PROCESS CONTROL: TIMELY FEEDBACK FOR QUALITY MILK PRODUCTION AT THE FARM

Jeffrey K. Reneau
University of Minnesota
St. Paul, Minnesota

Assembling, training, motivating, and retaining a skilled crew of dairy employees is a difficult challenge for herd managers. Routine monitoring and timely feedback of the effectiveness with which employees complete herd management protocols is needed to motivate employees toward continued improvement and for indications of when additional training or modifications of protocols are needed.

Statistical Process Control (SPC) as a Milk Quality Monitoring Tool

Statistical process control (SPC) is an excellent process monitoring method, which can be used to measure the output of a management process. "SPC is a way of thinking with charts acting as a catalyst for this thought process" (Wheeler and Chambers 1992). SPC is one of the most powerful tools for process improvement. However, unless SPC is used as a part of a production system where the idea of continuous improvement is embraced it is just another way of representing data in a graph (Polson et al., 1999). It is important at the onset of this discussion to emphasize this point. Experience has shown that application of SPC without commitment to the continuous improvement concept will not be a very productive or satisfying experience. SPC is not new. It has been successfully used in manufacturing businesses for over 70 years. SPC has not been extensively used in animal agriculture. SPC was first tried in swine production over twenty years ago (Wrathall, 1977). However, the principles of SPC are proven and use in animal agriculture is merely a shift of application to a biological production system. Although the biological system is more variable and thus presenting a greater challenge, there is great optimism that SPC techniques will become another valuable tool for livestock monitoring (Polson et al., 1999; Polson 1998; DeVries et al., 1997).

How great a deviation from "normal" constitutes real change? Is this change sufficient to merit the expense and effort of a recommended intervention? Sometimes the decision is a "no brainer" but too often you are not really sure. It is this lack of confidence that may weaken your resolve to take serious recommendations and initiate timely corrective action.

Each time we face this sort of dilemma we are in danger of making errors in interpretation. When we mistake random variation (common cause variation) for a real change in cow productivity or health, we may diagnose a non-existing change (Type I error or false positive). Application of unnecessary corrective action would truly be a waste of labor, time and money. Such action detracts from productive management. It adds complexity and creates management chaos. On the other hand, failure to identify an emerging problem quick enough to initiate timely corrections (Type II error or false negative) is also a great concern. The indecisive strategy of "Let's wait to see what it looks like next month" may squander the opportunity to nip the problem in the bud. Furthermore, subtle changes could go undetected for months creating a deep-seated herd problem.

SPC is a set of several analytical tools of which the control chart is an important one. This discussion will focus only on control charts. Control charts are helpful in signaling that a true change has occurred. The fundamental concept of control charts is to distinguish between inherent random variation and real changes in output, quality, or measured performance. Properly applied control charts can prevent the misinterpretation of inherent random variation due to "common causes" of variation. More importantly they provide a timely signaling of real change due to "special cause" variation. Common causes affect all data, are chronic, stable, and predictable within limits. Special causes affect some data, are sporadic, unstable, and unpredictable. SPC methods can be used to signal emerging problems, evaluate the positive or negative impact of a change in a management practice or the implementation of a new product.

Typical dairy management reports provide a plethora of data usually in tabular form. The inevitable result of having such a large volume of data presented in such a small area is that it requires much study and effort to interpret. The human mind does not do very well absorbing large amounts of data. In addition, most of us tend to be numerically illiterate (Wheeler, 1993). It's not that we don't understand the mechanics of arithmetic. Rather we don't intuitively know how to extract knowledge from data. The most common use of dairy management data is to compare this month's average with last month's average. Are we doing better or worse? The problem with such limited comparisons is that they are out of context. Context here means that the data should be interpreted in context of the time order in which they were generated. Context also means that the natural variation in the data and it's relationship with similar data generated by the process be taken into consideration.

