Understanding and Controlling Piggery Variation

1. Introducing PrimePulse.

PrimePulse is a Statistical Process Control computer program designed for layman use in the pig industry. PrimePulse protects the uninitiated user from "uninformed use" by automatically taking charge of statistical analysis. Just throw some data at it and it will think out how to analyse it and interpret the results for you as well.

No computer program will ever accomplish this as well as a professional biometrician using an industrial SPC package, but how many of these people have you seen lately?

PrimePulse can be used at any of three levels; Layman, Advanced or Super Users.

Layman require no understanding of SPC, Advanced Users require a basic understanding of the concepts of variation, Super Users require a sound understanding of Statistical Process Control analysis.

This paper is aimed at those people that aspire to progress from Layman Use to Advanced Use. The basic distinction between these two levels of use is that:

- Laymen will be content with the way PrimePulse analyses their data automatically.
- Advanced users will seek to customise SPC analysis to achieve better results faster.

Customising PrimePulse is a potentially risky business if you are unsure of what is happening inside the "black box". Meddle with custom PrimePulse analysis at your own risk. When you have finished reading this paper you will understand what a mouth full I just said. If you have a basic understanding of math and you read on, you could become an Advanced User in about an hour or two.

2. Confounding Variation

One of the laws of nature is that no two things are identical. Pig production managers readily accept the existence of weekly variation. Though most managers experience difficulty interpreting useful business conclusions from within confounding weekly variation. The standard response is to average it into months or quarters to make it go away!

Most pig production systems revolve around a recurring weekly batch system. This sets the logical period to collate production performance records. Less frequent collation will conceal weekly variation. More frequent collation will amplify and distort within week variation.

Weekly performance is always subject to a certain amount of variation as a result of chance. Some stable "system of chance causes" are inherent in any particular pig production process. Each production system will express it's own individual characteristics. Variation within this stable pattern is inevitable. The reasons for variation outside this stable predictable pattern may be discovered and corrected.

Key points:

- All pig production processes display weekly variation over time (eg a year).
- A portion of this variation will be of a consistent stable nature and always present and predictable.
- Another quite separate portion of this variation will be of an inconsistent erratic nature and will be spasmodically present for only short periods (eg a few weeks) and then disappear again.

These two distinct components of weekly variation are referred to as Controlled Variation and Uncontrolled Variation and are exhibited due to "Common Causes" and "Special Causes" respectively.

3. Types of Variation

a) *Controlled Variation.* Production traits vary because there are many factors at work in the production system that can influence their performance. Studying Average Born Alive per litter for example, the average parity of sows served each week varies constantly and can influence subsequent litter size. Similarly, mating duration, frequency of service, timing of service, volume of ejaculate, sperm density and sow body temperature on the day of implantation are but a few known factors that will vary from week to week.

That's why we call them "variables". Each variable has a very small impact by its self, but collectively they will also impact on each other to produce additional variation. Controlled Variation is always present and the sum effect is the result of many chance combinations of the many sources of variation. Controlled Variation is said to be caused by "Common Causes" (meaning common to the production system). It is called Controlled Variation because it is predictable in any given system and provides the basis from which to detect the transient presence of Uncontrolled Variation.

b) *Uncontrolled Variation.* In addition to the expected chance common causes within a system, there are other sources of variation that may impact upon a production trait, but which follow no stable predictable pattern. For example, a new staff member may commence work this week and make "unexpected errors" and be sacked next month. Other special causes may be; a heat wave of extreme temperatures for a few weeks, Mexican Poppy seed in a single delivery of feed grain or maintenance work interrupting water supply to a particular shed. These variables can be assigned to a specific person or localised condition. Thus the variation that arises from "assignable causes" is called Uncontrolled Variation. Uncontrolled variation is completely unpredictable (from data) but totally preventable in hindsight from experience or futuristically through Quality Assurance. Uncontrolled Variation is said to be caused by "Special Causes" (meaning that they are new to the production system).

Figure 1 presents data from a computer simulation designed to artificially create production data exhibiting only Controlled Variation. Repeat, there are absolutely no weeks in this six year data span that exhibit assignable Uncontrolled Variation. So if you were tempted to say there were any upward or downward trends in this data at particular points in time, you would be absolutely wrong. Worse still, if you reacted to any perceived trend by intervening in the production system it will only result in injecting more variation into the production process. Over or prematurely reacting in this manner will further destabilise the production system to make it more difficult to detect future assignable causes.

Run your eye over this data and visualise monthly averages. Can you find the place where one month averaging 9 piglets / litter is directly followed by a month averaging 11 piglets / litter? Would you pay the manager a monthly production bonus on this basis? Worse still, if you coincidentally changed the dry sow diet to a more expensive formulation and incorrectly assigned it to a positive response, you would seriously risk continuing the practice in perpetuity for no good reason other than wasting your money.

How many bad decisions have been made in the past and subsequently indoctrinated into production systems quite erroneously? I wonder! We may have much unravelling to do before attempting to progress forth! These fallacies will undoubtedly be fixed firmly in the minds of management and will require very convincing arguments to reverse.

The histogram to the right of figure 1 provides the founding basis to assess Uncontrolled Variation. Focusing on the trend graph in figure 1, there is only one week that exceeds 14 piglets / litter. As there are 312 weeks of data we can say that there is a 1 in 312 chance that this week is "normal". Thus there is less than a 1% (1 / 312 * 100) chance that any week exceeding 14 piglets / litter is normal (due to Common Causes). Conversely, chances are that we can be 99% certain that any week exceeding 14 piglets / litter is definitely "abnormal" (due to Special Causes).

