Using Statistical Process Control Methods to Improve Herd Performance

Jeffrey K. Reneau, DVM, MS[a] and Joanna Lukas, MS[b]

[a] Professor, Dairy Management, Department of Animal Science,
University of Minnesota, St. Paul, MN

[b] PhD Candidate, Dairy Production Systems, Department of Animal Science,
University of Minnesota, St. Paul, MN

[a] Corresponding author for proof and reprints:
Jeffrey K. Reneau, DVM, MS
Professor
225D Haecker Hall
1364 Eckles Avenue
St Paul, MN 55108
612-624-9791
612-625-1283 (fax)
renea001@umn.edu

[b] Coauthor address:
Joanna M. Lukas, MS
PhD Candidate
Department of Animal Science
380A Haecker Hall
1364 Eckles Avenue
St Paul, MN 55108
612-624-3415
612-625-1283 (fax)
stac0080@umn.edu

Using Statistical Process Control Methods to Improve Herd Performance

Jeffrey K. Reneau, DVM, MS and Joanna Lukas, MS
Department of Animal Science, University of Minnesota, St. Paul

Introduction

How consistently are your clients' livestock farms managed? How consistent and compliant do employees carry out the management protocols? It is common knowledge that livestock thrive well when herd management is consistently excellent. Dairy cows, for example, perform best when they are healthy, are milked exactly the same every day, and fed palatable diets that consistently provide all nutrient requirements day after day.

Variation is the opposite of consistency and is considered the enemy to process performance. Excessive variation interferes with the evaluation of performance. While it is true that high variability makes performance outcome unpredictable and difficult to interpret, understanding variation is the diagnostic key to improving process performance. Statistical process control is an analytical approach utilizing the theory of variation as a means of explaining with statistical certainty when process performance is improving, staying the same or getting worse.

Livestock farm managers and their consultants have in the past restricted their analysis to limited comparisons of performance means without full consideration of variation. For example, comparing last month's average of some herd performance variable with this month's average. Such an analysis may not only be misleading, it is usually out of context with the daily management activity. Ironically, although consistency in herd management is intuitively sought, analysis of variation in process output has been neglected. Consequently consultants and/or employees may be blamed or rewarded for random variation in performance and not on the basis of "real" change. This leads to management decision errors and frustration for everyone—the consultants, the managers and their employees (1). The need for fact-based management decisions as understood by Ishikawa (2) is apparent. Applying statistical methods to analyze data already available on the farm has the potential of improving process and personnel performance monitoring, thus providing more effective management tools for the livestock farm managers and their consultants. Moreover, it can assure more timely performance feedback to those directly responsible for the process (i.e. milkers, feeders, breeders) as compared with the retrospective monitoring garnered from once per month record analysis that is often out of time order context with daily management.

The Livestock Production System

Every livestock production system is made up of many interconnected processes that eventually result in the production of milk and/or meat. Every process has inputs that result in some output variable (Figure 1) which can often be routinely and accurately measured. The monitoring of these key process output variables by statistical process control (SPC) techniques characterizes the data providing with statistical certainty a "voice of the process" prediction of future performance.

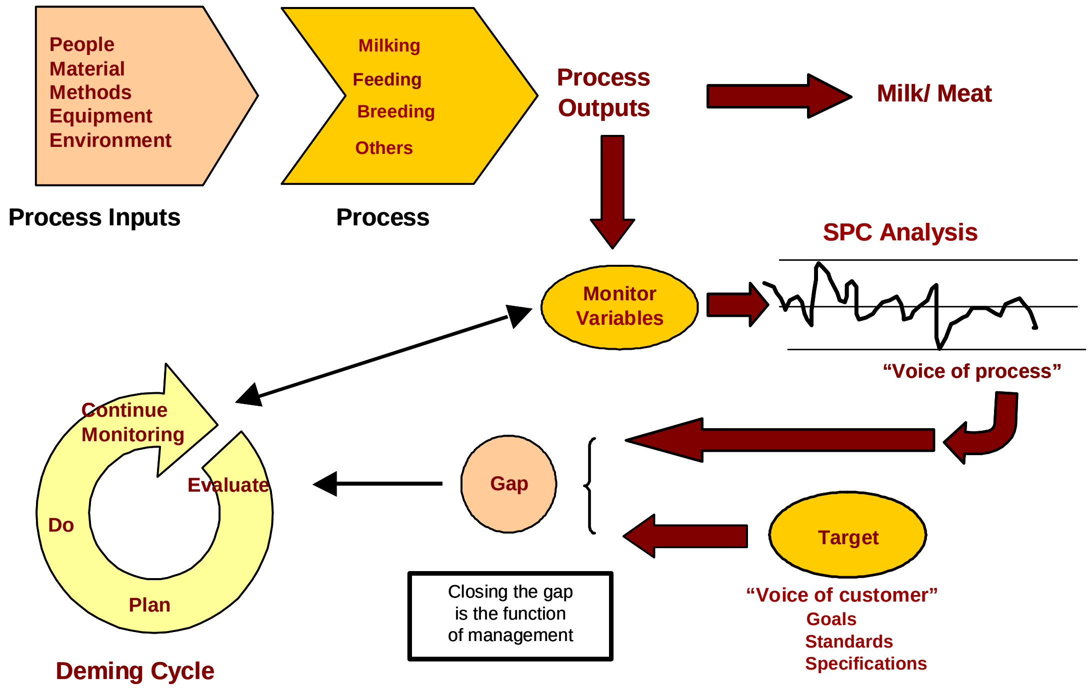


Figure 1. Process flow diagram.

What is SPC?

Statistical process control is more than another analytical methodology. It is a philosophy, a strategy, and a set of analytical methods for the improvement of systems, processes and outcomes (3). *"SPC builds an environment in which all individuals in an organization seek continuous improvement in quality and productivity"* (4). Making quality a responsibility of every employee starts with management and its commitment to creating the right working environment (1). Continuous improvement is achieved by implementing the following SPC family of problem solving tools which have the aim of process improvement by reducing variability (4):

- Histogram
- Check sheet *(used to record process performance data: who? what? when?)*
- Pareto chart *(used to identify the most common problems)*
- Cause-effect diagram *(used to search for root cause of errors/defects/process performance changes)*
- Defect concentration *(used to identify defect location)*
- Scatter diagram *(used to identify relationships between process variables)*
- Control charts

Although this chapter will focus almost entirely on the use of control charts, the authors recommend the reader familiarize themselves with the other six SPC tools.

Control charts were developed in 1920 by Walter A. Shewhart for the purpose of identifying and distinguishing between normal (common cause) and abnormal (special cause) variability. The output of every process is characterized by a certain level of variation which is due to a cumulative effect of many factors that are out of our control. This is called common cause variation. The level of common cause variation can be reduced by finding a way of controlling it. For example, if a bulk tank somatic cell count (BTSCC) is considered to be too high, the herd manager might try to find a way to improve:

- milking personnel skill by training them in standard operating procedures;
- the cows' environment by more frequent changing of bedding.

However, some level of variation is unavoidable since we do not know all the possible factors affecting process output or it might not be economically justifiable to control some of those that we are aware of. For example, we may tolerate a certain drop in milk production and increase in SCC in hot weather since building a barn with a fully controlled environment would be too expensive. When only common cause variation is present in process output, the process is said to be operating under the **state of statistical control**. The process enters an **out of control state** when some aspect of the process that is usually under our control changes and impacts process performance. The resulting variation is usually caused by machine/equipment problems, operator/personnel errors or defective raw materials. This is called special cause variation since its source can usually be traced and eliminated returning the process back to the state of statistical control. Table 1 summarizes the differences between the two types of variation.

Table 1. Source of process variation.

	Sources of variation	
	Common cause	Special cause
Synonyms	normal, unassignable cause, random, noise	abnormal, assignable cause
Definition	Predictable variation inherent in the process itself resulting from factors that we may not control.	Unpredictable variation resulting from factors that we usually have under control.
Cause of Variation Examples	1. Variable milking prep time per cow. 2. Effect of atmospheric humidity on DM content in feed. 3. Biweekly fluctuations in milk yield in cows supplemented with BST.	1. Increased incidence of pneumonia among calves. 2. Decrease in bulk tank SCC after milkers training.
Solution	Work on improving the process by: 1. changing the procedures 2. investing in equipment or other measures that enable better control of factors we previously were not able to control identifying factors influencing the output and learning how to control them (experiments)	Identify the reason for this variation and: 1. remove it if it is undesirable 2. try to repeat it if it is desirable
Solution Examples	1. Adopting a milking procedure that minimizes the variation in milking prep time. 2. Routine measurement of forage DM and adjusting diets to correct for moisture changes. 3. Administering BST to half the herd each week to level out milk yield.	1. Check for wet bedding in calf huts. 2. Establish mandatory yearly retraining for all employees.

