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Univariate statistical process control of super saver beans: a case of RMV supermarket, zimbabwe.

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ABSTRACT: Statistical Process Control (SPC) uses statistical techniques to improve the quality of a process reducing its variability. The main tools of SPC are the control charts. The basic idea of control charts is to test the hypothesis that there are only common causes of variability versus the alternative that there are special causes. Control charts are designed and evaluated under the assumption that the observations from the process are independent and identically distributed (IID) normal. However, the independence assumption is often violated in practice. Autocorrelation may be present in many procedures, and may have a significant effect on the properties of the control charts. Thus, traditional SPC charts are inappropriate for monitoring process quality. In this study, we present methods for process control that deal with auto correlated data and a method based on time series ARIMA models (Box Jenkins Methodology). We apply the typical Cumulative Sum (CUSUM) and Exponentially Weighted Moving Average (EWMA) charts as SPC techniques and the time-series method in determining packaging process quality.

Keywords: *Statistical Process Control; Control charts; Autocorrelation; Time Series; CUSUM; EWMA.*

1. INTRODUCTION

Statistical process control (SPC) refers to the collection of statistical procedures and problem solving tools used to control and monitor the quality of the output of some production process through the reduction of variance, Montgomery (2005). Statistical Process control is widely used in all aspects of business be it in the manufacturing and non-manufacturing industry. It is concerned with quality of conformance. Due to modern technology, systems or machinery are well designed but in any process no matter how well the system is designed, there exists a certain amount of variability in the output produced by the system. Miller (2003), states that all processes are subject to degrees of variation, and this process variability is due to assignable causes and non assignable causes. Non assignable or common causes are natural and are inherent in every process and somehow cannot be avoided. Assignable causes or special causes are identifiable and correctable and these include equipment out of adjustment, defective materials, changes in parts or materials, broken machinery or equipment, operator fatigue or poor work methods, or errors due to lack of training. If there is excess variation due to assignable causes the output product may malfunction or may not serve its intended use. Assignable causes if identified can be eliminated using Statistical Process control tools. Control charts have been widely used since 1920s since their discovery by Walter A. Shewhart because they have proven to be an efficient tool in dealing with process variations in SPC. A control chart is a statistical diagnostic tool used to distinguish between variation in a process resulting from common causes and variation resulting from special causes, Montgomery (2009). A process is said to be in a state of statistical control or simply in control if it is free from the influence of special causes. Otherwise, it is said to be out of control. In statistical terms, this means an in-control process variable has a constant distribution. In applications, however, it is generally considered sufficient for the process parameters such as the mean, and the standard deviation, to remain constant.

2. BACKGROUND AND LITERATURE

The ultimate goal of every business entity is to make profit, in order to maximize profitability while complying with government regulations regarding net package contents, food manufacturers and suppliers or packagers must ensure that they adhere to stated regulations. In Zimbabwe, the Standards Association of Zimbabwe (SAZ) is responsible for setting standards for evaluating net package contents of packaged goods for example foodstuffs and beverages. The standards include two basic requirements. The first one applies to the average net quantity of contents in each lot and the second one applies to each individual package. The average net content of packages in a lot must at least be equal to the label declared on the container. Any individual package net content must not be less or more than the label declared net content by an amount that exceeds the maximum allowable variation. The maximum allowable variation depends on the label content. Overfilling during packaging is inefficient and has a negative impact on profitability to a greater extent and also under filling results in significant risks of violating net contents regulations leading to potential penalties from government, loss of business reputation and impaired customer relations.

Many businesses use Univariate Statistical Process Control (USPC) in both their manufacturing and service operations, Montgomery (2009). USPC has been found to be particularly suited for many of the problems found in both manufacturing and non manufacturing industry. It provides a diagnostic tool for the comprehensive on-line statistical monitoring of a process and the on-line detection and diagnosis of process malfunctions and it is applicable when dealing with a single characteristic of a product at a time. Statistical techniques for process control, process improvement and sampling inspection trace their origins back to the early 1920's. Walter A. Shewhart introduced the concept of the control chart, whilst seven years in later 1931, the initial theory of statistical quality control was developed (Shewhart, 1931).