Data divorced from its' context can be misleading. Although several months of tabular data would provide ample context, most people find it difficult to assimilate and provide accurate interpretation. For example consider the relatively simple table of daily bulk tank somatic cell count (BTSCC) data for a Minnesota dairy (Table 1). Looking at the table, we might ask a few simple questions to aid our interpretation:

- How were the data collected and calculated? By whom?
- What is the highest value? The lowest? The average? The median?
- What is the normal, day to day, level of variation?
- What causes the normal variation?
- When is variation abnormal?
- When should we be worried?
- How does this herd compare to other herds?
- Is there potential for improvement? How much?
- Is intervention worth the cost?
- Does this herd currently have a problem as indicated by the BTSCC's?
- Have there been problems in the past?
- Is mastitis management "under control"? How can you tell?
- If mastitis was to go "out of control":
    - ◊ How soon would these data tell you?
    - ◊ How quickly would you react?
    - ◊ What would you do?

◊ How would you measure response?
◊ Would you be confident that your intervention had made a difference?

Obviously study of tabular data is overwhelming, time consuming, and often unproductive. The problem of how to analyze tabular data is depicted in the statement of a busy herd manager, “I don’t have time to study all the records, just give me the abridged version.”

Table 1. Bulk Tank Somatic Cell Count for a Minnesota Dairy (BTSCC x 1000)

Date	BTSCC	Date	BTSCC	Date	BTSCC
10/1/98	236	11/14/98	235	12/27/98	312
10/2/98	303	11/15/98	265	12/28/98	294
10/3/98	236	11/16/98	238	12/29/98	242
10/4/98	219	11/17/98	212	12/30/98	248
10/5/98	224	11/18/98	239	12/31/98	215
10/6/98	246	11/19/98	267	1/1/99	212
10/7/98	292	11/21/98	229	1/2/99	292
10/8/98	270	11/22/98	272	1/3/99	300
10/9/98	225	11/23/98	219	1/5/99	327
10/10/98	238	11/24/98	257	1/6/99	229
10/11/98	228	11/25/98	279	1/7/99	244
10/13/98	243	11/26/98	205	1/8/99	274
10/15/98	226	11/27/98	218	1/9/99	295
10/16/98	225	11/28/98	235	1/10/99	306
10/17/98	227	11/29/98	281	1/11/99	314
10/18/98	275	11/30/98	272	1/12/99	242
10/19/98	248	12/1/98	256	1/13/99	266
10/20/98	244	12/2/98	269	1/14/99	243
10/21/98	231	12/3/98	227	1/15/99	262
10/22/98	250	12/4/98	258	1/16/99	293
10/23/98	239	12/5/98	261	1/17/99	281
10/24/98	267	12/6/98	250	1/18/99	278
10/25/98	271	12/7/98	230	1/19/99	238
10/26/98	226	12/8/98	266	1/20/99	233
10/27/98	244	12/9/98	262	1/21/99	257
10/28/98	189	12/10/98	219	1/22/99	271
10/29/98	303	12/11/98	271	1/23/99	232
10/30/98	229	12/12/98	266	1/24/99	244
10/31/98	242	12/13/98	220	1/25/99	275
11/1/98	255	12/14/98	243	1/26/99	213
11/2/98	217	12/15/98	180	1/27/99	254
11/3/98	205	12/16/98	213	1/28/99	312
11/4/98	238	12/17/98	221	1/30/99	352
11/5/98	214	12/18/98	276	1/31/99	303
11/6/98	250	12/19/98	268	2/1/99	284
11/7/98	220	12/20/98	334	2/2/99	227
11/8/98	212	12/21/98	303	2/3/99	298
11/9/98	241	12/22/98	323	2/4/99	347
11/10/98	265	12/23/98	329	2/5/99	325
11/11/98	261	12/24/98	285	2/6/99	281
11/12/98	242	12/25/98	241	2/7/99	336
11/13/98	255	12/26/98	275	2/8/99	349

Time Series Charts

Since we are visually oriented, and tables of data are visually boring, graphs make data more accessible to the human mind. Graphs can remove extraneous detail while providing context for visual interpretation. Management data will usually have a time order. Therefore, a time series chart of data improves interpretation. Consider again the BTSCC data for a Minnesota dairy in a time series chart (Figure 1). Compared to the tabular format, the plotted data provide a much clearer idea of the BTSCC changes and trends over time. We can use our prior knowledge and experience of BTSCC data to form a general impression of udder health of this herd. We can see that this herd's BTSCC is generally too high with possibly a slightly upward shift. However, a simple time series chart doesn't have sufficient resolution for more meaningful interpretation. It is still difficult to identify subtle changes or to know if the BTSCC in this herd is "in control" or "out of control". This is because the inherent random variation (noise) masks real changes. Noise, like static on a car radio, makes listening annoying and difficult to understand. The Shewhart control chart is the simplest method to separate potential signals from probable noise.

