PRACTICAL TOOLS TO MEASURE AND MONITOR VARIATION

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Introduction

Variation is a major issue on large dairy herds in the Pacific Northwest. Too much variation is definitely bad, leading to fluctuations in production and health. As costs to operate dairies continue to escalate it will be important for nutritionists to better understand, measure and monitor variation on the dairy. Tightening variation should translate into more efficient operations and improved profits. This paper will focus on practical examples of variation and introduce monitoring tools that the authors have been using in the field. Specifically, we will show examples related to variation in dry matter intake and milk fat in Pacific NW dairies. We will also discuss the use of statistical process control charts, and examine a dataset of Pacific NW herds to determine the typical variation and generate a prediction equation for milk fat in this region.

Variation in Dry Matter Intake (DMI)

Figure 1 contains an example of variation in intakes. Shown are daily DMI from an 80-cow pen of Holstein cows. Forage DM were determined weekly before 9/20, and daily thereafter. All forage was briefly premixed in the mixer wagon, unloaded, and then used in load preparation. Some of the apparent spikes in DMI (e.g. 11/21, 11/29, and 12/13) occur on approximate increments of seven, and are probably related to weekly animal movements. The decreases in intakes occurring around 10/20 and 12/20 were correlated with an increase in new corn silage and an outbreak of winter dysentery, respectively. Actual intakes can and should be within five percent of predicted intakes (based on experiences with CNCPS), or some on-farm investigating and possibly a ration adjustment may be needed.

The real question to consider when looking at data like these in the below figure is 'are the changes normal or do they represent real change?' To answer this question we can use Statistical Process Control techniques.

Statistical Process Control Techniques to Determine When a Real Change Occurs

Statistical Process Control (SPC) involves using statistical techniques to measure and analyze the variation in a process. Several researchers (Lukas et al, 2005; Dooley et al, 1997) have used statistical process control (SPC) techniques to separate random variation from true changes. Originally developed for use by manufacturing industries, SPC shows promise for dairies wherever:

a. routine measures of management (i.e. milk production, dry matter intake, bulk tank components) can be made, or better yet, are already being made; i.e. free information.
b. timeframe/seasonality can be determined and predicted
c. variability of the response measure will be equal to or less than the desired observed response in a controlled setting

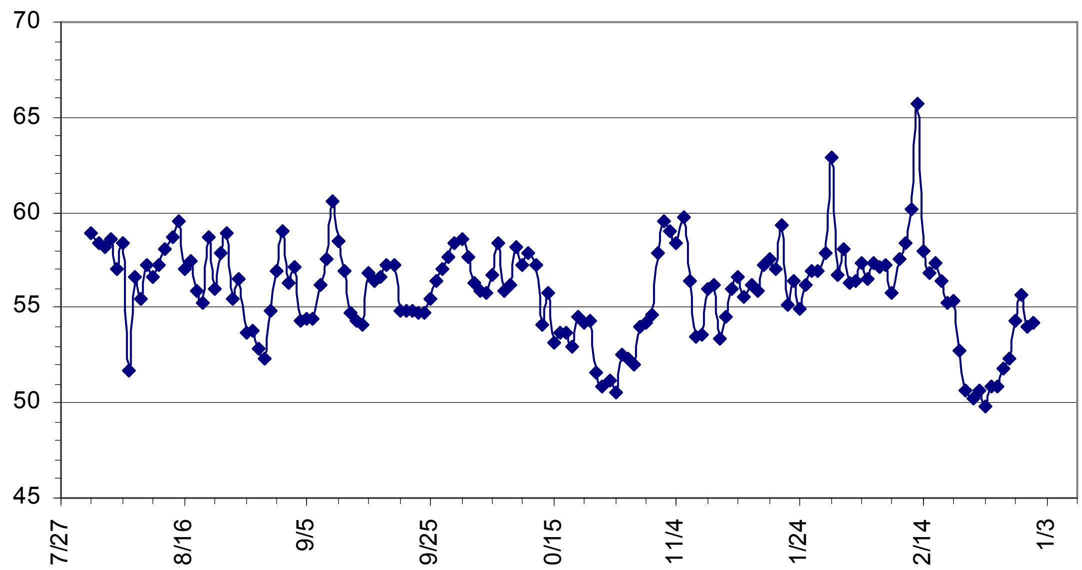

Figure 1. Daily DMI (pounds) in a pen of 80 Holsteins.