So the secret to observing abnormal trends in weekly data signalling the presence of Special Causes is to look carefully to the extreme ranges of weekly performance.

From the histogram in figure 1 it can also be calculated that there is a 97% ([1- 8 / 312] * 100) chance that any week exceeding 13 piglets / litter is abnormal.

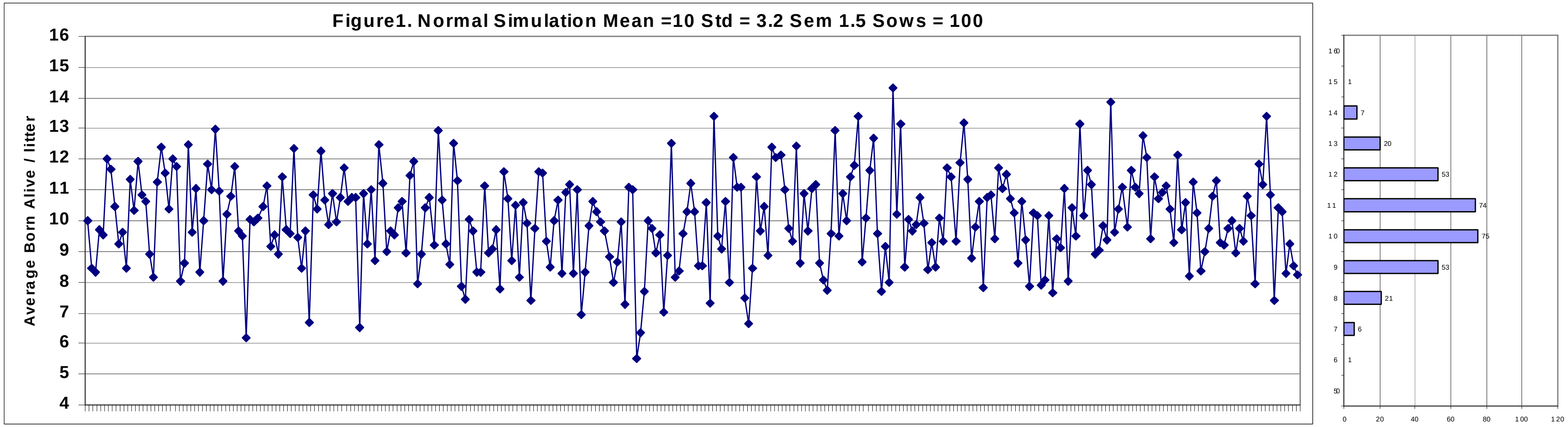


Figure1. Normal Simulation Mean =10 Std = 3.2 Sem 1.5 Sows = 100
Average Born Alive / litter
16
15
14
13
12
11
10
9
8
7
6
5
4
15 1
14 7
13 20
12 53
11 74
10 75
9 53
8 21
7 6
6 1
0 20 40 60 80 100 120

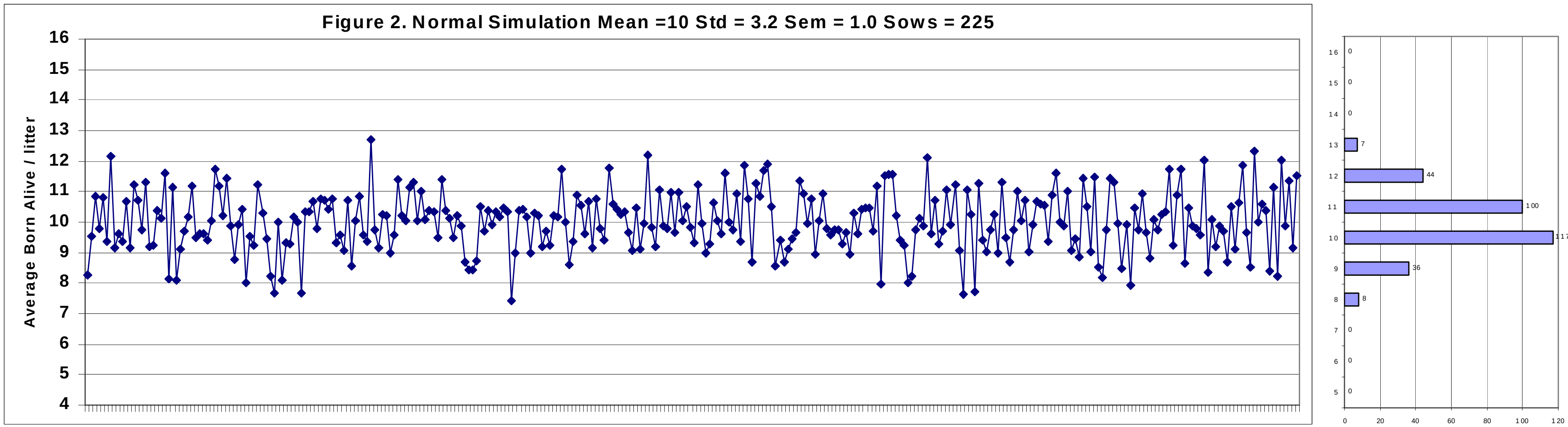


Figure 2. Normal Simulation Mean =10 Std = 3.2 Sem = 1.0 Sows = 225
Average Born Alive / litter
16
15
14
13
12
11
10
9
8
7
6
5
4
16 0
15 0
14 0
13 7
12 44
11 100
10 117
9 36
8 8
7 0
6 0
5 0
0 20 40 60 80 100 120