Once the underlying principles of the control charts are understood, application to a livestock operation can begin. Developing SPC charts involves these four steps:

Step 1. Decide what to chart. The data should:

- be sensitive to changes (in method, people, environment, machine, materials, etc.) so that they can be used to monitor their performance
- be easily, inexpensively, routinely and frequently collected (to provide timely feedback)
- have an economic value attached
- have a measure that is possible to standardize/specify
- be familiar or easily understood by process operators

- be collected at an appropriate process level (ideally low enough to tie process performance with possible sources of variation, but high enough to avoid plotting too many charts that will eventually be ignored)

Step 2. How will samples be collected? Rational subgrouping will determine the sampling scheme. Rational subgrouping basically means grouping data in a way that makes logical sense so that only random effects are responsible for observed variation within a sample. Decisions about when to sample, how frequent and how big (single or multiple) the individual samples should be will be critical to achieving meaningful analysis. The subgrouping should be designed to help detect possible sources of special cause variation between samples. In summary, the key to creating rational subgrouping is to sample as much the same as possible yet be representative of the process characteristic that is to be monitored.

Step 3. Develop the charts. This step involves choosing the appropriate charts. There is a wide range of charts that have been developed for both measurement (continuous) data (I, Xbar, S, R charts) and attribute (count or proportional) data (C, U, P, NP charts) (Figure 2). With measurement data, both mean and variations can be monitored for change by separate charts.

- **X-bar and S** charts are used to monitor the mean and variation, respectively, in situations where rational groups of **multiple measurements** can be collected. For example: collecting all the individual cow milk weights to calculate the mean and standard deviation of all the milk weights in a group of cows each day. However, in a production setting the variation between animals (common cause, within sample) could be greater than day to day variation (special cause, between samples). Therefore in a biological system plotting an X-Bar chart may not be a recommended approach unless relatively homogeneous groups can be sampled.
- **I and Moving Range** charts are generally used when rational grouping requires a **single measurement.** For example, the simple daily milk production average for a pen of cows expressed in lbs/cow/day or a daily bulk tank SCC or milk component test result.

When using attribute data due to the relationship between mean and variance, it is sufficient to monitor only the mean.

- **Np-Chart:** *requires a constant sample size*; used for monitoring the **number** of times a condition occurs when each unit can either have this condition or not have this condition. For example, the number of dystocias or retained placentas per 20 consecutive calvings.
- **p-Chart:** *does not require a constant sample size*; used for monitoring the **proportion** of samples having the condition when each sample can either have this condition or not have this condition. For example, the percent of animals with some disease or condition during a defined period of time.
- **c-Chart:** *requires a constant sample size;* used for monitoring the number of times a condition occurs when each sample can have more than one instance of the condition. For example, the number of recurrent cases of clinical mastitis per a set number (20 or more) lactating cows over a specific period of time.
- **u-Chart:** *does not require a constant sample size;* used for monitoring the percent of samples having the condition when each sample can have more than one instance of the condition. For example, the number of cow days in the sick pen per week.

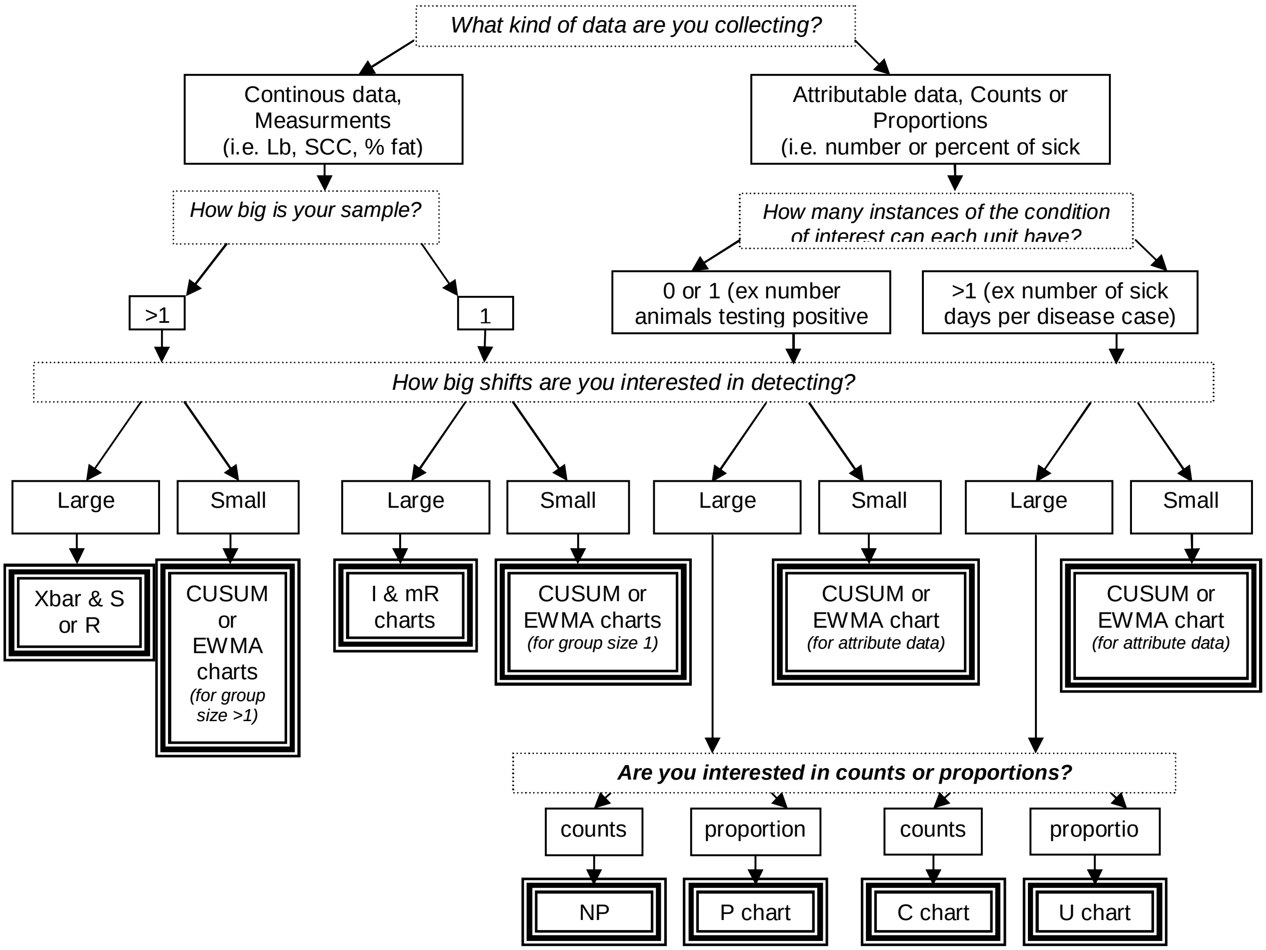


Figure 2. Chart choice diagram.

More detailed information about choice, design and application of SPC charts can be found at the following website: www.qualityamerica.com/knowledgecente/index.htm.

In general control charts for measurement data are more powerful for detecting special cause change than charts for attribute data; that the X-Bar and S charts are more powerful than I-Charts; and the C-chart or U-chart more powerful than the P-Chart (3). Control chart choice will also depend on what degree of anticipated change is expected. Classic Shewhart charts (I-charts and X-bar charts) are designed to detect large shifts in process performance. However, run rules like the following Western Electric rules have been developed to make detection of more subtle changes possible on I and X-bar charts:

- A single point more than 3 sigma away from the mean.
- At least nine successive points on the same side of the mean.
- At least two of three successive points 2 sigma away and on the same side of the mean.
- At least four of five successive points 1 sigma away and on the same side of the mean.

Whenever any of these conditions are met, you can be sure that real change has occurred. When using all the Western Electric rules, there will be a false alarm approximately 2% of the time. It would seem that the probability of being right about whether a change is "real" 98% of the time are pretty good odds for most management circumstances.