The intent of SPC is to monitor a process and correct it when it gets 'out of control'. A primary tool used for SPC is the control chart, a graphical representation of certain descriptive statistics for specific quantitative measurements of the manufacturing process. These descriptive statistics are displayed in the control chart in comparison to their "in-control" sampling distributions. The comparison detects any unusual variation in the process, which could indicate a problem.

Figure 2 includes the data in Figure 1 with SPC techniques applied. The terminology used in SPC charts includes XBAR (mean); sigma (nearly equivalent to a standard deviation), UCL and LCL (upper and lower confidence intervals equal to +3 and -3 sigma away from the mean; and various SPC rules. The areas between 1-2 sigma and 2-3 sigma away from the mean are sometimes referred to the B and A zones, respectively.

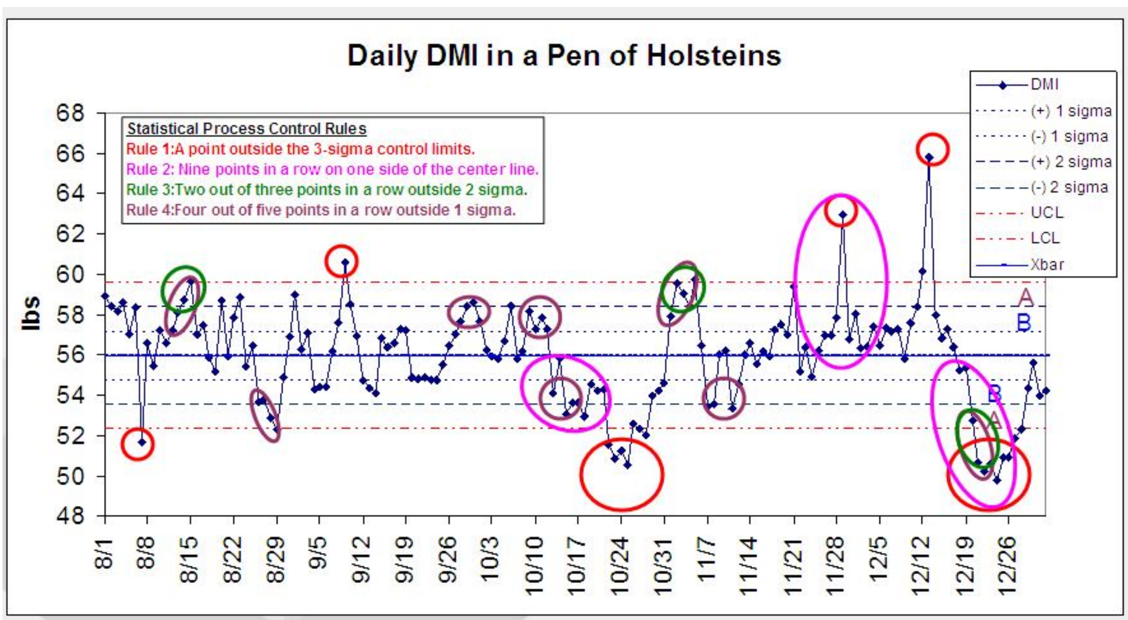

Figure 2. Daily DMI (pounds) in a pen of 80 Holsteins with SPC charting techniques applied to the data.

As we saw in Figure 1 there are obvious differences when looking at the chart. However by applying different SPC rules, other real changes that are not as easy to notice by eye can be picked up days before the obvious ones appear (circled data annotations in Figure 2). This allows quicker corrective action, more stability in the process and likely increased profit on the dairy.

Using SPC Techniques on Bulk Tank Milk Component Data

Dry matter intake data are sometimes not recorded on a regular basis. However, milk components are normally analyzed in each bulk tank shipment of milk and can be collected from processor websites. Milk fat data can often be used as a proxy for monitoring the feeding program. This is because there is often a link between milk fat percent in the bulk tank and variation in the feeding program. Using SPC techniques can be a valuable aid in monitoring milk components and thus related changes in feed programs.

Figure 3 shows a screen shot of an SPC tool that Diamond V has been developing to monitor milk components. The chart shows thirty average weekly milk fat averages from a dairy. The mean, UCL, LCL, and sigma values are indicated and determined from the last twenty weeks in the data set (the open circles are not used in the SPC calculations). The large square symbols indicate when a real change has occurred. For example, the last four weeks signify a real (and positive) change in milk fat. Often milk processors includes several past years of data which can be useful to determine if the recent changes are due to seasonal patterns or something else (like a nutritional change).