4. Herd Size Effects on Variability

Figure 2 shows a second computer simulation that is exactly the same as figure 1 except that it comes from a piggery approximately twice the size. Figure 1 is a 100 sow piggery farrowing 4.5 sows per week on average. Figure 2 is a 225 sow piggery farrowing 10 sows per week on average. Both piggeries experience the same controlled variation in that all sows' litter sizes vary from 0 to 20 piglets and average 10 piglets / litter. So as the number of sows farrowing per week increases, the normal weekly average range decreases. Weekly averages for figure 2 now range from 8 to 13 as opposed to 6 to 15 in figure 1 (see histograms).

Taking this argument to extreme, a piggery farrowing one sow per week would have a weekly average ranging from 0 to 20 piglets / litter.

The salient messages concerning differences in herd size are:

- It is dangerous to compare weekly ranges between herds of different sizes.
- Smaller herds are far more likely to misinterpret "normal trends" and falsely assign imaginary causes and consequently risk over correcting the production process.
- Larger piggeries will be more sensitive to detecting assignable causes of any given absolute magnitude.

5. Using Control Limits to Detect Special Causes.

Figure 3 uses the same simulated data presented in figure 2 to demonstrate how control limits are used to detect Uncontrolled Variation (Figure 4 uses the same data from figure 1 to repeat the example for the 100 sow herd). The upper and lower control limits have been added to depict the normal data range (refer to histogram on the right hand side of figure 3).

Uncontrolled variation has been introduced at six randomly selected positions within the six year period. Each injection of Uncontrolled Variation lasted ten weeks and averaged 1.0 unit (std 0.1). If this example is Average Born Alive per litter, 1.0 unit would equal one piglet / litter on average.

The Combined Variation line adds the Uncontrolled variation from each week to the Controlled Variation. The object is to try and use the control limits see if we can detect the presence of six special causes from within the Combined Variation line.

Of the six special causes introduced, only one of them was found (the fifth one because a week crossed the upper control limit). The second injection did not even go close. The immediate reaction is to improve the detection process by shifting the Control Limits. If we reduced the Upper Control Limit from 13 to 12 we would have detected five of the six special causes. The cost of doing this is that we would also have wrongfully detected another six common causes.

Figure 3. Detecting Special Causes in a 225 Sow Piggery.

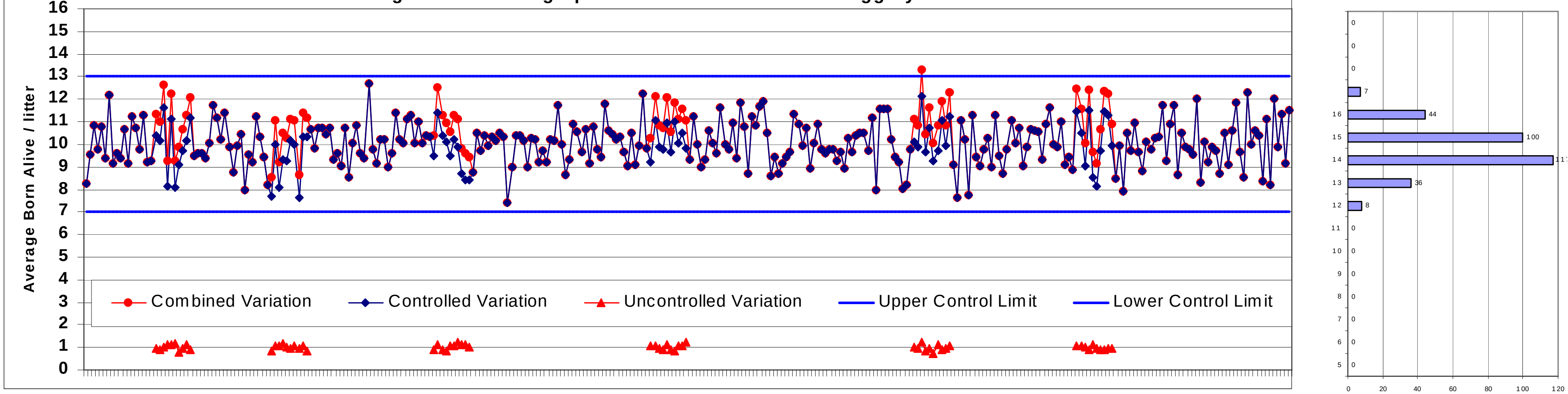
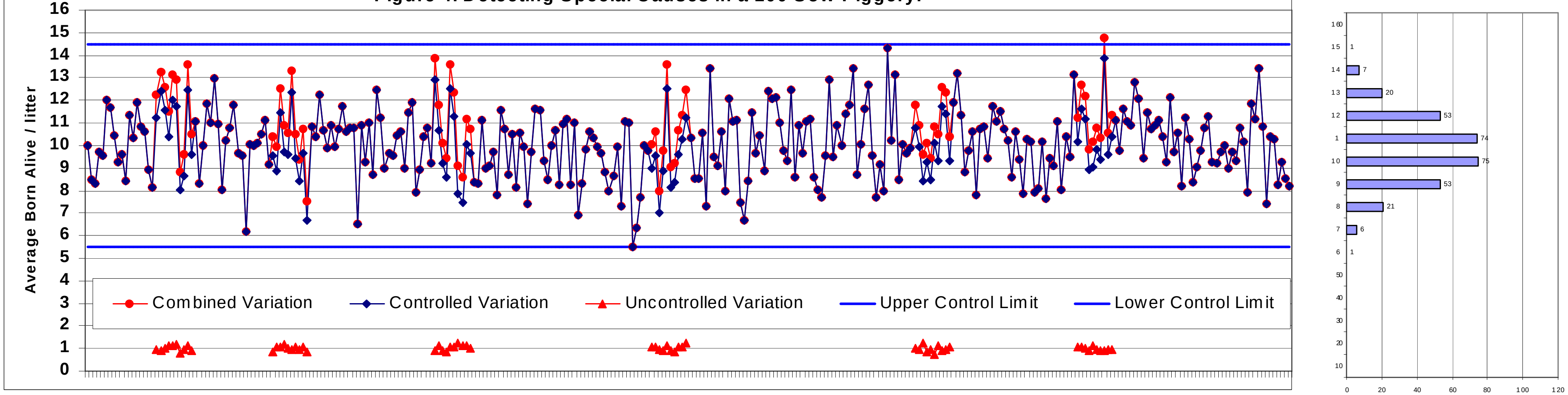


