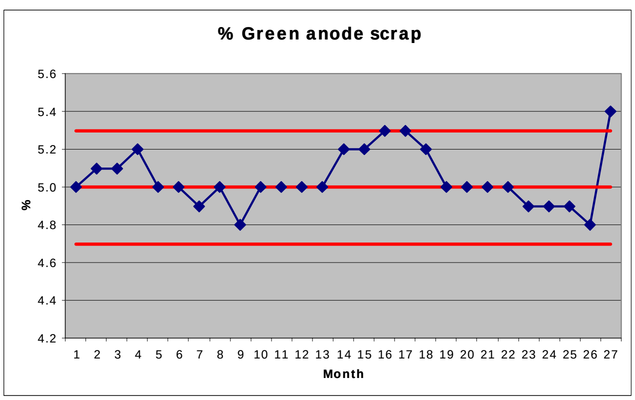

Figure 10. Control chart of green scrap generation

Again the last data point is within plan and would not be expected to generate comment or action from the binary analysis of Table III. It can be seen from Figure 10, however, that the last point will have an assignable cause - it is too high to be expected from common cause variation. Something has changed in the process and now is the time to act to avoid higher scrap rates.

What should Managers be doing?

We have now seen several examples of how the absence of statistical thinking by management can lead to waste and lost opportunities in a business. What follows are some actions for Managers that will help avoid these pitfalls.

Managers must:

- Define the process accountabilities of the people that report to them and decide the measures to monitor their performance.
- Ensure that role descriptions define accountability for process improvement at different levels.
- Ensure that statistical thinking – in principle and in practice is understood and used from the *top floor to the shop floor*.
- Have an explicit and measurable understanding of how targeted reductions in variation will create value for the business (and customers).
- Question the quality of data presented to them, seeking an understanding of the sources of variation.
- Discourage the use of binary thinking to interpret data and lead the way using statistical thinking principles.
- Seek out explanations and actions to remove the root cause of special cause variation and require standardized responses to signals in process data.
- Help to determine if changes to the process are justified to improve business value when processes exhibit only common cause variation.
- Build statistical tools and thinking into management processes. This requires a move beyond just the reporting application of charts.
- Use charts as tools to help make decisions and improve the process.
- Change existing business systems that are not consistent with statistical thinking (i.e. tabular vs. time series analysis of performance data).

References

1. W. Edwards Deming, *Out of the Crisis*. (Cambridge, MA.: MIT, 1986).
2. K.A. Sinclair, "IPM Popcorn Factory Workshop Manual", (Sinclair Associates, Inc., 2001).
3. M.G. Leitnaker, "Using the Power of Statistical Thinking", ASQ Stat. Div. Spec. Publ., Summer 2000.
4. R.D. Snee, "Getting Better Business Results – Using Statistical Thinking and Methods to Shape the Bottom Line", Quality Progress, June 1998, 102 – 106.
5. K.A. Sinclair, "Integrated Process Management – Aligning the Top Floor with the Shop Floor", (Sinclair Associates Inc., Rev.4, Aug. 2002).
6. T.W. Nolan; L.P. Provost, "Understanding Variation", Quality Progress, May 1990, 70 – 78.
7. D.J. Wheeler, *Understanding Variation – the Key to Managing Chaos.* (Knoxville, Tenn.: SPC Press, 1993).