Effect of Statistical Process Control For Monitoring Seeds Production: A Case Study

H. G. Dikko[1]; H. Muhammad[2]

Department of Statistics,
Ahmadu Bello University,
Zaria, Nigeria.
e-mail: sarkist28@gmail.com[2]

Abstract **— Seed production and certification have taken a new turn (dimension) in Nigeria with the establishment of private seed companies. The National Seed Service that used to be the primary source of improved seed also expanded its facilities, widened its scope and hired better trained staff. Thus, improved seeds are readily available to farmers. Therefore, this paper seeks to suggest the use of Statistical Process Control (SPC) tools to monitor and Control quality characteristics of seeds.**

Keywords-*Manufacturing Process, Statistical Process Control, Control Chart, Exponentially Weighted Moving Average (EWMA).*

I. Introduction

Statistical Process Control (SPC) has become an important approach for process industries since 1920s. The aim of SPC is to achieve higher product quality and lower the Production cost due to the minimization of the defect product. One of the greatest tools is the statistical process control chart developed by [18]. He also introduced the idea of the control chart in the 1920s, and the original applications were primarily in manufacturing processes. After decades of development and improvement, the practical applications of control charts nowadays extend into many areas such as engineering design, environmental science, pharmaceutical process, finance, accounting, and marketing (see Ryan [15], [10] and [18]. In any process, no matter how well it is designed, there exists a certain amount of variability in the outcome measurements of a quality characteristic. The origins of these process variations can be framed in terms of common (non-assignable) causes and special (assignable) causes. Variation due to common causes is the natural phenomenon constantly active within the system and is to some extent unavoidable.

On the contrary, special causes may lead to excessive variation in process outcomes, resulting in malfunctioning of the product. Because special causes can be eliminated from the system if they are detected, quality improvement becomes possible by detecting and removing special causes of variation via the control chart. In the basic form of a control chart, samples are taken from the process at regular time intervals, and measurements are obtained. Sample statistic, say the sample mean, is plotted versus the sample time or versus the sample number, and then compared to a pair of so-called control limits. If the statistic falls within the bandwidth of two control limits, then it is assumed that the variability is only due to common causes and the process is in-control. If a statistic falls outside of control limits, it is called an out-of control signal and indicates the presence of special causes of variation [5].

As a result, investigation and corrective action is required to identify and eliminate the special causes responsible for this change in the process. However, an out-of control signal may sometimes be a false alarm, i.e. an out-of control signal is given when the process is actually in-control. Thus, in order to maintain the reliability of a control chart, a good choice of control limits is essential, which is a compromise between quick detection of a process change and avoidance of a high false alarm rate [4].

The standard assumptions in SPC are that the observed process values are normally, independently and identically distributed (IID) with fixed mean μ and standard deviation σ when the process is in control. Due to the dynamic behaviour, these assumptions are not always valid. The data may not be normally distributed and/or auto correlated, especially when the data are observed sequentially and the time between samples is short. The presence of autocorrelation has a significant effect on control charts developed using the assumption of independent observations. [1] investigated the impact of autocorrelated data on the traditional Shewhart Chart and reported an increased number of false alarms. [10] suggested that there is a tremendous need for improvement in the area of SPC in industries such as the food, chemical, automotive and manufacturing industries, given that these industries inherently deal with numerous variables which are highly correlated.

[22] Stated that the application of SPC involves three main sets of activities. The first understands the process, and this is achieved by business process mapping. The second is measuring the sources of variation assisted by the

use of control charts. The third is eliminating assignable (special) sources of variation. It can be used in various industries for improving the quality of the product and helps in lowering the product costs as it provides a better product and/or service. However, it part of disadvantages of implementation of statistical process control; that the SPC can take time to apply rigorously but applications do show that there are few, if any, disadvantages to SPC. Its application must remain relevant and useful, rather than becoming a system 'for its own sake'. Problems can occur in introducing it to avowed innumerate.