Figure 4. Detecting Special Causes in a 100 Sow Piggery.



Is this a clever thing to do? Remember that this is only one trait, we may have to monitor 20 or more traits to manage a piggery. Logistically, we should leave the confidence limits were they are and work with a few polished diamonds rather than a bag of fools gold with the odd nugget thrown in for token measure. Once you have wasted three days investigating a swag of false alarms you will inevitably come to the same frustrated conclusion. Work smarter not harder!

Dr W. A. Shewhart invented Control Charts back in 1931 and he was no fool because he was also able to work out a way of having his cake and eating it too! A single point estimate of change is not using all the evidence available to you. He added Warning lines to Control lines and worked out a few extra rules to speed up the detection process without suffering extra false alarms. The Warning Limit in figure 3 would be drawn at 12 (mean + 2 sem), and the new crucial rule is: any 2 out of 3 weeks that cross the Warning Line together are equal to a single week crossing the Action Line alone (new name for the Upper Control Limit = mean + 3 sem).

Now applying this new rule, we can confidently pick up four of the six special causes without any extra false alarms.

These new rules are called "run tests" and there are literally hundreds of them. As usual there is no free lunch. These rules make interpreting control charts a little more labour intensive.

6. Using PrimePulse to Detect Special Causes.

Literally hundreds of clever statisticians have continued to develop Shewhart's original theories. A plethora of very sophisticated techniques are now available that are extremely rigorous at detecting special changes.

PrimePulse uses the best of these techniques automatically to simply present you with a single detection arrow to say:

- This is the very first point in time that I am confident that a special cause is present in the system.
- The data spanning from the beginning of the step to the detection arrow contains the evidence that triggered the detection (special evidence span).
- The data spanning from the detection arrow to the end of the step confirms (because it is not statistically different from the special evidence span) the detection arrow is validly found.

Figure 5 demonstrates a PrimePulse Analysis of the combined variation data presented in Figure 3. Five of the six special causes (marked by black rectangles) were detected. Even a super user would not detect the second special cause because the Uncontrolled Variation was randomly deceasing at the time. Note that some of the steps are longer than ten weeks indicating that some Uncontrolled Variation has been inevitably snared within the span.