Monitoring dairy cow activity with pedometers has been shown to help detect developing metabolic disorders (5). Figure 3 is an example of a Shewhart I chart of daily single cow activity (Dr. Dick Wallace, University of Illinois, personal communication, May 2005). To develop the chart, an arithmetic mean was calculated and a sigma estimated from the average moving range of size two. A center line has been plotted at the mean along with upper and lower control limits 3 sigma above and below the center line. Applying Western Electrics run rules (2 and 3) identified a significant drop in activity as a result of developing ketosis as early as 7/22. The 3 sigma rule (1) did not signal until 7/29, four days after diagnosis of ketosis was made. This example shows how additional run rules increased the sensitivity of the control charts as opposed to just using the 3-sigma rule.

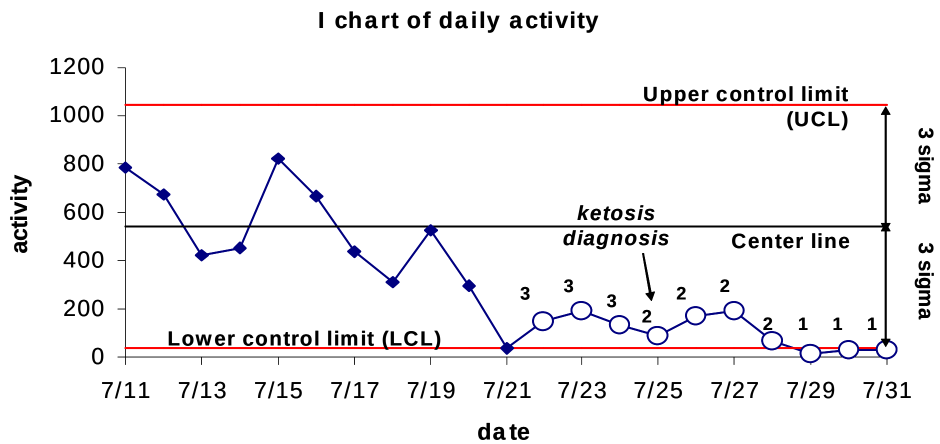


Figure 3. Anatomy of an I chart. Upper (UCL) and lower control limits (LCL) are marked as lines 3 sigma away from the center line (CL). The data point labeled by the white circle indicates a point out of control. Number above data points indicate which Western Electric Rule identified the point to be out of control. The arrow indicates when the diagnosis of ketosis was made. (See text for additional comments.)

More recently, however, more sensitive and specific charts have been developed to detect smaller sustained shifts in process performance. These more sophisticated techniques include EWMA and CUSUM charts (4) and can be designed for optimal performance in detecting shifts from 0.5 to 2 sigma. Classic Shewhart charts are easy to develop and interpret. Supported with Western Electric run rules, they are usually the first step in monitoring process for change and gaining familiarity with SPC tools. However, the currently recommended technique is to plot simultaneously classic Shewhart and CUSUM or EWMA charts. That way both large and small sustained shifts can be detected.

Step 4. Plot the process output data and apply the control limits to observe for special cause variation. When a data point is observed "out of control" (outside the control limits or meets run rule criteria), then search for the root cause, eliminate it, and restore the process to its state of statistical control.

Why use SPC in livestock management?

SPC has proven to be an effective quality management tool in manufacturing businesses for over 80 years improving product quality and reducing process waste. First attempts to implement principles of SPC in livestock industry go back to 1977 with Wrathall et al. (6) studying applicability of individual measurement SPC chart application. Since then, the use of SPC charts has been researched in all the four major livestock species: swine (7, 8, 9), beef

(10), poultry (11, 12) and, more recently, dairy (13, 14, 15). Wrathall and Hebert (16) first identified the need for SPC application in livestock because of growing herd size and increasing remoteness between managers and livestock. More current studies underline the applicability of SPC methods in continuous improvement effort at the farm (17, 18). Although the research in SPC application in livestock production has at least a 28-year history, only recently has the idea become practical. This has been largely due to advances in computer capability. News of SPC has been reaching livestock producers' through professional magazines (Progressive Dairyman, Midwest Dairy Business, Pig Letter, etc.) as well as practical application through websites that chart process output variables on SPC charts (MilkLab™ at www.dairyperformance.com) and include SPC in software packages analyzing farm performance data (i.e. 100-Day Contract Manager™)[1]. In addition, increased use of on-farm technology with computerized milking, feeding and estrous detection systems, to name a few, provide resources by creating enormous amounts of data available on a daily or hourly basis. Analyzed properly, this data can be helpful in monitoring the performance of these critical processes as well as the employees that carry them out. Below is a summary table of SPC charts' application to variables across the four main species (Table 2).

Table 2. Application of SPC charts to monitor livestock production variables.

Specie	Variable	Chart type	Reference
Dairy	bulk tank milk urea nitrogen	I	www.dairyperformance .com
	bulk tank protein percent		
	bulk tank butter fat percent		
	milk/cow/day		
	DM/cow/day		
	bulk tank SCC	I	14, 28
	percent pregnant	P	13
	estrous detection ratios	P CUSUM	15
Swine	percent return to service	I CUSUM	6, 7
	number of pigs per litter	Xbar	6
	percent fetuses born dead/alive	I	6, 8
	snout-deformity score	CUSUM	10
	farrowing rate	I	8
	number of piglets weaned	I	
	number of services		
	feed conversion rate		
	non productive sow days		
	water usage		
	shots administered		
	weight out (nursery)		
	number of sows and gilled culled		
	number of females mated	I	8, 9
Beef	weight gain	Xbar	10
Poultry	weight	Xbar	11
	survival rate	I	12

The table includes only variables that have been considered by previous research. As mentioned earlier the automation of many processes on the farm, including data collection, creates the opportunity for SPC charting of many other performance measures. For example, in dairy production, these could include: feed efficiency, activity monitoring, electric conductivity of milk, parlor throughput, milk bactoscan test results, water and DM intake and others.

[1] Trademark owned by Pfizer Animal Health

The goal of a commercial dairy farm is to consistently produce high quality and safe milk in a manner that enhances animal health and productivity (19). This goal is consistent among all food producing livestock enterprises. Controlled basic research studies provide cause and effect knowledge of the effectiveness of a management or product intervention. Although such studies are possible, they are not practical under day-to-day conditions on commercial livestock facilities. There is no control group and only a single stream of data on commercial livestock facilities. Yet, it is important to determine with some degree of certainty whether a management intervention or product introduction is working and whether the processes are improving or getting worse. It is in this circumstance that SPC analysis is not only appropriate but superior to other statistical or monitoring techniques. This argument alone provides a compelling reason for the application of the SPC tools in commercial livestock production systems. However, it should be remembered that since before and after comparisons are being made from a single stream of data, it is important to emphasize a need for the process to be stable (in a state of statistical control) before the new protocol or product is introduced to be sure that any observed process change was valid. It should be further noted that the smaller the process variation is prior to introducing a known intervention, the greater the sensitivity for detecting small changes in before and after comparisons.

The authors conclude that SPC can be successfully applied in livestock production systems. The time is right. The availability of large amounts of automatically collected data, the advances in computer capability, and the obvious need for more timely fact-based information for day-to-day management make SPC application the next step forward in improving herd management quality.

Examples of Control Chart Use

Example 1. Monitoring swine water intake by a time series plot and an I chart.

Recent studies (20) show that monitoring water intake can help detect potential health problems in growing pigs. Individual readings plotted on a time series plot can provide insight into a developing crisis (Figure 4) and offer a quick and easy way to monitor water intake on growing pigs in the barn. However, two difficulties arise in using time series plots. Reading a time series plot is subjective and leads to differences in interpretation depending on the person examining the plot. Was there a “real” change in water intake between days 15 and 27? How sure would you be by looking at this time series chart? When did the change begin and end? Using SPC charts to present this same data (Figure 5B) standardizes the interpretation so that every person reading the chart draws the same conclusion and can implement an appropriate standard intervention procedure without hesitation. However, as in any intake monitor for growing animals, readings have a tendency to increase with time. Plotting the raw values on an SPC chart will eventually cause signals to occur due to a natural increase of water intake in growing pigs rather than due to any special cause. Different methods have been developed to deal with this lack of independency between subsequent data points (autocorrelation). One of the methods is to model the dependency (in this case against time) and plot the residuals on an SPC chart. Figure 5 is an example of an I chart where the time effect has been modeled and the residuals are plotted to monitor for special cause variation. As mentioned previously, control limits on an SPC chart make the interpretation independent of who is looking at the plot and can therefore help in making timely, fact-based decisions, in this case, concerning potential health problems among growing pigs.