According to [12] permanent monitoring of processes is needed, especially for detecting the presence of special causes that generate disturbances in the process, also serving as base for making decisions. The disturbances that affect the processes may be classified into two types. Minor perturbations caused by natural variations in process, derived from an ordinary or random cause, represents small deviations that do not compromise or are negligible to the result. The special causes, on the other hand, are major perturbations that can shift the average of its target, as well as increase its dispersion. The perturbations are usually derived from problems or abnormal operations, and are mostly related to physical conditions and structural projects or deficiencies in standards work. Special causes of variation are caused by known factors that lead to an unexpected change in the process output. If the process is subjected to Special Causes of variation, the process output is not stable over time and it is not predictable. The special causes may lead to a process shift.

In many applications, three-sigma control limits are customarily employed. When the statistics being plotted are normal and independent, using three-sigma control limits corresponds to a false alarm once in every 370.4 samples, on average, for a control chart in its basic form and with known parameters. Note that “sigma” refers to the standard deviation of the statistic plotted on the chart, not the standard deviation of the quality characteristic [9].

A control chart is a useful statistical tool that aids practitioners in statistically controlling and monitoring one or more variables, when the quality of the product or the quality of the process is characterized by certain values of this or these variables. By the term controlling, we mean the ability of the control chart at any time to determine if the process or the product characteristic is statistically “in control”. The term statistically “in control” refers to a process that operates with only chance causes of variation. A process that is operating in the presence of assignable causes is said to be statistically “out-of-control”.

However, the number of applications reported in domains outside of conventional production systems has been increasing in recent years. Implementing SPC chart approaches in non-standard applications gives rise to many potential complications and poses a number of challenges [21].

Alwan [1] investigated the impact of autocorrelated data on the traditional Shewhart chart. His work shown that autocorrelation deteriorates the ability of the Shewhart chart to correctly separate the assignable causes from the common causes and consequently reported an increased number of false alarms.

[2] study the effect of autocorrelation on EWMA chart which is used alternative to Shewhart Control Chart specially in detecting small shifts in the process both for positive and negative autocorrelation, the effect on EWMA control limits are studied.

[3] have provided a class of new control charts, AEWMA charts on the basis of EWMA to detect shifts of all types for independent data. The chart weights the past observations of the monitored process using an appropriate function of the current. Thus, the chart offers better protection against shifts of different sizes.

[16] characterized of the dynamic behavior of the manufacturing process with the appropriate monitoring procedures; also developed an adaptive monitoring procedure for the processes.

[13] In their paper an EWMA chart for monitoring standardized variance is developed which is having several advantages over the existing charts such as sample number free design, use in the joint monitoring scheme of process mean and variance and fit to multivariate monitoring. In industrial application, this chart can be used to monitor few variables in one display simultaneously.

[16] suggested using two EWMA controls simultaneously, one for process mean and another for process variance to tackle detection of small shifts with abrupt changes.

Control Charts

In any production process, no matter how well designed or carefully maintained it is, a certain amount of inherent or natural variability will always exist. Natural variability is the cumulative effect of many causes. When this variation is relatively small it is generally considered an acceptable level of performance of the process [8]. In the context of statistical quality control, this natural variability often called "a stable system of special causes" is said to be in statistical control. Control Charts are used to examine whether or not the process is under control, i.e., indicate only random causes are acting on this process. Synthesize a wide range of data using statistical methods to observe the variability within the process, based on sampling data. Can inform us at any given time how the process is behaving, if it is within prescribed limits, signaling thus the need to seek the cause of variation, but not showing us how to eliminate it [11].

In General, a control chart is very easy to be implemented in any type of process. Thus, control charts are extensively used in manufacturing area nowadays, preserving the quality of the process or the final product. What makes the control chart such a useful tool is the fact that the chart can reveal the amount of variation by time, thus enabling the user to observe patterns for interpretation and the discovery of changes in the process. The controlling and monitoring is done over either the mean level or the variance of the process or quality characteristic. [7]provides an excellent discussion about Statistical Process Control procedures in the manufacturing industry.