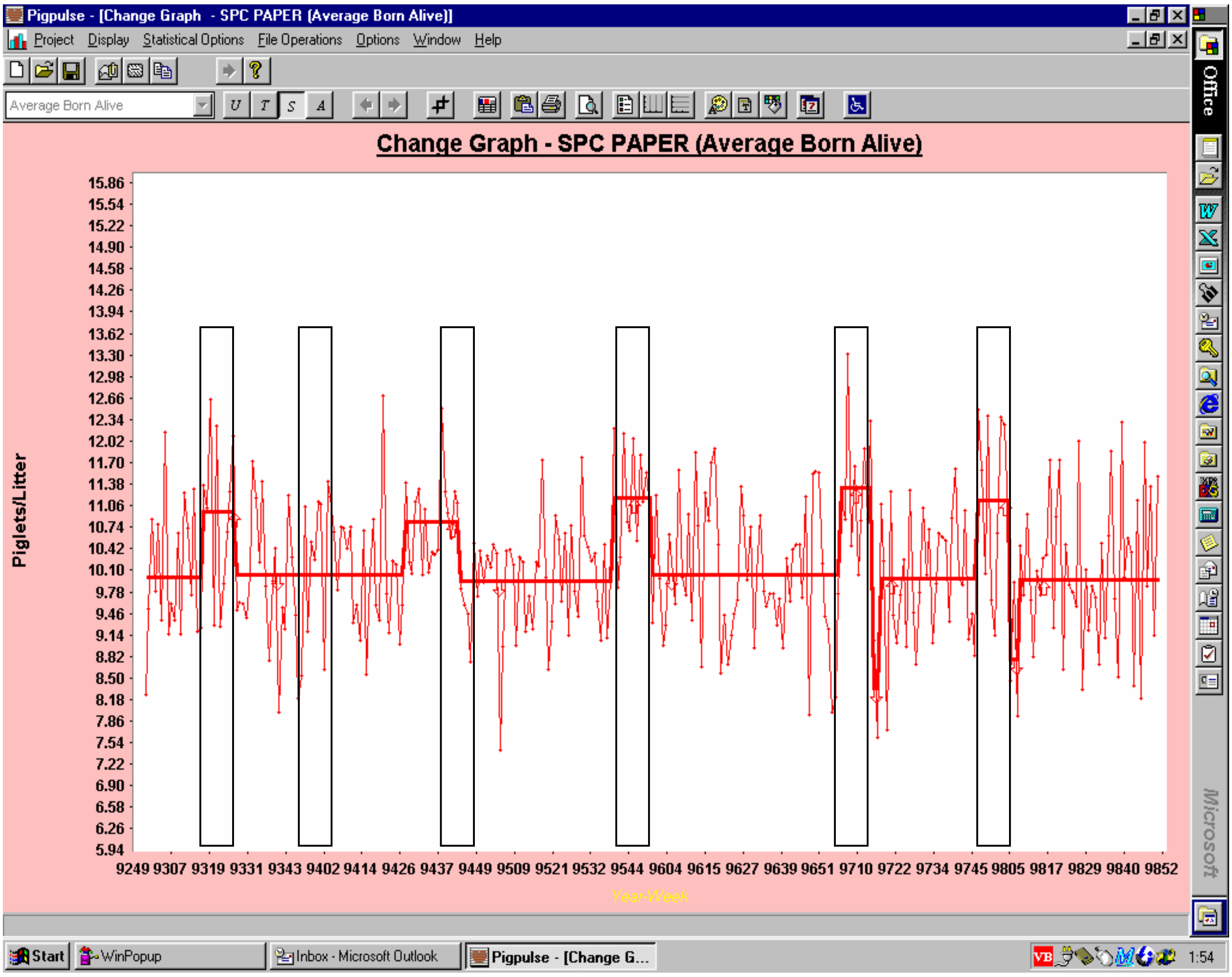


Figure 5. PrimePulse Analysis of Special Causes in a 225 Sow Piggery.

7. How is Controlled Variation Partitioned and Measured?

Computer simulations are easy, real life piggeries are a very different kettle of ~~fish~~ pigs altogether. As you have now observed, the validity of detecting Uncontrolled Variation is prefounded upon predicting Controlled Variation first.

Fortunately, PrimePulse does this for you automatically the first time you import your data. PrimePulse looks at all your historic data to estimate Controlled Variation. This process is quite valid as a starting point, but can be improved upon with some "local knowledge" of the production system to fine tune the estimate.

PrimePulse errs on the safe side and will tend to slightly overestimate Controlled Variation. The consequence of this is that Uncontrolled Variation may take longer to be detected, or may fail to detect some causes cunningly concealed in the data.

Fine tunning this estimate is simply a matter of pointing PrimePulse to a time span of historic data that is most representative of a stable production period. In selecting this period you should consider each production trait individually. It should be a time span of a least 20 weeks that is as recent as possible and contains no known assignable / special causes. Revert into past data to avoid assignable / special causes. Avoid weeks where wide variation potentially occurs due to data recording errors.

Once PrimePulse is calibrated to this period there is no reason to recalibrate the trait until there is evidence that Controlled Variation has changed. For instance, if Weaning to Service Interval changed for the better in response to new lactation diets preventing sow weight loss you would recalibrate 20 weeks latter as the "production system" has now changed. We know that lactation nutrition has influenced WSI and we also know that every sow in the "WSI system" will be fed the new diet. Similarly, recalibrate if the mating shed is renovated to incorporate DMA and is then insulated to bring sows on heat quickly. Every sow will pass through these new facilities which have proven to repel some assignable causes. Thus you must ask yourself, have I changed the production system?, and are all production units (boars or sows or piglets etc) equally effected?

If you are still dissatisfied with change graphs after you have successfully re-calibrated PrimePulse, you should first consider if the apparent trend is a chance trend from a common cause. Taking Parity as a common cause for example, If parity seems to be driving the trend it will probably recede naturally by it's self. If it doesn't, it will eventually exceed the ascribed limit and be identified as a special cause. "Special Cause" meaning: much more than prevalent in the calibration period.

The key point here is that if Parity is a common cause, it can be monitored separately. Thus to conclude that Parity is responsible, monitor Parity directly. Large herds may also consider monitoring Average Born Alive sub traits by Parity as this would focus directly upon the subset at issue.

The final option is to reduce the confidence of PrimePulse change analysis. This is not recommended for routine analysis but may be warranted to "preview" the likelihood of a future detection in a few weeks time. This is achieved by setting the change analysis start date at the commencement date of the present step and setting the expected mean value to the steps local average. Once this is achieved, set the sensitivity to achieve your desired level of risk.

The sensitivity of change analysis can be set at one of three levels, Low, Medium or High. If you have custom calibrated PrimePulse, a low setting is recommended to stay on the safe side.

As sensitivity increases, change graphs tend to have more steps (changes) of shorter duration. A high sensitivity setting will result in finding changes relatively quickly. That is, on average, an upward or downward trend in the data will be detected a few weeks earlier. Thus as sensitivity increases, response time decreases. There is a cost to increasing sensitivity in that more false alarms will be raised. Results are found more rapidly but you may have less confidence in the results purportedly found.