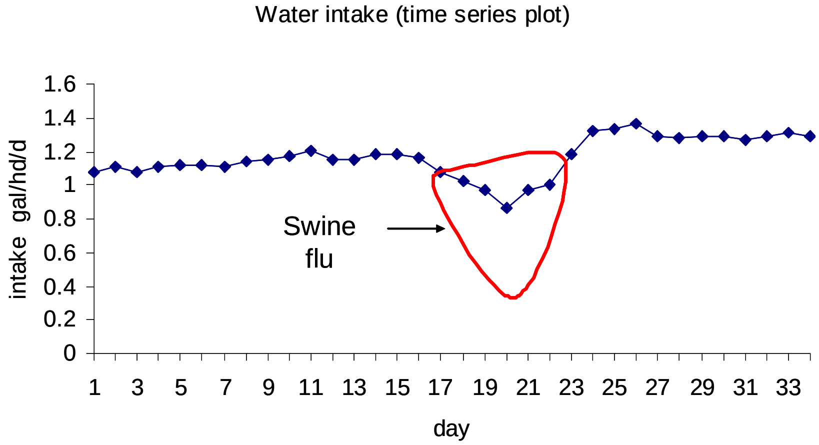


Figure 4. Time series plot monitoring water intake (gallons/head/day) for growing swine. The circled period indicates time when swine flu occurred. Data taken from http://porkcentral.unl.edu.

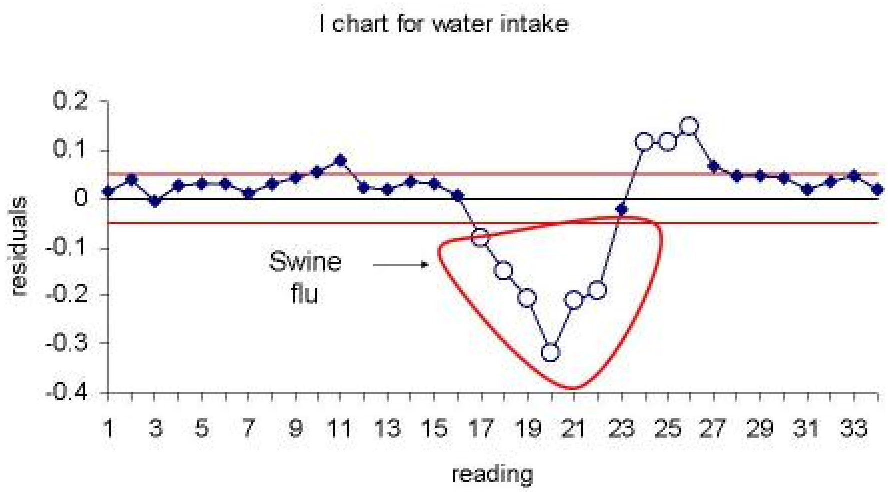


Figure 5. I chart monitoring water intake for swine by plotting residuals of the fitted model (See text for details). The data points labeled by white circles indicate points out of control according to the three sigma rule. The circled period indicates time when swine flu occurred.

Example 2. I and EWMA chart comparison used to monitor BTSCC.

Bulk tank somatic cell counts are a reflection of many on-farm processes that contribute to milk quality (milking routine, milking system, bedding routine, dry/fresh cow management, etc.). They are therefore a good monitor of people, equipment and animal performance. The following shows an example of BTSCC being monitored by an I chart (Figure 6) and an EWMA chart (Figure 7). A change in milking routine was implemented on the 22nd of March and a significant drop in BTSCC was identified by the I chart two days later while the EWMA took another five days to signal. This illustrates an important characteristic of EWMA (and CUSUM) charts. They can be designed for optimal performance for a specific change in mean/variation and they will perform well if the magnitude of occurring change is reasonably close to the anticipated design value. Generally, however, the I or Xbar chart will signal a large shift sooner than an EWMA or CUSUM chart. Therefore, the recommended approach, as mentioned previously, is to plot both charts alongside each other if both large and small shifts are to be detected.

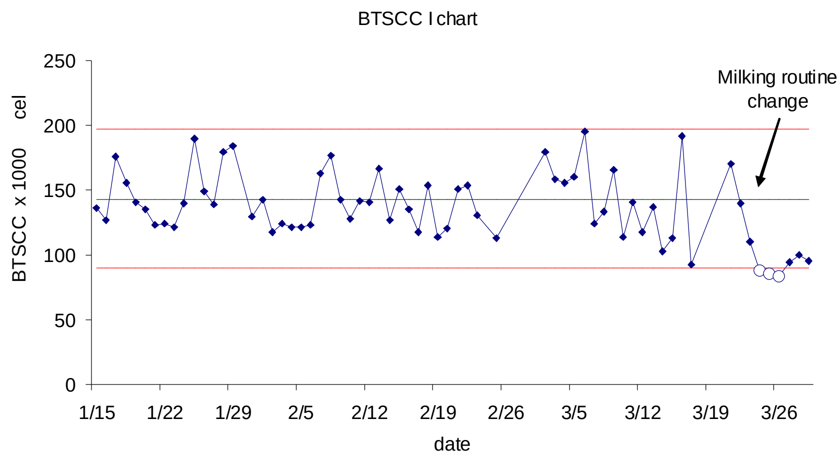


Figure 6. Figure 6. I chart for the bulk tank somatic cell counts (BTSCC). The arrow indicates the time a change in milking routine was implemented. The data points labeled by white circles indicate points out of control according to the three sigma rule.

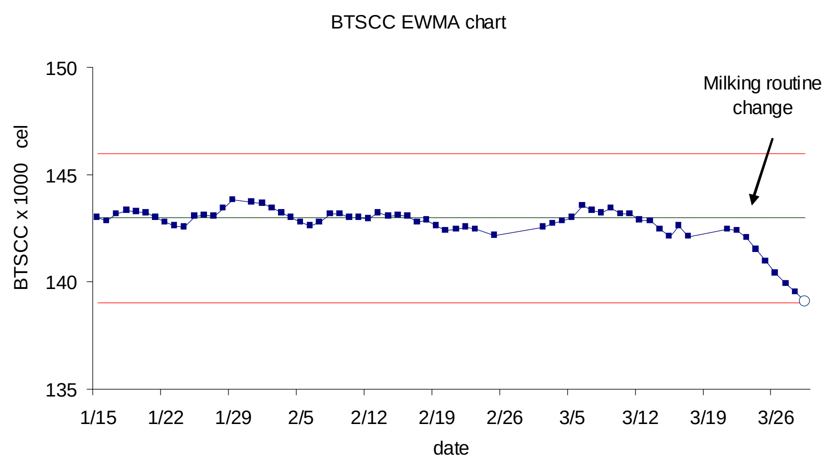


Figure 7. EWMA chart for the bulk tank somatic cell counts (BTSCC). The arrow indicates the time a change in milking routine was implemented. The data point labeled by the white circle indicates a point out of control according to the three sigma rule.

Example 3. Percent of fresh cows in the first week post calving with fever monitored by a P chart.

The number of fresh cows with fevers during the first 10 days after calving is indicative of dry, close up and fresh cow management (Mark Kinsel, Ag Information Management Inc., Ellenburg, WA, personal communication, June 2005). On this 2000-cow dairy, the proportion of cows with fever was being monitored daily and compiled on a weekly basis giving a sample size of around 40 (Figure 8). For simplicity it is assumed that the sample size (number of cows calving per week) is fairly constant throughout the year. Three "out of control" points on the lower side of the mean following a manager change indicate a significant decrease in percent cows calving with fever and provide excellent feedback to the owner on his hiring decision. This is assuming both the old and new managers recorded all the fever incidences among fresh cows.