II. Materials and Methods

A. *Data Description*

The study uses the approach of Statistical Process Control techniques to capture the variability of the process variables of some selected varieties of maize seed produced by seeds production company (Premier Seeds Nigeria Limited). This study intends to show the effect of statistical process control in monitoring the production of seeds. The three varieties are: Oba supper one (Oba1), Oba super two (Oba2) and Oba 98. ONE. The study considers the germination percentage as the most reliable process variable which is given as 92% by Nigerian Agricultural Seed Council (NASC). A traditional control chart is introduced. The data was collected from the company, Statistical software are used to carry out the analysis for the data.

B. *Methodology*

Exponential Weighted Moving Average (EWMA)

EWMA chart was first introduced by [19] to achieve faster detection of small changes in the mean. Exponentially Weighted Moving Average (EWMA) chart improves upon the detection of small process shifts. Rapid detection of small changes in the quality characteristic of interest and ease of computations through recursive equations are some of the many good properties of EWMA chart that make it attractive. Similar idea for exponentially weighted moving-range (EWMA) control chart are CUSUM Charts. The only difference is that for EWMA, the weights that are given to the measurements decrease geometrically with the age of the sample mean. In this paper we focus on the application of EWMA on quality monitoring.

The Exponentially Weighted Moving Average (EWMA) is a statistic for monitoring the process that averages the data in a way that gives exponentially less and less weight to data as they are further removed in time. EWMA is defined as:

$$Z_t = \lambda \bar{X}_t + (1-\lambda) Z_{t-1} \quad 0 < \lambda \le 1 \; Z_0 = \mu_0 \qquad (1)$$

where $0 < \lambda \le 1$ is a constant and the starting value (required with the first sample at i =1) is the process target, so that $Z_0 = \mu$ .The sequence of values Z_t , t= 0, 1, 2, … is called an exponentially weighted moving average.

$\bar{X}_t$ is an observation at time with $t \in$ □

It can be used as the basis of a control chart. The procedure consists of plotting the EWMA statistic Zi versus the sample number on a control chart with center line CL=μ_0 and upper and lower control limits at

$$UCL = \mu_0 + k\sigma\bar{x}\sqrt{\frac{\lambda}{2-\lambda}\left[1-(1-\lambda)^{2t}\right]} \quad (2)$$

$$LCL = \mu_0 - k\sigma\bar{x}\sqrt{\frac{\lambda}{2-\lambda}\left[1-(1-\lambda)^{2t}\right]} \quad (3)$$

The term $[1-(1-\lambda)^{2t}]$approaches unit as i gets larger, so after several sampling intervals, the control limit will approach the steady stage values.

$$UCL = \mu_0 + k\sigma\bar{x}\sqrt{\frac{\lambda}{2-\lambda}} \qquad (4)$$

$$LCL = \mu_0 - k\sigma\bar{x}\sqrt{\frac{\lambda}{2-\lambda}} \qquad (5)$$

Process Capability

This is the ability of the process to meet design specification for a service or product. An important aspect of SPC is to determine the process capability ratios, which indicate the capability of the process to produce acceptable products. Whether the product is acceptable is determined by the user-defined Upper and Lower Specification Limits. Capability is the amount of variation inherent in a stable process. Capability can be determined using data from control charts and histograms and is often quantified using the Cp and Cpk indices [10]. This capability index has been widely used and is considered one of the first capability indexes. The researcher used this because it uses the natural tolerance of a process.

If the researcher assumes normal distribution and the process mean is centered, a of 1 would be an indication of a capable process. To account for process drift, a of 1.33 is generally accepted. The larger the , the more capable the process is. Using a six sigma process that produces 3.4 defects for everyone million opportunities, the is 2. If the process is centered, 99.73% of the population would fall between ±3 sigma from the normal specification.

Assuming a normal distribution of the response, the process capability ratios C_p and C_{PK} are defined as:

$$C_p = \frac{USL - LSL}{6\sigma} \qquad (6)$$

$$C_{PK} = \min\left(\frac{USL-\mu}{3\sigma}, \frac{\mu - LSL}{3\sigma}\right) \qquad (7)$$

Where μ and σ reflect the process mean and standard deviation, respectively. Note that C_p is insensitive with respect to the location of the mean, whereas C_{PK} is not. The value of C_{PK} lets the researcher know if the process is truly capable of meeting the design specifications. Like the value, + 1 is necessary, + 1.33 is desired, and +2 values is considered to be six sigma. The C_{PK} is different from the C_p value because the C_p will show the researcher the possible gainin the process by centering the process.