There are relatively few occasions where high sensitivities are warranted. Low sensitivities are appropriate for herds experiencing many special causes. This will in effect reduce the number of detections listed in the change report so that you may initially focus on fewer issues more confidently (particularly if you are servicing multiple herds).

A false alarm is a change that was detected when it should not have been. It may be characterised by a very short duration with a quick correction back to the original performance level.

Here is a simple interpretation of a false alarm rate. If a false alarm is expected once in every 50 weeks, then when a change is found you can be 98% sure that the change is real.

Because: 1 false alarm in 50 weeks = 2 false alarms in 100 weeks.
Thus there is a 2% chance of a false alarm each week (ie 2/100).
Then there is a 98% chance that the change found this week is real.

Thus if sensitivity level 5 is selected, Change graphs will (on average) erroneously detect a change every 20 weeks and ascribe it as Uncontrolled Variation when it is actually only observing Controlled Variation. Change graphs will also be prone to oscillating over correction patterns (step high, step low, step high etc). High sensitivity settings should be reserved for previewing suspicious trends only.

To assist in your judgement of sensitivity selection, these response times and false alarm rates are provided:

Table 1. PrimePulse Sensitivity Settings.

SENSITIVITY	AVERAGE RESPONSE TIME	AVERAGE FALSE ALARM FREQUENCY
Low	16 weeks	10000 weeks
Medium	10 weeks	1000 weeks
High	6 weeks	100 weeks

The average response time is the mean time lag it takes to accumulate enough evidence to detect a special cause. The average false alarm frequency is an estimate of how often PrimePulse will incorrectly register a special cause (detection arrow).

8. Stepwise Progressive Reduction of Weekly Variation.

It should now be apparent that there are two distinctly different approaches to reducing the variability of any given production trait. They are fundamentally different concepts and must be attacked in the correct order and appropriate manner.

a) *Eliminate "Assignable Causes".* If a trait shows Uncontrolled Variation (PrimePulse detection arrows), then it could be returned to a controlled state by eliminating the assignable cause(s). This will require investigating the current period in comparison to the previous period (as described in the change report). This investigation will always proceed in the following order:
   - Check that data is recorded accurately (not just an artefact eg the definition of a piglet born dead differing between relieving staff etc).
   - Refer to event diaries to relate relevant historical observations to changes.

- Analyse sample data between periods to quantify significant relationships. Focus your initial investigations at individual observations at the negative extreme (ie beyond predicted control limits).

The prompt identification and removal of assignable causes will reduce overall variation and restore weekly variation to within predicable limits once again. Hence the first step is *always* to bring the system into "control" by removing Uncontrolled Variation.

b) *"Change the Process".* Once a controlled or stable process is achieved (by addressing assignable causes), changes to the basic nature of the process will be reflected in a change in the pattern of weekly variation. This also dictates that solid cause and effect relationships can only be built when a process is held within a stable state. Thus, when stable, investigations can be made to partition chance causes of variation in order to redesign the production system (eg housing) or production processes (eg mating management) to protect against or exclude chance causes of variation.

For example, replacement gilts may be sourced from two breeding companies. A valid comparison can only be made when the system is stable, as an assignable cause may by chance alone bias a particular source. Within a stable system, a decision could be made to discontinue one source and reduce overall variability whilst improving average weekly performance by the marginal difference between sources.

The cascading process of discovery followed by design will tend to oscillate in a never ending cycle of continuous improvement. Each time Controlled Variation is reduced, assignable causes that have previously escaped detection reveal themselves for attention (eg the second special cause in figures 3 and 5).

9. Example Analysis of Special Causes

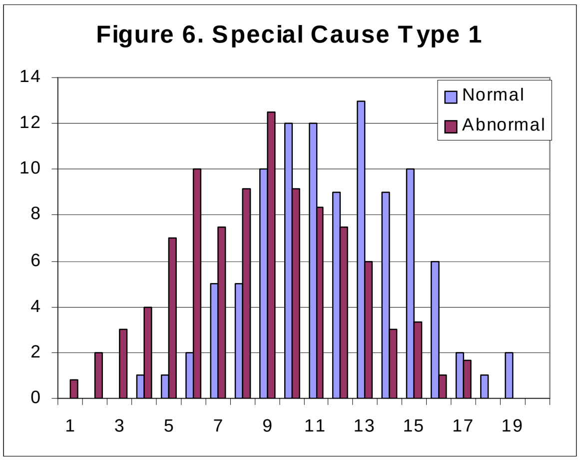
A useful first step to investigate for special causes is to generate relative frequency distributions for the two periods under study. The second period will be termed the "abnormal" span and the first period (immediately preceding the abnormal span) will be termed the normal span.

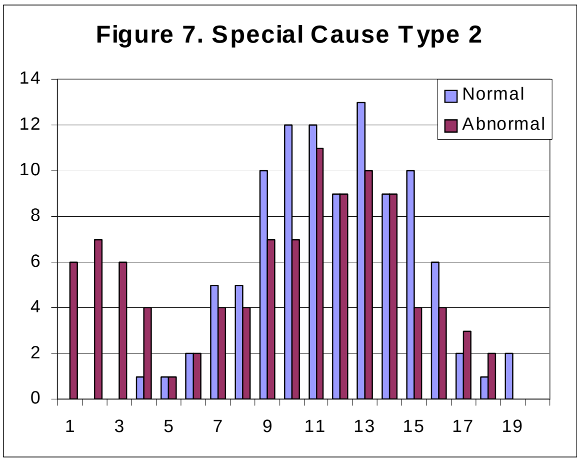
Figures 6 and 7 show two types of situations that may commonly arise. Figure 6 demonstrates a general shift of mean effect where the abnormal span has been uniformly depressed (moved to the left). If the trait is Average Born Alive, small medium and large litters seem equally effected. The effect is small in magnitude but widespread in nature.