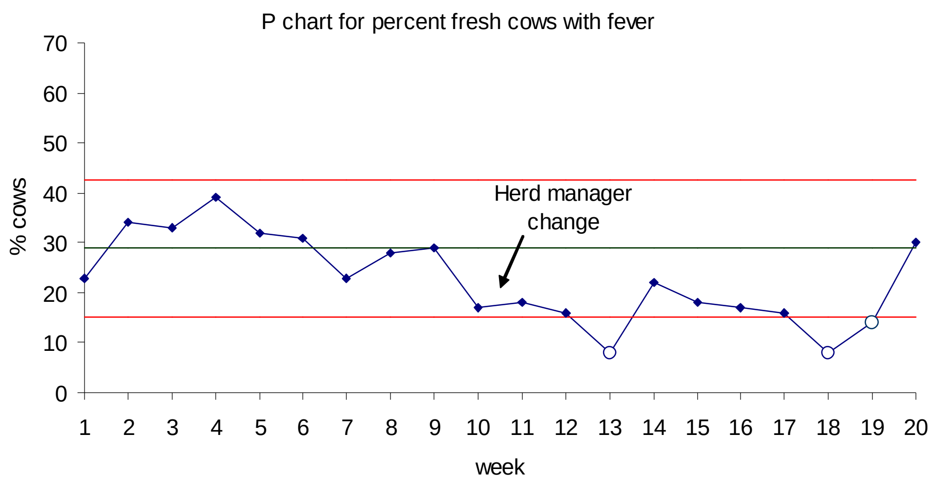


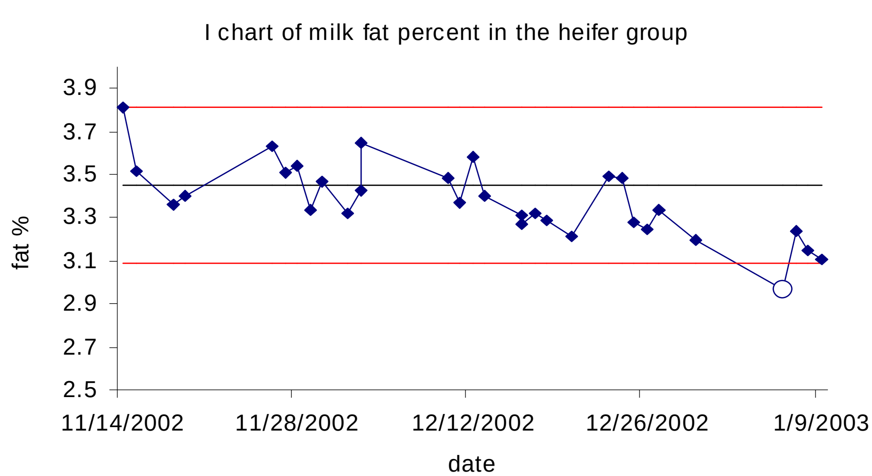
Figure 8. P chart for monitoring percent fresh cows with fever. The data points labeled by the white circles indicate points out of control according to the three sigma rule. The arrow indicates the time a new herd manager was hired. (See text for additional comments).

As mentioned previously, many variables that can potentially be plotted on SPC charts to monitor process performance are already being collected on farms. The following are examples (Figures 9 and 10) of two such variables and their possible role in monitoring herd nutrition.

Example 4. Butter fat depression in a group of first lactation cows.

Figure 9 is an I chart of milk fat depression of the first lactation group of Holstein cows preceding an episode of displaced abomasums. An investigation into the root cause of the increase in the occurrence in displaced abomasums (DAs) revealed a problem with the feeding process. A newly hired feeder had been routinely over mixing the TMR prepared for the heifer group causing the feed for that group to be deficient in effective fiber, resulting in milk fat depression and increase in DA occurrence in the group. There were 5 DAs in that group the week following the control chart "signal".

Figure 9. I chart for monitoring daily milk fat percent in the first lactation heifer group sampled with a line sampler. The data points labeled by the white circles indicate points out of control according to the three sigma rule. The arrow indicates the time of signal. (See text for additional comments).



Example 5. Milk Urea Nitrogen (MUN) response to changes in dietary protein.

It has been well documented that MUN responds quickly to dietary changes (21). Figure10 shows a response of the bulk tank milk urea nitrogen to known changes in crude protein concentration in the diet of a late lactation group of cows at the University of Minnesota research herd in Morris, MN.

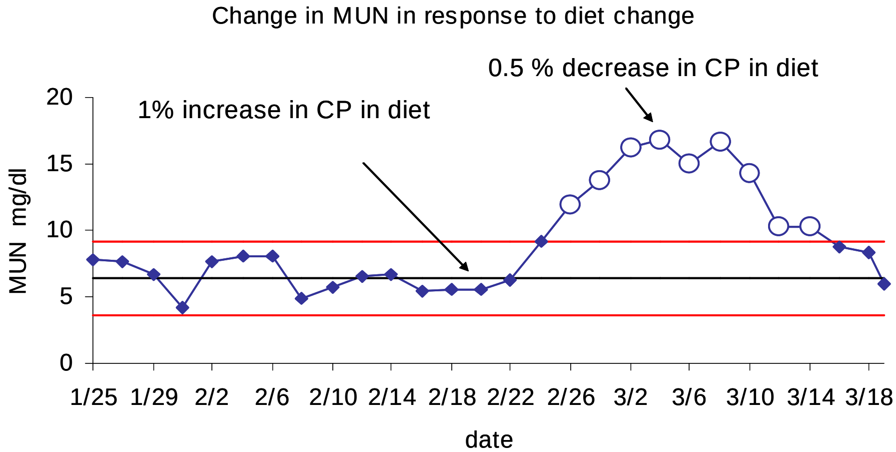


Figure 10. I chart monitoring the milk urea nitrogen (MUN) response to dietary crude protein change. The data points labeled by white circles indicate points out of control according to the three sigma rule. Arrows indicate the time of change in crude protein (CP) concentration change in diet.

Benchmarking Variation

Benchmarking variation is not traditionally recognized as an SPC technique. Benchmarking is, however, a recognized quality management tool for determining the strengths and weaknesses of a business and an excellent method of motivating improvement. Because many livestock databases are standardized, benchmarking between farms is possible. Since each Shewhart control chart provides calculation of the process variable means and a sigma value, comparisons of process variation between farms is possible. The following dairy experience provides an example of how benchmarking variation can give insight into process quality and/or protocol consistency

Variation as a tool in managing milk quality.

W. E. Deming summarizes his Theory of Management in this often quoted sentence: *"If I had to reduce my message to management to just a few words, I'd say it all has to do with reducing variation."* While we have found this idea intuitive among dairy managers, study of herd data indicates there is a great amount of process variation found on dairy farms today. Perhaps this can be best demonstrated in exploring day-to-day variability in bulk tank somatic cell counts (BTSCC). It has been widely documented that the somatic cell count (SCC) level is inversely correlated to the quality of herd management (22). The incidence of intramammary infection is correlated to the quantity of bacteria on teat surfaces (23, 24, 25). Bodoh et al (26) concluded that daily management and cow hygiene has more influence on BTSCC than dry cow therapy. Dairies with management styles described as "clean and accurate" had lower BTSCC compared to those described as "quick and dirty" (27).

Answering the question, "how consistently do your clients manage their livestock operations?" is important in assessing the quality of herd management. Understanding process variation will be helpful in differentiating whether it is the process or the personnel or both that need improvement.

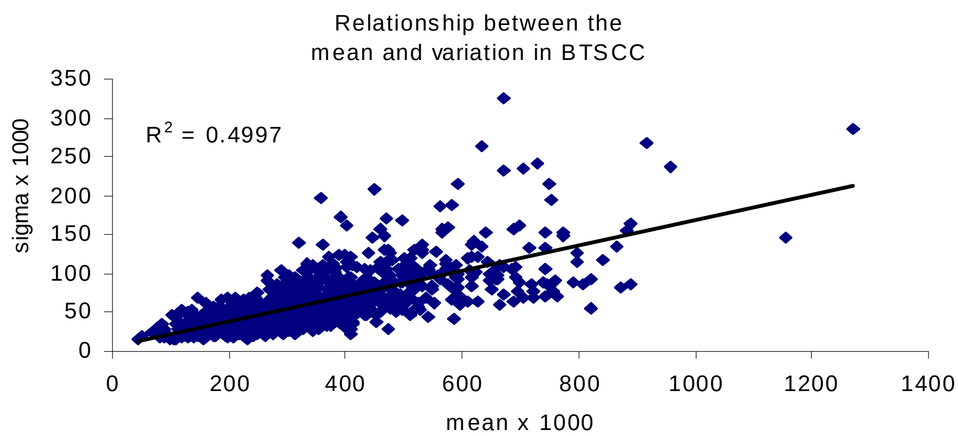


Figure 11. Scatter plot of bulk tank somatic cell count (BTSCC) sigma versus mean. Solid line plotted on the figure marks the regression line. R^2 value indicates the strength of the relationship between BTSCC mean and sigma.