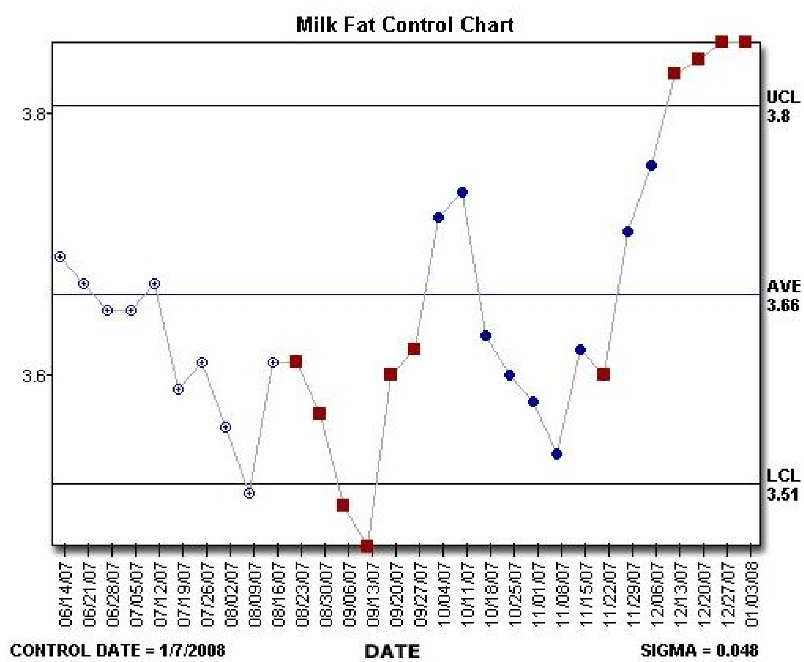

Figure 3. Weekly milk fat data in bulk tank shipments from a large western US dairy with SPC charting techniques applied to the data. The large squares indicate a ‘real change’.

A Database from Nineteen Pacific NW Holstein Dairies for use in Monitoring Milk Fat

Once a ‘real change’ in milk components is found it would be valuable to know if the changes are specific to a certain season of year or to some other factor. To help answer this question we assembled data from nineteen Pacific NW (Oregon, Washington, and Idaho) dairies to determine average milk fat components during the last 24 months. The goal was to collect recent data from a large population of cows and generate ways to help predict ‘normal’ values due to season.

Figure 4 displays a scatter graph of the individual herd bulk tank milk fats. Two things are clear from the information: One, the data have a lot of variation; and two there is a seasonal pattern.

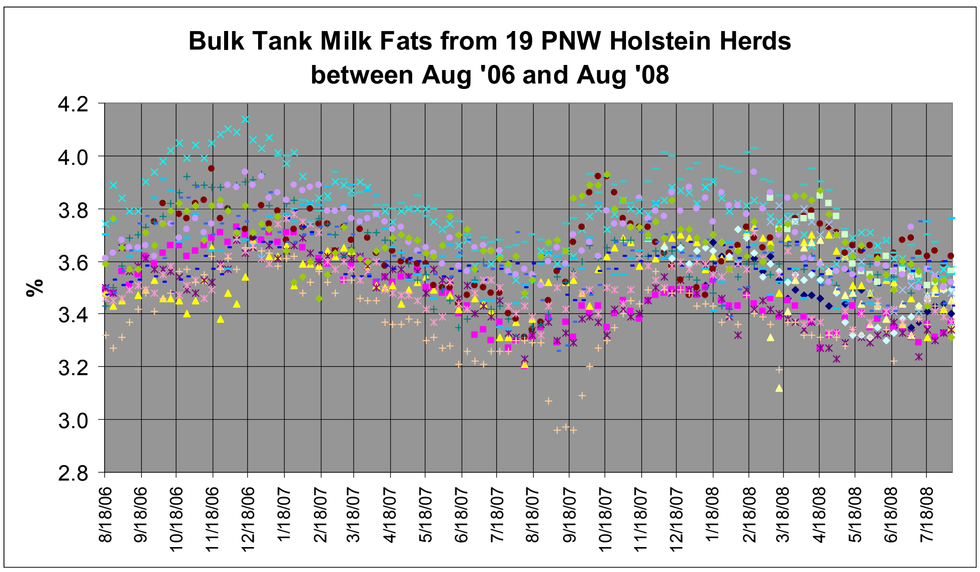

Figure 4. Weekly milk fat data in bulk tank shipments from nineteen Pacific NW Holstein dairies.