The American government realizing that they needed to increase efficiency and quality in the industrial sector especially in the manufacture of weapons, they applied SPC by the help of Edwards Deming during World War II. Deming was instrumental in applying SPC to wartime production to reduce variation in production processes. In 1951 Deming became part of the Japanese Union of Scientists and Engineers (JUSE) because of his excellent skills in the continuous improvement of processes and quality through the use of SPC techniques. In this regard, Japanese manufacturers achieved the highest standards of production efficiency in the history of manufacturing (Mann, 2010).

According to Deming (2000), the late 1950s saw the application of Statistical Process control in the field of automotives. Toyota Motor Corporation had problems that affected their production systems for example motor vehicle parts could not fit precisely after manufacturing, waste of material and so many production inconsistencies, so the company applied SPC to identify and iron out production inefficiencies. Toyota Production System focused on ironing out these problems by identifying the sources of variation in production systems using control charts to objectively identify process inefficiencies. By the end of the 1970s, Toyota's production of vehicles had increased from 154,770 in 1960 to 3,293,344 in 1980 with unsurpassed efficiency Deming (2000). In 1988, the Software Engineering institute in America suggested that SPC could be applied to non manufacturing processes such as software engineering processes. This marked the application of SPC in non manufacturing processes. Since then there has been tremendous applications of SPC in various fields although not much has been documented on its applications but it still has made a lot of impact in the improvement of processes and quality.

Woodall and Faltin (1993) presented an overview and perspective on control charting. Grigg et al. (1998) presented a case study of Statistical Process Control in fish product packaging. This study highlighted the role of statistical process control in packaging control of fish. (Weller (2000) discussed some practical applications of Statistical Process Control. Srikaeo and Hourigan (2002) discussed the use Statistical Process Control to enhance the validation of critical control points (CCPs) in shell egg washing. Mohammed (2004) adopted Statistical Process Control to improve the quality of health care. Mohammed et al. (2008) illustrated the selection and construction of four commonly used control charts (xmr-chart, p-chart, u-chart, c-chart) using examples from healthcare.

On packaging control Djeckic et al. (2014) applied SPC to analyze the food packaging process in seven food companies in Serbia.

2.1 Cumulative Sum (CUSUM) Chart

The Cumulative Sum (CUSUM) control chart is an alternative to the Shewhart type chart, which can be used as an ordinary control chart except that it has more advantages than the ordinary Shewhart control chart. It was first introduced by Page in 1954 and has been widely studied by a number of authors over the past years. CUSUM charts are generally used to detect small process shifts. A CUSUM chart uses all the information in a sequence of values of a statistic by plotting the cumulative sums of their deviations from a target value. Crosier (1986) defined a two sided CUSUM method that requires only one cumulative sum for monitoring lower and upper shifts. The main advantage of Crosier CUSUM is the possible generalization to multivariate CUSUM scheme useful in case of multi variable processes.

Yaschin (1987) recommended that the CUSUM should be preferred over the Exponentially Weighted Moving Average (EWMA) chart. He proved that the possibility of a EWMA statistic being in a disadvantageous position is serious than a two sided CUSUM, which use resets and do not have a significant inertia problem. Gan (1991) discussed the importance and use of Cusum control charts and came to the conclusion that Cusum control charts were the best SPC technique in the identification of out of control signals and detecting small shifts in process parameters. The design of the conventional CUSUM chart involves evaluation of the control chart performance based on average run length (ARL). The conventional CUSUM chart is designed to minimize the out-of-control ARL for a mean shift while maintaining a given in-control ARL (Bagshaw and Johnson (1975), Moustakides (1986)).

Arnold et al. (2001) studied the properties of CUSUM control charts with variable sample size and sampling intervals. The ability to detect all but very large process shifts is improved by using either the VSS or VSI feature in a CUSUM control chart. Ling Yang et al. (2010) developed a novel CUSUM - control chart for monitoring the process sample mean with outliers. In their study they compared the Novel CUSUM - control chart method to several mean control charts, CUSUM median control chart, EWMA median control charts with various shifts of the process sample mean.