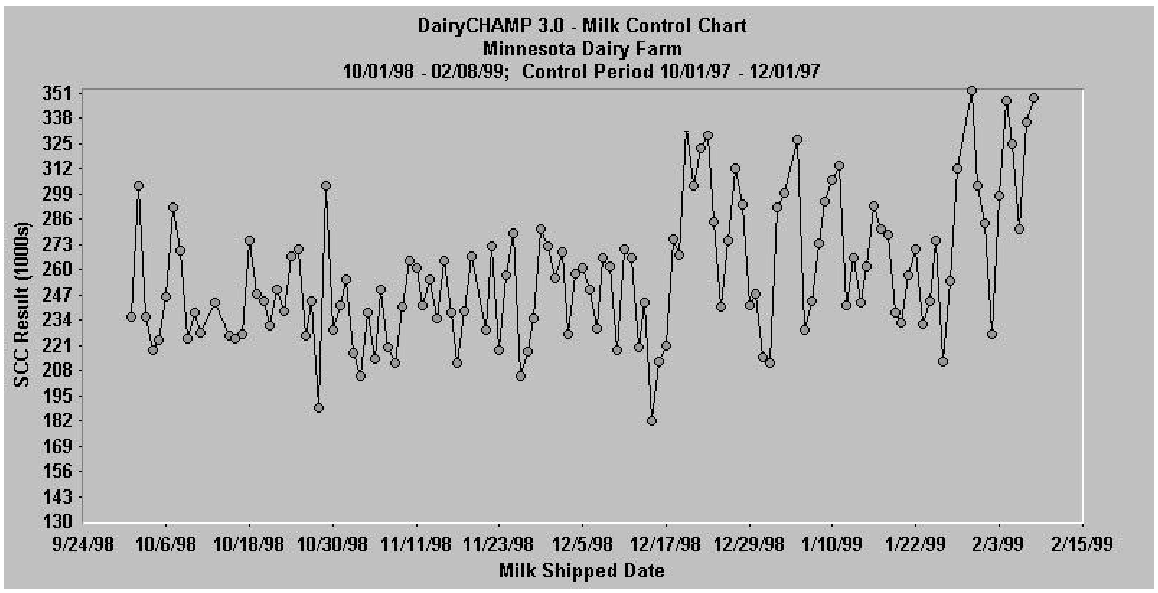

Figure 1 is a time series plot of the daily BTSCC for a 200 cow Minnesota dairy. The upward trend is more apparent than the tabular data but how certain could you be on December 18th that the processes contributing to BTSCC were "out of control".

Control Charts

In the 1920's, Dr. Walter Shewhart at Bell Laboratories invented control charts to help interpret data which is generated over time. Control charts provide further insight into data by displaying the level of normal, random variation in the data and by revealing the observations that indicate real change. This approach affords the practical application of statistical theory in a visual, easy to interpret context. The steps to develop a Shewhart control chart are as follows:

1. Start with a time series chart.
2. Add a centerline (mean) for central reference.

3. Add control limits, computed from the data and based on the common cause variation only, equidistant on either side of the centerline.
4. Apply tests to distinguish between data points due to special causes from data points due to common causes only.

Control limits are calculated by two methods. One method uses standard deviation, which is a common measure of variation. Experience has shown three standard deviations away from the center line is a good balance between the number of false positive signals (type 1 error) and false negative signals (type 2 error). The other method (mean range method) uses the mean of the values plus or minus the average range between values times a constant. The constant depends on the number of values within each subgroup and is looked up in a table. The mean range method gained acceptance historically because in the early years of SPC calculation of standard deviations was difficult. Both methods are designed to give the same approximate answer. Today even relatively inexpensive hand calculators will compute standard deviations. It should be noted, however, that the standard deviation method is more prone to error when there are more than one subgroup of data being considered (Wheeler and Chambers, 1992). However, if calculation of control limits are done correctly both methods will result in nearly identical control limits as well as the same interpretation.