In a study of 1500 Upper Midwest dairies where SPC control charts (28) were completed for each milk pickup during 2003, we found a positive correlation between mean BTSCC level and day-to-day variation (sigma values). Herds with low BTSCC also had low day-to-day variation and vice versa. The r-squared value was 0.4997 (Figure 11) indicating that although 50% of the variation can be explained by the change in SCC level alone, 50% of the variation can be attributed to the quality of the processes that result in the BTSCC. In a related study of 275 Minnesota DHI herds where SPC control chart techniques were used to evaluate SCC and milk components, it was found that those herds with the highest milk production also had the lowest mean BTSCC and the lowest BTSCC variation (Figures 12 and 13). The conclusion then conforms to Deming's hypothesis that variation can be used to assess process quality.

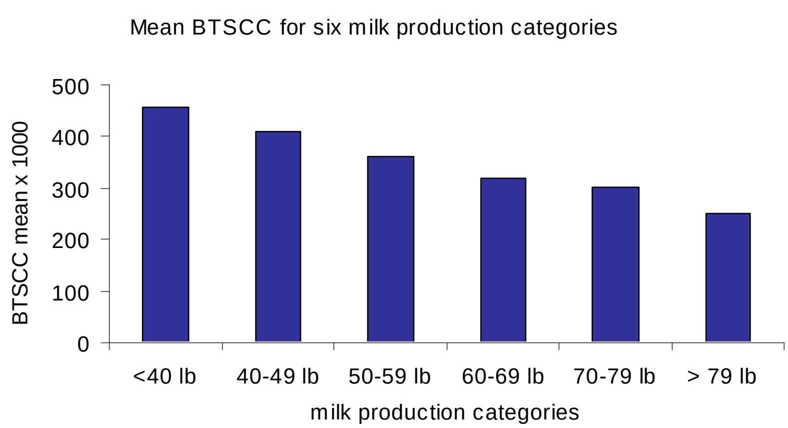


Figure 12. Bulk tank somatic cell count (BTSCC) mean by production category for 275 Minnesota DHI dairies. The herds were divided into six production categories based on the average pounds of milk per cow.

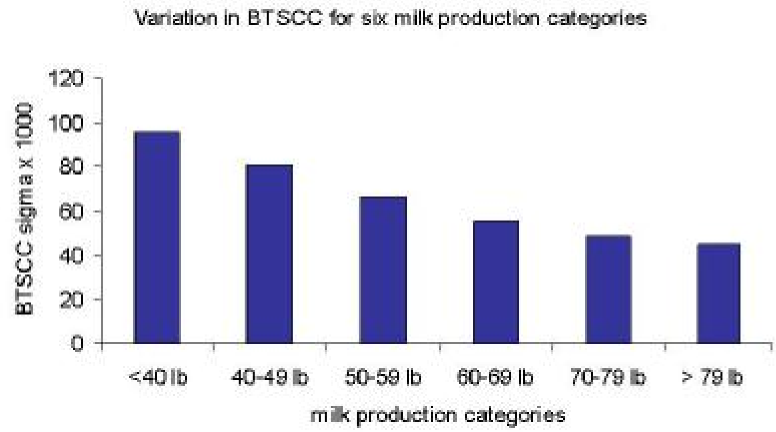


Figure 13. Bulk tank somatic cell count (BTSCC) variation by production category for 275 Minnesota DHI dairies. The herds were divided into six production categories based on the average pounds of milk per cow.

There are two factors needing consideration in assessing process quality. The first is the process itself as measured by a variable mean. For example, in the case of BTSCC, a low mean BTSCC indicates that the management procedures (protocols) are both appropriate and effective for achieving a low BTSCC. The second factor to consider is the process variation. Low day-to-day sigma values (variation) are a strong indication that personnel are applying protocols consistently every day. High sigma values (variation), on the other hand, would indicate a need to improve the consistency in applying process protocols. Benchmarking of process means and sigma values can serve as a method of determining answers to the common management questions: "Is this a process problem?" or "Is this a personnel problem?"

Figures 14 indicates the relationship between BTSCC level and the expected day-to-day variation based on analysis of daily BTSCC control charts for 1500 Upper Midwest dairies over two years. Since herd size will have an effect on the degree of expected BTSCC variation, the 1500 herds were categorized into herds greater than 100 cows and herds less than 100 cows.

Therefore, if you know a herd's average BTSCC and the day-to-day variation (sigma), you can determine the process quality relative to both the level of herd management and/or the consistency with which protocols are being applied at the farm.

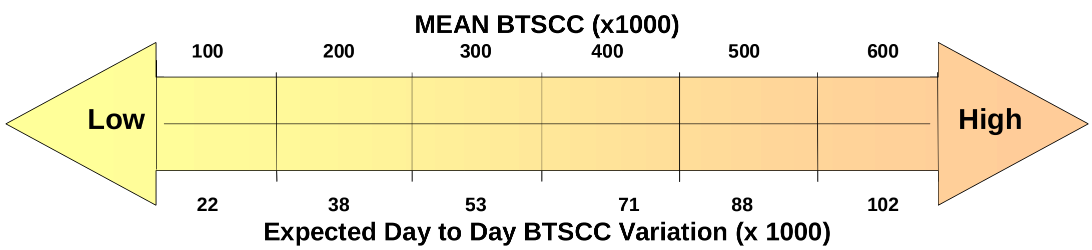
What if variation is low? When the variation is low, the good news is that the employees are being consistent in their work. The bad news is that if the dairy is still not producing milk of desired quality, some things are being done consistently wrong. Take a closer look at how all tasks are performed, take measurements and make observations. Some examples of the measurements to take when attempting to lower the SCC are: cow density, bedding cultures, cow hygiene score, bulk tank cultures and a number of other indicators that might help identify the root cause of the problem.

What if variation is high? If the variation is higher than expected, this suggests a need to improve process compliance and consistency. Evaluation of employee compliance to protocols and/or the consistency with which protocols are followed is needed. On farms where SOPs (standard operating procedures) are not in place, encouragement should be given to write them. Routine employee training should be implemented to be sure that each employee understands their duties and is committed to following all SOPs. Training is effective in reducing variation. Recent University of Wisconsin studies (29) indicated that herds with more frequent training of milkers had lower BTSCCs.

What if variation is average? If the variation for BTSCC is somewhere in the middle of the indicated range and there is a desire by the dairy to lower BTSCC, then improvement in both consistency of people performance and the processes themselves is needed. Experience has shown that it is best to start by improving consistency and protocol compliance. This makes it easier to identify true improvement in performance. By first reducing the variation in performance, when changes are made to the procedures used, it will be easier to determine if the implemented changes actually resulted in any improvement in milk quality.

Let's take, for example, a 200-cow dairy with a BTSCC mean of 300,000 and a day-to-day variation of 22,000 (sigma value of 22). Assuming the herd's goal is to qualify for the quality premium for a BTSCC under 200,000, what should be done? Should personnel be hassled about the consistency of milking and bedding management routines or should we explore methods of improving the total process? The answer is obvious. Since day-to-day variation is lower than expected for a BTSCC of 300,000, the current BTSCC level is NOT likely to be the result of inconsistent application of protocols by milking personnel. It is more likely that the personnel are consistent in applying the protocols BUT the protocols themselves are not capable of delivering a BTSCC of less than 300,000. What is the solution? Work on improving the process protocols.

ARROW A (Herds less then 100 cows)



ARROW B (Herds 100 cows or more)

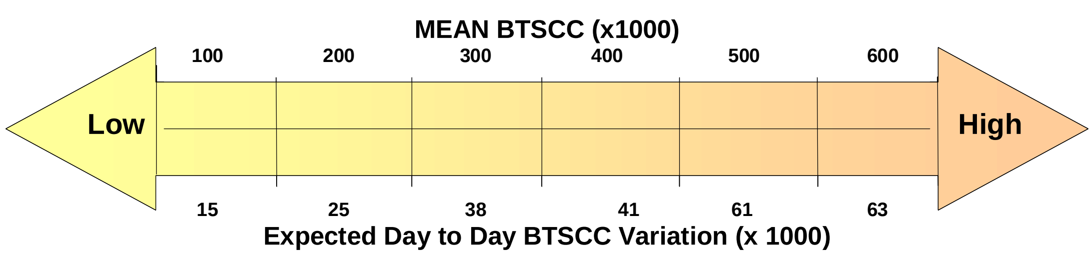


Figure 14. Diagram for benchmarking bulk tank somatic cell count (BTSCC) mean and variation in 1500 upper Midwest dairies. (See text for further comments).