Figure 7 depicts a different scenario where the effect is large in magnitude but isolated (randomly from small medium and large litters because each abnormal bar is a bit shorter than it's comparative normal bar).

Figure 6 depicts a special cause that is perhaps a common cause that got out of hand for a short time, for example, a surge of gilts farrowing, or a special cause like a heat wave during the first four weeks of pregnancy.

Figure 7 depicts a very severe local event that has targeted selected sows. They may have all farrowed on cold nights without creep areas heated (thus this is also a recording error as they were probably born alive and then died). Or, they may all have been mated by the same sire.





Figures 6 and 7 falsely portray diagnosis of causes and effects as a simple visual exercise. Seldom will the pictures appear so clearly, particularly in smaller herds, appropriate care should be exercised to avoid jumping to the wrong conclusions. Remember a mistake at this stage risks injecting more Uncontrolled Variation. A Students t Test or ANOVA would be comforting if possible.

10. Example Analysis of Common Causes

Figure 8 shows Pre-Weaning Mortality data that has been simulated to exhibit only Controlled Variation. The histogram appears quite normal. This data has been simulated from two farrowing sheds, one has environmentally controlled creep areas (shed A), the other does not (shed B). Loading of farrowing sows alternates from shed to shed each week.

Figure 9 is a histogram sourced from shed A (odd weeks), figure 10 from shed B (even weeks). Figure 11 compares shed A with shed B to demonstrate that shed B is causing the problem. It also quantifies the difference in physical terms that may be transformed into financial terms to evaluate the return on investment to rectify the issue.

Note also that this finding could also have been identified doing a single histogram for all farrowings irrespective of which shed and focusing on the extreme low end of the distribution to reveal that the majority of these sows originated from shed B.

If these sheds were loaded in series and not alternatively, (ie shed A for four weeks followed by shed B for four weeks), this may have resulted in PrimePulse identifying a special cause if it was relatively severe enough (only has four weeks to find it).

Thus the path of sows through the piggery may exhibit profound effects upon production (particularly in old piggeries that have progressively expanded) and depending on which way you look at it, create special or common causes.