The resulting zone between the center line and one standard deviation is called Zone C, between one and two standard deviations is Zone B, and between two and three standard deviations (the control limit) is Zone A (see Figure 2). These zones are important for applying the interpretive tests discussed later.

Control limits are calculated based in the data collected in a time frame called the "control period". Experience has show that 20 data points are needed to calculate credible control limits (Wheeler and Chambers, 1992). When initiating a control chart it is appropriate to use the first 20 data points collected as the control period. Once control charting is established the control period can be set depending the question being asked. If the intent is to monitor a process for the purpose of maintaining a stable process then using data from an apparently stable period makes sense. If the intent is use the control chart to evaluate the introduction of a new product or a change in process procedure etc. then the control period should be calculated from data collected just prior to the introduction of the product or change in procedure. The control limits for our example using the BTSCC's were calculated using the October 1998 – December 1998 BTSCC data, since there was no indication of special variation in that period and so the process appeared to be "in control". Mean BTSCC for the designated control period was 243,000 and the standard deviation was 24,300. Thus the limits for Zone C were 243,000 ± 24,300 (between 218,700 and 267,300). The limits for Zone B were 243,000 ± 2 x 24,3000 (between 194,400 and 218,700 and again between 267,300 and 291,600). Finally, the control limits were calculated as 242,000 ± 3 x 24,300. Zone A, therefore, is between 170,100 and 194,400 and again between 291,600 and 315,900 (see Figure 2). Calculation of control limits using the mean range method gave the same results.

Note that the picture becomes more clear than a time series plot but it remains difficult to interpret the data without a formal and standardized approach to distinguish between "normal" (common cause) variation and variation that deserves more attention.

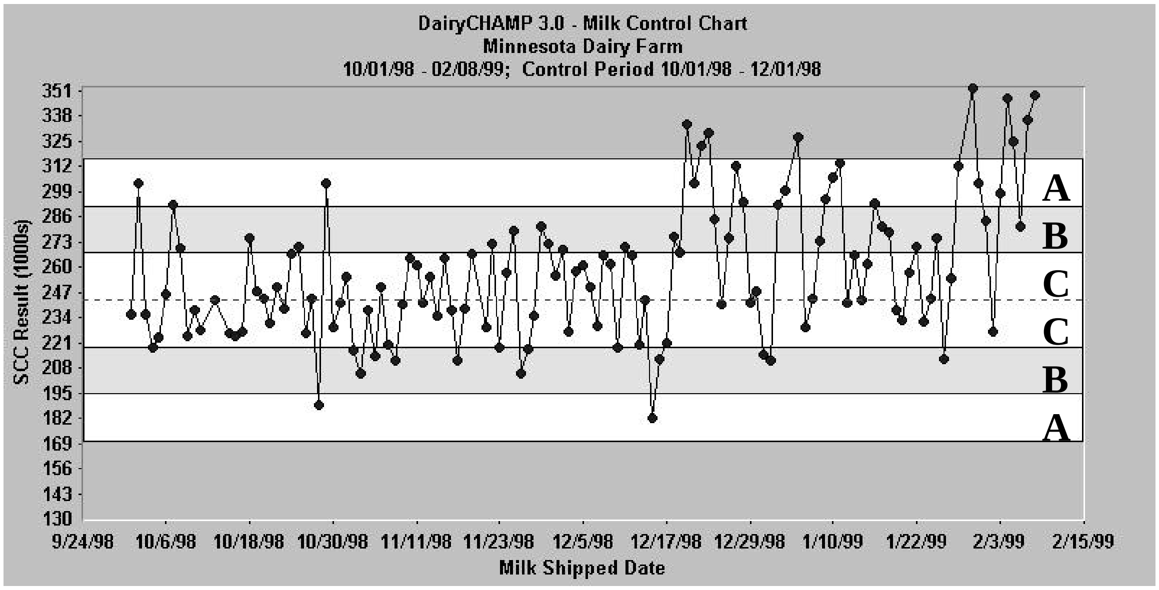

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Figure 2 is BTSCC for a Minnesota dairy plotted in a Shewhart control chart. The mean and three standard deviations (Zones A, B, and C) were calculated using the daily BTSCC data for the period from October 1, 1998 to December 1,1998.