<u>Benchmarking variation as a tool in managing feeding consistency.</u>

Can analysis of day-to-day variation of milk fat, protein, milk urea nitrogen (MUN), dry matter (DM), dry matter intake (DMI), lbs of milk per cow per day, or feed efficiency give insight into feeding management? Although the jury is still out, evidence is building that SPC use could be useful tools for managing dairy herd nutrition. Regardless of how well formulated a diet, it needs to be fed consistently to achieve its desired results. Variation between the formulated diet and that consumed by the cow is common. This variability can be caused by variability in the feeds, the feeder or the cow (30, 31).

Figures 15, 16 and 17 show the correlation between day-to-day butterfat %, protein % and MUN variation, and the levels of butterfat %, protein % and MUN. These plots are interesting because they indicate that there is no relationship between the degree of variation and the level of either butterfat %, protein % or MUN. In contrast to the BTSCC where only half of the variation can be attributed to the processes involved in producing a BTSCC, all the variation at any milk fat, protein or MUN level may be due to the management and/or the biological processes that effect these variables. In addition, there were no great differences in the degree of variation because of herd size. This may be good news for nutritionists because interpretation of variation is simplified.

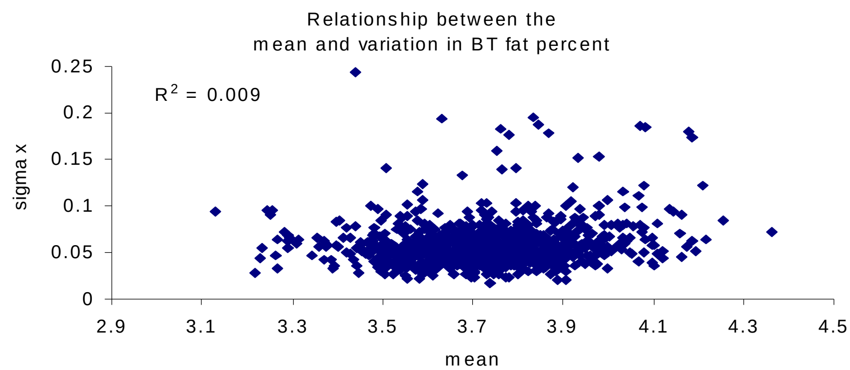


Figure 15. Scatter plot of bulk tank milk fat percent sigma versus mean in 1500 upper Midwest dairies. R^2 value indicates the strength of the relationship.

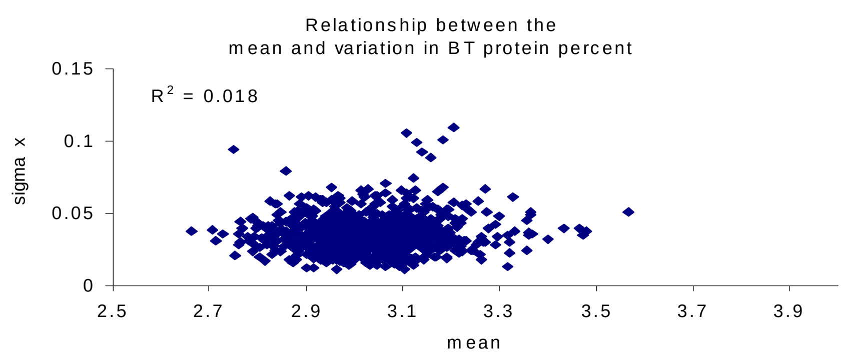


Figure 16. Scatter plot of bulk tank milk protein percent sigma versus mean in 1500 upper Midwest dairies. R^2 value indicates the strength of the relationship.

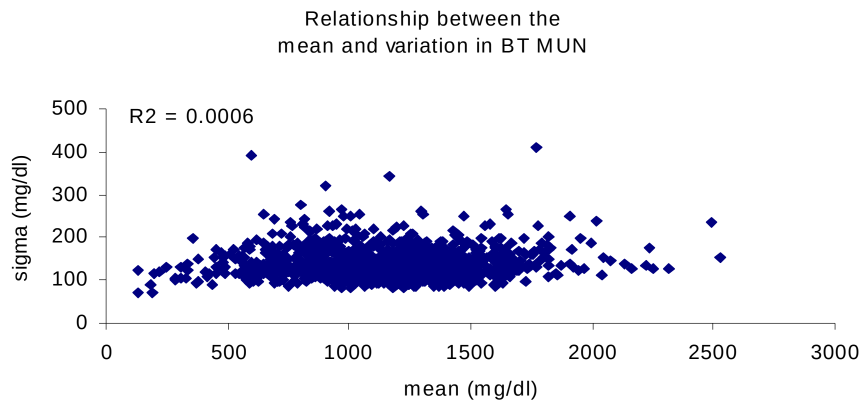


Figure 17. Scatter plot of bulk tank milk urea nitrogen (MUN) sigma versus mean in 1300 upper Midwest dairies. R^2 value indicates the strength of the relationship.

Figure 18 shows the spectrum of day-to-day variation in bulk tank butterfat % and protein % for 1500 Upper Midwest dairies monitored at each milk pickup in 2003. The MUN variation (Figure 18) was from 1300 dairies of the same data set monitored at each milk pick-up for 6 months and, therefore, may not fully represent seasonal variation in MUN. It should also be pointed out that this milk component data represents whole herd bulk tank samples and not individual feeding groups.

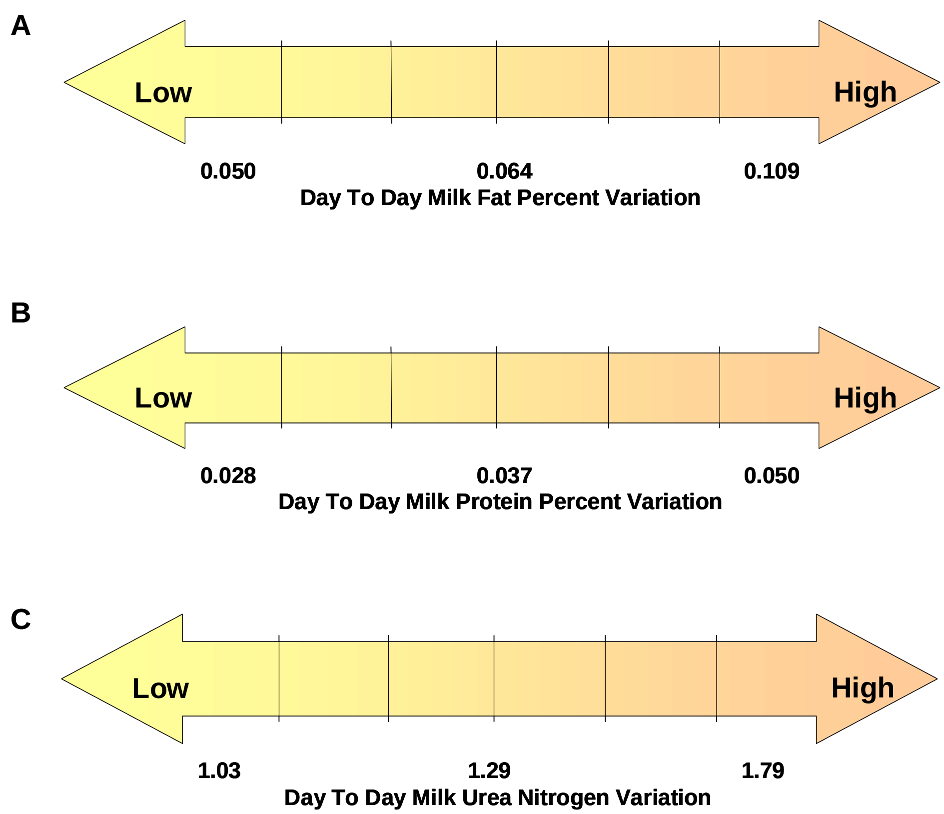


Figure 18. A. Diagram used for benchmarking variation in bulk tank milk fat percent. B. Diagram used for benchmarking variation in bulk tank milk protein percent. C. Diagram used for benchmarking variation in bulk tank milk urea nitrogen.