III. Analysis

The analysis for X-bar-Chart and S-Chart are displayed which clearly indicates that the variability among the process variables of the product are stable (in-control). Also indicates how small changes can easily be detected on application of Statistical Process Control. We can also see the capability analysis for the process of producing all the product. The process is not capable of producing up to 99.73% of the product within the design specification limits. Thus, the process needs some little adjustment.

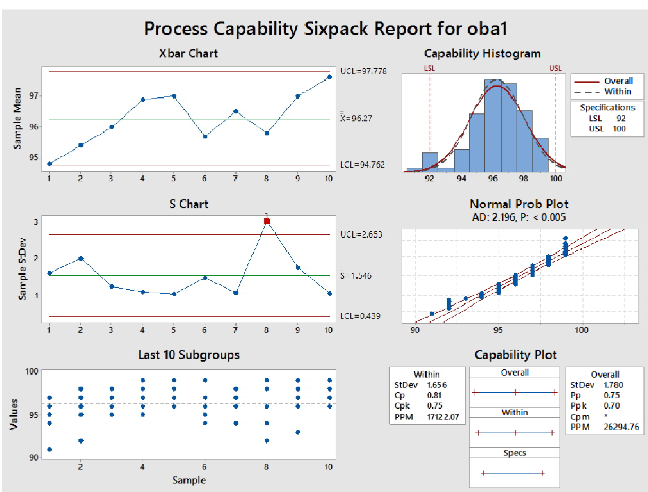

Figure 4: X-bar Chart, S-Chart plots and Capability Plot for Oba1

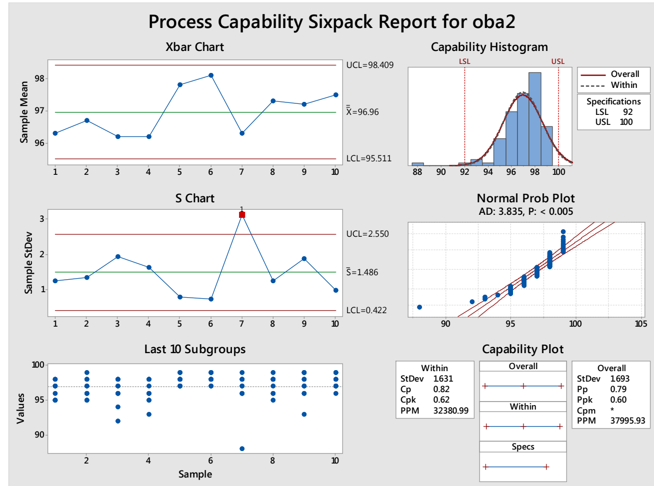

Figure 5: X-bar Chart, S-Chart plots and Capability Plot for Oba2

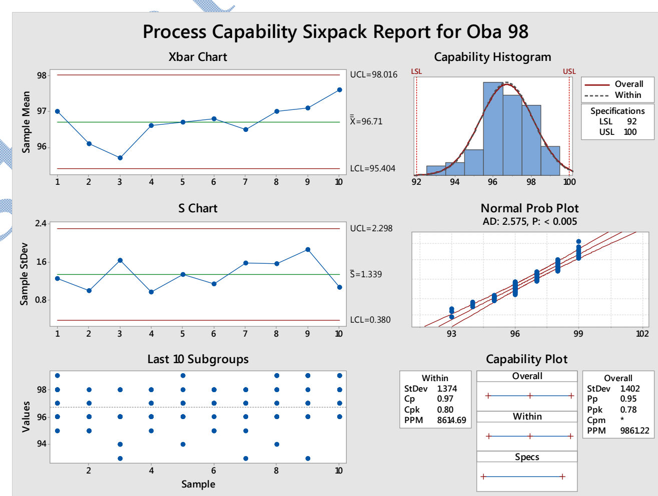

Figure 4: X-bar Chart, S-Chart plots and Capability Plot for Oba98

From the above figures 4-6, we can see that, irrespective of the value of lambda the value of C_P and C_{PK} are less than 1. Therefore, the process is not capable of producing good products within the specification limits.