Interpreting Control Charts Using Tests

Several tests exist that can help in the correct interpretation of control charts. When a single data point is observed outside one of the control limits, the probability that this point is not a real change (false positive) is only 3 out of 1000. Seven additional tests using multiple data points to indicate, with a high probability, that a real change has occurred (Nelson, 1984). Using several tests simultaneously for signaling special causes increases the sensitivity of a control chart, but also increases the possibility of a false positive. The combined probability that any of the eight tests indicate a "real change" when there is none, is about 20 out of 1000, or 2%. Thus it is generally safe to assume that the process is "out of control" when any one of these tests indicates a change. The eight tests are:

- **Test 1** - A single point outside one of the control limits.
- **Test 2** - Nine points in a row on one side of the centerline.
- **Test 3** - Six points in a row either all increasing or all decreasing.
- **Test 4** - Fourteen points in a row alternating up and down.
- **Test 5** - Two out of three points in a row in or beyond Zone A on either side of the centerline.
- **Test 6** - Four out of five points in or beyond Zone B on either side of the centerline.
- **Test 7** - Fifteen points in a row in Zone C on either side of the centerline.
- **Test 8** - Eight points in a row on either side of the center line with none in Zone C.

Wheeler summarized these eight tests into three simple tests that he feels are adequate for most management situations. They are as follows:

- **Test 1 -** A single point outside control limits.
- **Test 2 -** Three out of four consecutive points closer to the control limit than to the centerline.
- **Test 3 -** Eight or more successive points on one side of the centerline.

Any time the conditions of any one of these three tests are met you can be certain the process is has changed and is by definition "out of control". Considering these tests as new data becomes available ensures timely signaling of real changes. Using Wheeler's three tests to detect special cause variation, now let's again consider the control chart of BTSCC data (Figure 2).

Wheeler's second test indicates that starting on December 18th, there it is clear and significant upward shift in the level of BTSCC. The process is "out of control". There is no need to vacillate since you can be 95% certain that the shift is "real" and it is not just normal variation. Since data should be interpreted in their context, these observations may or may not be a surprise to the dairy manager. For example, in this case the distractions of the Christmas Holiday may have disrupted normal herd management. If this were the case, this may well explain the shift in BTSCC level. The control chart then confirms our expectation about the BTSCC level. However, if no explanation can be readily given, then investigating the probable causes of the shift in BTSCC is well worth the effort and cost. There are two basic questions regarding a breakdown in the process:

- Is this a personnel management issue? (i.e., protocols not being followed)
- Is there some flaw in the process itself? (i.e., breakdown in equipment or an inadequate protocol)

For example, maybe the new employee does not do a good job scraping the stalls or the replacement bedding material is contaminated. Control charts provide a means for early detection of "real" changes enabling the opportunity to nip the problem in the bud. In this particular case there was no action taken. As one can see the consequences resulted in further process entropy and obvious deterioration of those processes contributing to BTSCC level.

Control charts also offer a means to evaluate efforts towards continuos process improvement. Figure 3 is a control chart of a large Wisconsin dairy that has kept their herd bulk tank count less than 200,000 for 20 years. During the period between January 1, 1999 through mid February the BTSCC was averaging 140,000 and was "in control". However, the herd manager felt that the herd BTSCC should be 100,000 or less, as had been the case during previous years. During the March 21, 1999 meeting with the milking parlor staff there was a consensus reached:

- that more attention be placed on pre-milking teat end sanitation, and
- that cows with extremely high SCC quarters would be identified with a leg band so that the high SCC quarters could be milked into a quarter bucket.

The plan was implemented immediately. Did the program work? Study of Figure 3 clearly indicates a dramatic and significant decline in herd BTSCC. Wheeler's test # 2 indicated that by March 26th the herd manager knew with 95% certainty that the plan was working and could use the chart as positive feedback to the parlor crew to reinforce their dedicated effort.