It is currently thought that benchmarking day-to-day variation of milk components can be useful in giving insight to dairy farm feeding management of lactating cows. Generally speaking, low day-to-day variation in milk protein, fat and MUN implies that a very consistent feeding program is being implemented on the farm. High variation would then imply the opposite is true. However, since most larger dairies have several feeding groups, greater sensitivity in assessing the feeding process variation can be achieved by collecting line samples from each feeding group (32). This sampling is consistent with our previous discussion about rational subgrouping design. Then each feeding group could have control charts completed for lactating group inputs (i.e. DMI) and process outputs (i.e. milk components and average lbs/cow/day) simultaneously charted providing well-rounded real time feedback to facilitate more timely day-to-day nutritional management decisions.

If the variation is high, this suggests a need to improve process compliance and consistency. When the variation is low, the good news is that the feeds, the employees and the cows are consistent. The bad news is that if the cows are still not performing up to expectation, then maybe some things are being done consistently wrong. For example, consistently feeding poor quality forages or routinely over mixing the TMR. What should be done? Take a closer look at how all tasks are performed, take measurements and make observations. Your evaluation should include bunk space, feed dry matter change, TMR mixing time, manure score, particle size of feed that is fed to the cows and the refusals, just to mention a few. As was previously mentioned but is well worth repeating, experience has shown that it is best to start by improving consistency and protocol compliance. This makes it easier to identify true improvement in performance. By first reducing the variation in performance, when changes are made to the procedures used, it will be easier to determine if the implemented changes actually resulted in any real improvement in process quality.

SPC Tools Available

PC-based software: There are numerous SPC software products available for PC application ranging from Microsoft Excel add-ons to very sophisticated stand alone SPC software products. The price range for these products will be from $129 to $600. The advantage of PC-based software is largely more independence and flexibility. The disadvantage is that you must not only be more knowledgeable in SPC software use, but also you are the custodian of the data which usually includes the time consuming effort of data entry and report generation. The following are recommended websites where you can find product information.

http://www.qualityamerica.com/QAProducts/softwareproducts.htm
http://www.statistix.com/home.html
http://www.excel-spc-software.com/excel-spc-software.html
http://www.ozgrid.com/Services/statistical-Quality-Control.htm

Web-based SPC tools: The advantages of the web-based SPC tools are numerous. The web-based system frees you of data storage and software updates. Neither you nor your clients will need to worry about software compatibility, and SPC results can be accessed from any Internet computer terminal anywhere and at any time. Since much of the data is automatically uploaded to the web server, manual data entry is minimized or entirely eliminated. Automated email alert systems can provide you and your client a 24/7 vigilance over critical farm processes without having to be physically at the farm. The disadvantage to a web-based system is that only a few variables are tracked and there may be less flexibility in tracking the variable of your interest. At the time of this writing, there is only one web-based SPC product that is limited to dairy use: MilkLab™ at www.dairyperformance.com offered by Ag Information Management Inc.

Summary

SPC techniques have been used successfully for 80 years in manufacturing as a quality management tool to improve the timeliness and accuracy of management decisions as well as improve personnel performance. It is apparent that these techniques can be applied equally well to livestock production systems and will improve herd management and profitability.

References

1. Deming WE. Out of the crisis. London: The MIT Press; 1986.
2. Ishikawa K. What is total quality control? The Japanese way. Englewood Cliffs; Prentice-Hall, Inc; 1984.
3. Carey RG. Improving healthcare with control charts. Milwaukee: ASQ Quality Press; 2003.
4. Montgomery DC. Introduction to Statistical Quality Control. New York: John Wiley & Sons, Inc; 2005.
5. Edwards JL, Tozer PR. Using activity and milk yield as predictors of fresh cow disorders. J Dairy Sci 2004;87(2):524-31.
6. Wrathall AE. Reproductive failure in the pig: diagnosis and control. The Vet Rec 1977;100:230-237.
7. Wilson MR. McMillan I, Swaminathan SS. Computerized health monitoring in swine health management. Pig Veterinary Society Proceedings 1980;6:64-71.
8. Kniffen, T. Potential uses of SPC in a pork production system. In: Statistical Process Control. Proc. Allen D. Leman Swine Conference. University of Minnesota. St Paul, MN. 1994, p. 1-12.
9. Koketsu Y, Duangkaew C, Dial GD, Reeves DE. Within-farm variability in number of females mated per week during a one-year period and breeding herd productivity on swine farms. J Am Vet Med Assoc 1999;214:520-4.
10. Sard, DM. Dealing with data: the practical use of numerical information – (14) Monitoring changes. Vet Rec 1979;105:323-8.
11. Ravindranthan N, Unni AKK. A study on consistency in body weights of chicks using Shewhart control charts. Cheiron 1990;19:156-8.
12. Cowen, P., Fernanadez, D. and Barnes, H. J., 1994 Surveillance strategies for monitoring variation in animal health and productivity: the use of statistical process control in turkey industry. The Kenya Veterinarian 18:202-204.
13. Marsh WE, de Vries A, Reneau JK, and Kinsel ML. Monitoring performance: statistical process control in dairy herd management. In: Annual Northeast Dairy Production Medicine Symposium, 6th ed. Syracuse: 1997, p. 34-46.
14. Reneau JK, Kinsel ML. Record systems and herd monitoring in production-oriented health and management programs in food producing animals. In: Herd Health. Philadelphia: W. D. Saunders Company; 2001.
15. de Vries A, Conlin BJ. Design and performance of statistical process control charts applied to estrous detection efficiency. J Dairy Sci 2003;86: 1970-84.
16. Wrathall AE, Hebert CN. Monitoring reproductive performance in the pig herd. Pig Veterinary Society Proceedings 1982;9:136-48.
17. Cowen P, Fernandez D, Barnes HJ. Surveillance strategies for monitoring variation in animal health and productivity: the use of statistical process control in turkey industry. The Kenya Veterinarian 1994;18:202-4.
18. Polson D. SPC = statistical pig control. International Pigletter 1998;18:43-6.
19. Natzke D. ‘Statistics’ key piece of process analysis. Midwest Dairy Business. 2005;Jan:9-10.

20. Brumm MC. Water as a predictor of tomorrow's pig performance. Available at: http://porkcentral.unl.edu/water%20predict.pdf. Accessed June 29, 2005.

21. Wattiaux MA. Fine-tuning test-day MUN records for DHI-related variables. Proceedings of the Four-State Dairy Nutrition and Management Conference. Dubuque: 2005, p. 75-83.

22. Bennett RH. Milk Quality and Mastitis: The management connection. Proceedings National Mastitis Council. Orlando: 1987, p. 133-50.

23. Neave FK, Dodd FH,. Kingwill RG. A method of controlling udder disease. Vet Rec 1966;78:521-725.

24. Guterbock WM, Blackmer PE. Veterinary interpretation of bulk-tank milk. Vet Clin North Am Large Anim Pract 1984;Jul;6(2):257-68.

25. Pankey JW. Premilking udder hygiene. J Dairy Sci 1989;2:1308-12.

26. Bodoh GW, Battista WJ, Schultz LH. Variation in somatic cell counts in Dairy Herd Improvement milk samples. J Dairy Sci 1976;59:1119-23.

27. Barkema HW, Van der Ploeg JD, Schukken YH, Lam TJGM, Benedictus G, Brand A. Management style and its association with bulk tank somatic cell count and incidence of clinical mastitis. J Dairy Sci 1999;82:1655-63.

28. Lukas J, Kinsel ML, Reneau JK. Consistency Index as a Dynamic Field Measure of BTSCC Variation. [Abstract W248] In: ADSA ASAS PSA Joint Meeting Abstracts. St Louis: 2004, p.375.

29. Ruegg P. Pre-milking cow preparation – Secret methods of producing high quality milk. In: Proceedings of the National Mastitis Council Regional Meeting. Bloomington: 2004, p. 34-40.

30. Stone WC. What is acceptable variation in the nutrition program and how can it be managed? In: Proceedings of the Southwest Nutrition Conference. Tempe: 2005, p. 1-10.

31. Weiss WP. Variation exists in composition of concentrate feeds. Feedstuffs 2004;May:11-13.

32. Godden SBR, Reneau JK, Farnsworth R, LaValle M. Field validation of a milk-line sampling device for monitoring milk component data. J Dairy Sci 2002;85(9):2192-6.