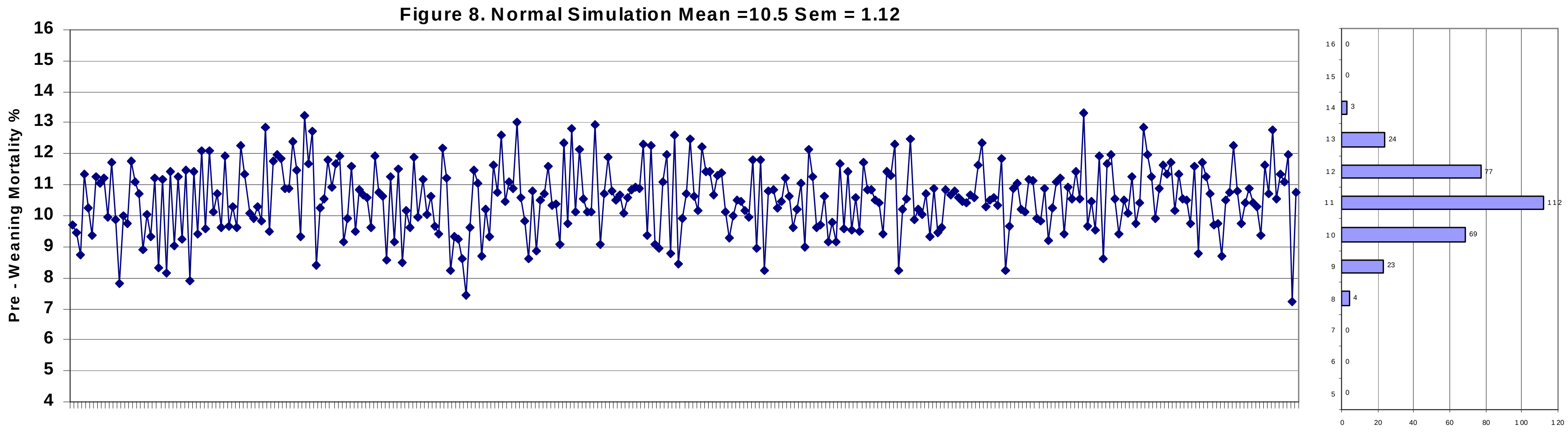


Figure 8. Normal Simulation Mean =10.5 Sem = 1.12
Pre - Weaning Mortality %
16
15
14
13
12
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9
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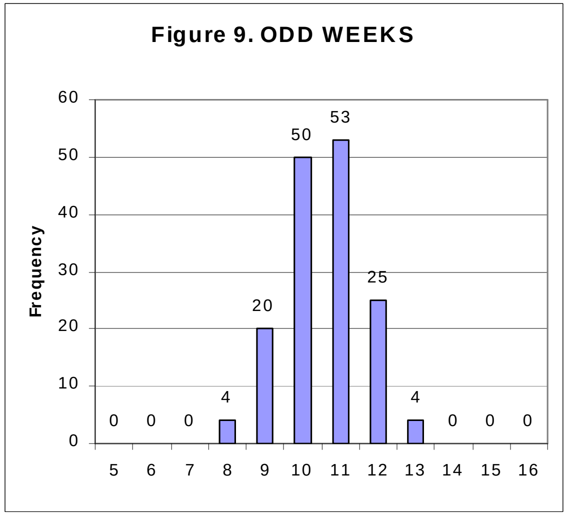
Figure 9. ODD WEEKS
Frequency
60
50
40
30
20
10
0
0 0 0 4 20 50 53 25 4 0 0 0
5 6 7 8 9 10 11 12 13 14 15 16

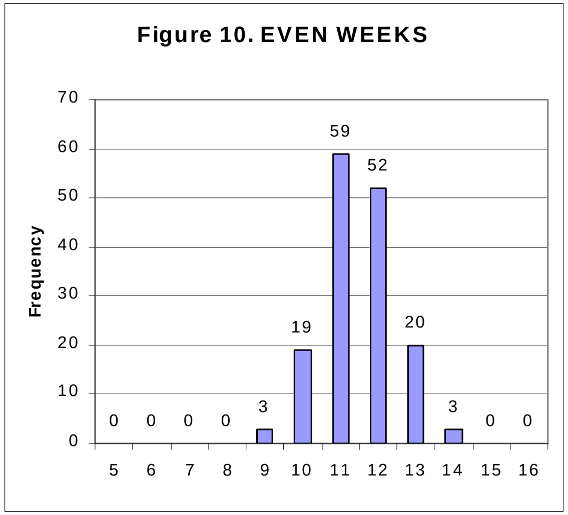
Figure 10. EVEN WEEKS
Frequency
70
60
50
40
30
20
10
0
0 0 0 0 3 19 59 52 20 3 0 0
5 6 7 8 9 10 11 12 13 14 15 16

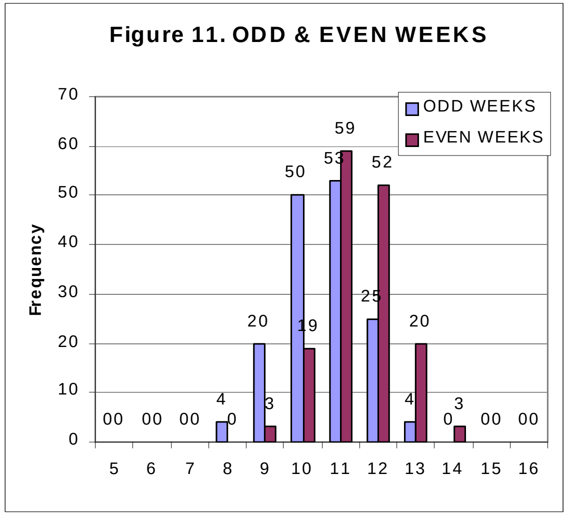
Figure 11. ODD & EVEN WEEKS
ODD WEEKS
EVEN WEEKS
Frequency
70
60
50
40
30
20
10
0
5 6 7 8 9 10 11 12 13 14 15 16

11. Accountability of Weekly Variation

Assignable / Special causes do not belong to the system. They are foreign to the system in that they only exist within the system temporarily. Their very nature indicates who is responsible for their occurrence and what must happen by whom to restore the stable balance.

Accountability for the special circumstances that invoke Uncontrolled Variation will be specified by a local condition or individual. For example, if a delivery of feed grain contains toxic weed seeds that are not identified during the unloading procedure, a specific individual is directly responsible (the sucker who signed the grain receipt and inspection ledger).

Similarly, if sows farrowed in dry sow stalls due to a surge in farrowing throughput, a particular location is at fault (dry sow stalls used as farrowing crates) and the staff that caused and or failed to prevent this occurrence are directly responsible.

Conversely, common causes of Controlled Variation are part of the system. Operational staff will have absolutely no control over these causes. They are "prisoners of the process" and can not be held accountable for the ultimate consequences. Improvement will only materialise by managerial intervention to alter the production system or production processes.

Only management staff are empowered to strategically or physically alter the production system / process. For example, if the vaccine is ineffective against the present serotypes causing the problem, operational staff can vaccinate all they like and make no difference what so ever.

12. Achieving Production Targets

Only when the true divided nature of production variation is fully understood will it be possible to informatively evaluate the stringent use of production targets within the management sphere. Production targets will still have their place, but their application may well be limited to throughput traits only. Even with throughput traits, production targets must be considerate of control limits. For instance, buffering absolute weekly mating targets to consider four week rolling totals may be more appropriate.

We largely need to throw out the single production target paradigm and replace it with the paradigm of two control lines that define the upper and lower limits of predicted Controlled Variation. Thereby enabling operational staff to be rewarded for staying with the limits, and, management staff to be rewarded for tightening and favourably shifting the limits.

Clearly demarking the conceptual difference in evaluating either component of the workforce will enhance productive communication between staff sectors. This approach assures that each sector can factually maintain arguments in their own defence and cooperatively participate in problem solving from an informed perspective. This system of staff assurance will ultimately foster alliance between traditional "opponents" and integrate staff into a mutual continuous improvement process.