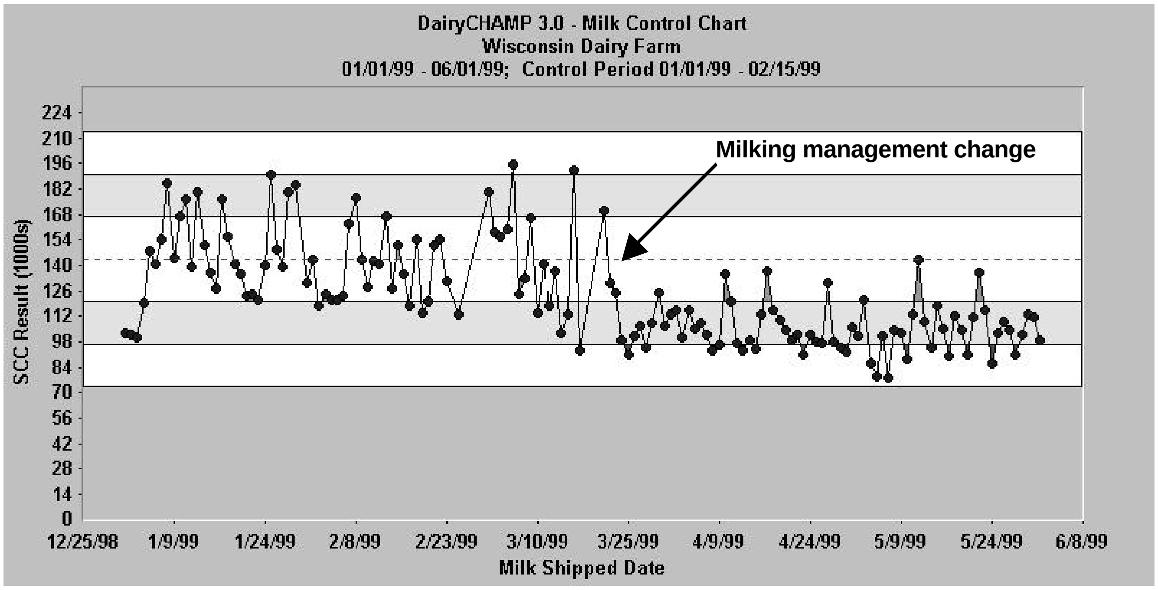

Figure 3 is a Shewhart control chart of daily BTSCC on a Wisconsin 700 cow dairy. Control chart use allowed the herd manager to know with certainty on March 26, 1999 that the changes in parlor management implemented March 22, 1999 were working.

Control charts are commonplace in the manufacturing and service industries. They have great potential for improved decision making in dairy management. Monitoring BTSCC with a Shewhart control chart is a good example of a valid application. Plotting of frequently collected individual data in a control chart (i.e., daily feed intakes, daily milk weights, milk components including MUN) is the simplest of SPC techniques. There is still much research work to be done in confirming which variables are appropriate for SPC applications. Generally data suitable for SPC application is:

- Data that is easy and practical to collect.
- Data that is collected on a frequent basis (daily, weekly) is preferable.
- Data of economic significance.
- Data that as directly as is possible reflects process behavior.

Besides monitoring the mean of a process, the range of the data points can also be monitored. When individual raw data is average into subgroups of data, (i.e., weekly BTSCC averages) then it would be necessary to monitor both the mean and the range to adequately detect “signals” caused by special cause variation. These methods can be extended and refined to a greater degree, for example the sensitive CUSUM can be used to detect small shifts in the process mean. A CUSUM is a cumulative sum of deviations from a prediction or target. At present more study is needed to determine the appropriateness of applying all of the SPC techniques in monitoring livestock production systems.

Although SPC and the use of control charts are useful monitoring tools, there are pitfalls. The greatest pitfall is initiating SPC techniques without the right mind set. If these techniques are attempted where management is not willing to embrace the philosophy of continuous improvement they will inevitably fail to produce anticipated results. Another pitfall is improper calculations of control limits, as was previous mentioned resulting in too many false signals. However, these techniques are robust and when used appropriately are very effective herd monitors. It is expected that SPC will play a major role in dairy herd monitoring in the future.

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