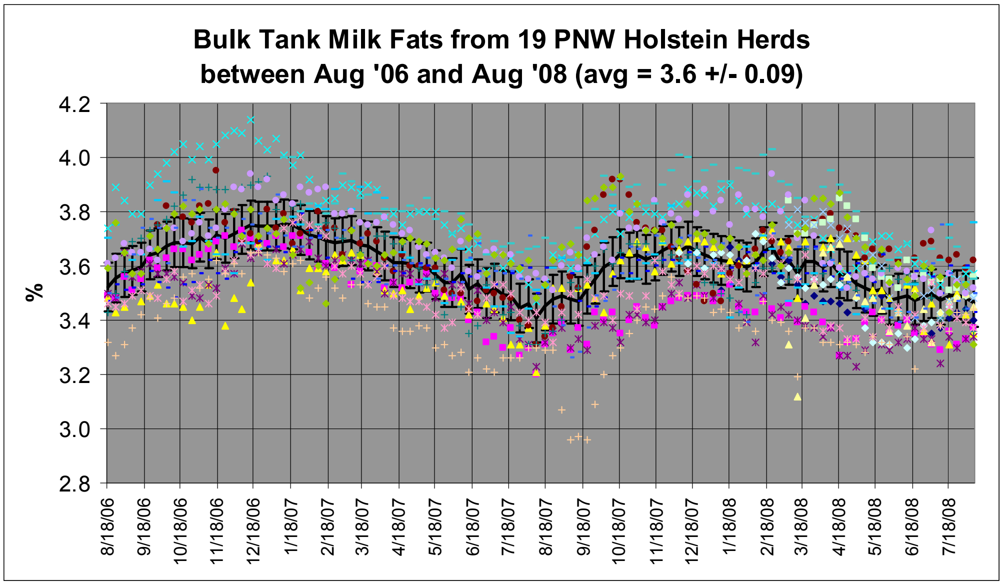

Figure 5. Weekly milk fat data in bulk tank shipments from nineteen Pacific NW Holstein dairies. The solid line with error bars shows the average +/- 1 standard deviation. Overall bulk tank milk average = 3.6% +/- 0.09.

Figure 5 shows the average of the data in Figure 4 +/- 1 standard deviation. The seasonal pattern appears to consist of two linear components – one between January and August and one between August and January. These sections were plotted in figures 6 and 7 and fit with a linear regression line.

In Figure 6 the data points between January and August were plotted. The average slope from both years equals -0.0012% units/day. An example of how to use this information would be to use it to predict an average milk fat value in August based on January data. To do this, take the average slope and multiply it by the number of days between January and August (-0.0012 * 210 days = -0.25). Then add this value to the average value in January (3.7 – 0.25 – 3.45). Thus an average Pacific NW herd with 3.7% milk fat in January could be expected to average 3.45% milk fat in August.

Similar plots were made for the August through January data points in Figure 7. Using the data from these months, it was found that milk fat typically increases 0.2% units between August and January.