IV. Results

The analysis indicates that the data are independent, as shown in Figure 1-3. This typically causes sigma to be estimated and hence generates very wide control limits. This is the reason why there are so many 'in-control' points on the EWMA chart (Figure 1-3). This EWMA plots shows the progress of the weighted moving averages across the 10 subgroups. There does not appear to be an indication of a change in the process mean. The EWMA Chart in figure 1-3 with smoothing parameter lambda $(\lambda) = 0.2$ cater for such defects and provide a powerful and reliable control charts showing clearly that the product process variables are statistically stable and conform to specification.

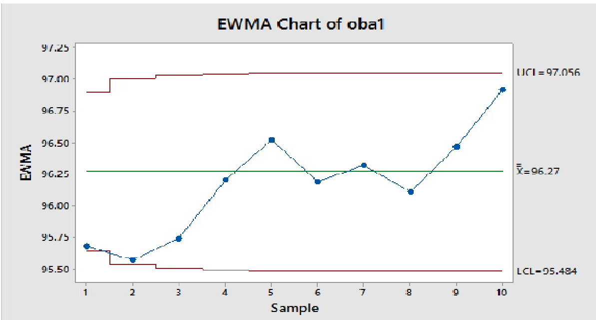

Figure 1: EWMA Chart for Oba1 with subgroup of 10 and $\lambda = 0.2$

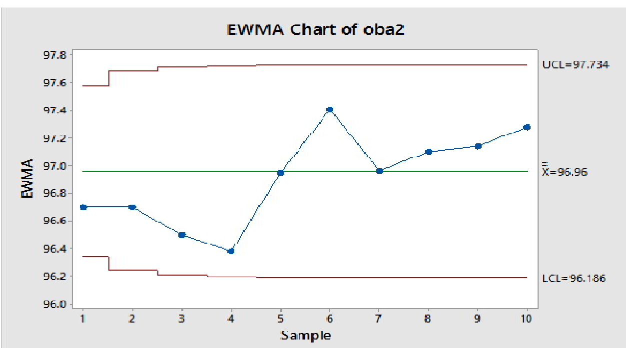

Figure 2: EWMA Chart for Oba2 with subgroup of 10 and $\lambda = 0.2$

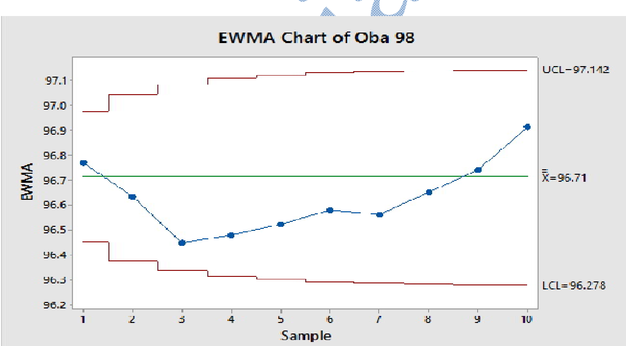

Figure 3: EWMA Chart for Oba98 with subgroup of 10 and $\lambda = 0.2$

V. Discussions

Based on the analysis above it shows that the data are independent. Therefore, EWMA Control chart is suitable to monitor the stability of these variables. Also since the assumption of independent is true for the data, we can then realize many in-control points on the EWMA charts.

VI. Conclusion

Many manufacturing industries rely on their conventional of way monitoring the quality of a product or a process. However, the use of Statistical Process Control has become the most important approach to achieve high product quality.

The seeds production companies also do not put interest on using SPC in their production. This paper shows the effect of SPC in monitoring the quality characteristics of seeds during its production. Despite the standard in-control behaviour of the process, the Process Capability analysis revealed that the process is not capable of producing good product within the specification limits. Thus, this study provides a framework for statistical process control methods of such manufacturing process situations and develops techniques in order to improve their detection speed.

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