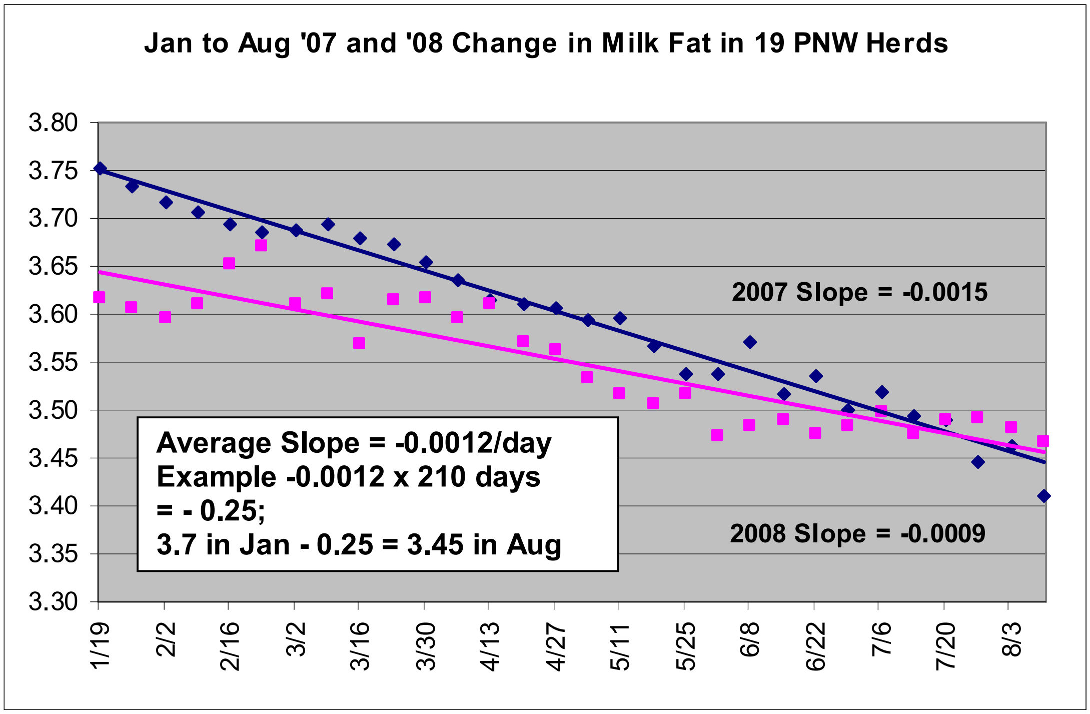

Figure 6. Average bulk tank milk fat data from nineteen Pacific NW herds during January through August in 2007 and 2008. A linear regression line was fit to the data to estimate the slope or average daily change. See the text for an explanation of how to use this information for prediction.

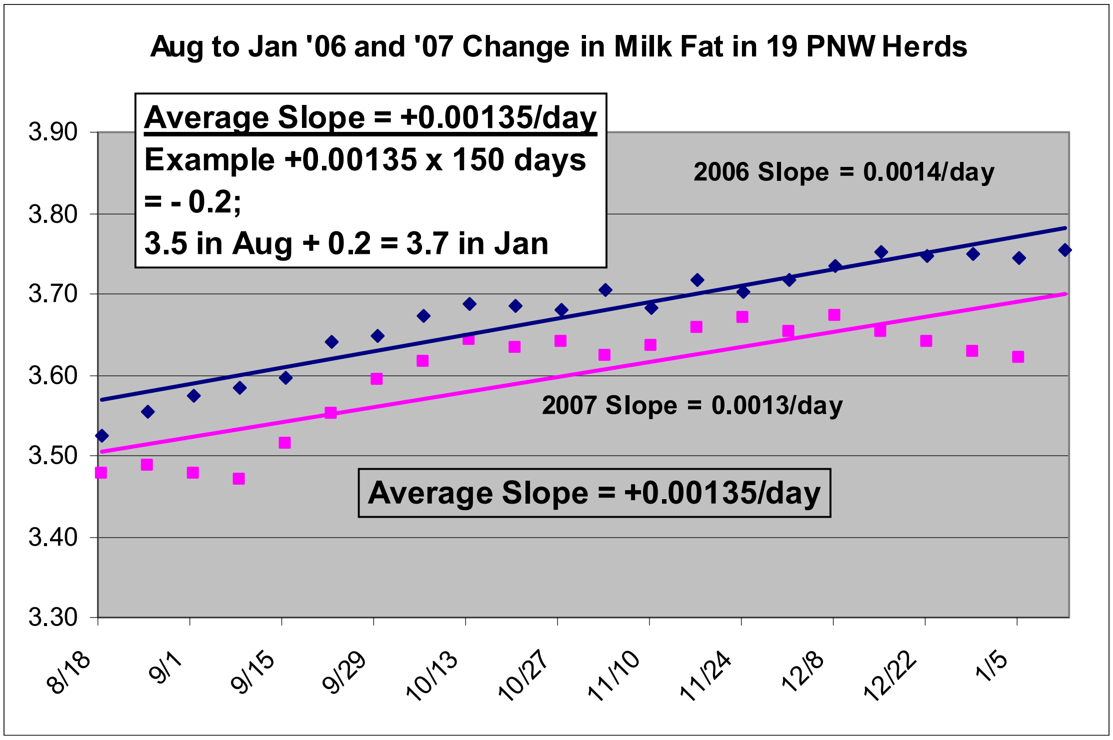

Figure 7. Average bulk tank milk fat data from nineteen Pacific NW herds during August through January in 2006 and 2007. A linear regression line was fit to the data to estimate the slope or average daily change.

Conclusions

There are lots of examples of variation on large dairy herds. Understanding, measuring and monitoring variation should enable dairies to become more consistent in key areas that impact profits. With statistical process control techniques we may be better able to determine when a real change occurs. An analysis of data from Pacific NW Holstein dairies shows that season of year is a key factor causing variation in bulk tank milk fat and the average seasonal changes can be predicted.

References

Lukas, J.M., D.M. Hawkins, M.L. Kinsel and J.K.Reneau. 2005. Bulk tank somatic cell counts analyzed by statistical process control tools to identify and monitor subclinical mastitis incidence. J.Dairy Sci. 88:3944-3952.

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