2.2 Exponentially Weighted Moving Average (EWMA) Chart

An alternative to the Shewhart-type control chart, especially when one wants to detect small and moderately-sized sustained process shifts, is the Exponentially Weighted Moving Average (EWMA) control chart. The Exponentially Weighted Moving Average (EWMA) control chart is a well known tool for process monitoring. The EWMA chart was introduced by Roberts (1959) and it is used to detect persistent shifts in a process. The main advantage of this chart is that it is able to detect quickly small and moderate shifts. They are however slower in detecting large process shifts in the process mean and typical run tests cannot be used due to the inherent dependence of data points. The application of the EWMA control chart is suggested for processes where repeated sampling is not possible or appropriate Warthon and Ringer (1971).

According to Hunter (1986), the EWMA chart performs like the Shewhart Control chart as the weighing factor becomes closer to one and it performs like a CUSUM control chart as the weighing factor becomes closer to zero. This type of chart provides a forecast of where the process will be in the next instance of time and thus provides a mechanism for dynamic process control (Hunter 1986). Lucas and Saccuci (1990) evaluate the run length properties of EWMA control schemes by representing the EWMA statistic as a continuous -state Markov chain. Gan (1990) proposes three modified EWMA charts for Poisson data. Domangue and Patch (1991) proposed another type of control chart called the Omnibus EWMA chart which is based on the exponentiation of the absolute value of the standardized sample mean of the observation. Omnibus EWMA chart were said to perform better in detecting the shifts in process variance than the shift in the process mean. The EWMA chart is used extensively in time series modeling and forecasting for processes with gradual drift, (Box, Jenkins, and Reinsel, 1994). EWMA charts have also been used to detect shifts in the number of nonconforming items.

2.3 Autocorrelation of Observed Values and ARIMA

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. Observed data may not be normally distributed and independent as expected and when these assumptions are violated, data is more likely to be auto correlated. The presence of autocorrelation significantly reduces the control chart performance. It was shown that autocorrelation deteriorates the ability of the Shewhart chart to correctly separate the assignable causes from the common causes (Alwan, 1992). Montgomery (2005) argues that this is a common consequence of processes that are driven by inertia forces in process industries and frequent sampling in the process industries. The presence of autocorrelation has got the effect of increasing false alarm signals in control charts (Harris and Ross 1991).

Two methods have been advocated for dealing with the autocorrelation of observed values in Statistical Process Control. The first approach uses standard control charts on original observations, but adjusts the control limits and the methods of estimating parameters to account for the autocorrelation in the observations (VanBrackle and Reynolds, 1997; Lu and Reynolds, 1999). This approach is particularly applicable when the level of autocorrelation is low. A second approach for dealing with autocorrelation is to fit a time series model such as ARIMA models to the process observations. The procedure forecasts observations from previous values and then computes the forecast errors or residuals. Montgomery (1997) recommended three approaches for monitoring auto correlated observations. (i) Fit an ARIMA model to data then apply traditional control charts such as CUSUM and EWMA to monitor residuals. (ii) Monitor the auto correlated observations by modifying the standard control limits to account for the autocorrelation. (iii) Eliminate the autocorrelation by using an engineering controller.

In 1997, Kramer and Schmid (1997) discussed the application of the Shewhart chart to residuals of $AR(1)$ process and in the same year Reynolds and Lu (1997) compared performances of two different types of EWMA control charts for residuals of $AR(1)$ process. Yang and Makis (1997) compared the performances of CUSUM and EWMA charts for the residuals of $AR(1)$ process. Zhang (1997) remarked that the detection capability of an X bar residual chart was poor for small mean shifts compared to the traditional X bar chart, EWMA and CUSUM charts for $AR(2)$ process. Two years later, Lu and Reynolds (1999) compared the performances of EWMA control chart based on the residuals from the forecast values of $AR(1)$ process and EWMA control chart based on the original observations.

Jiang et al. (2002) proposed proportional integral derivative (PID) charts for residuals of ARMA(1,1) process. Snoussi et al. (2005) studied on residuals for short run auto correlated data of auto correlated process. They compared the performances of Shewhart, CUSUM and EWMA control charts for residuals of $AR(1)$ process. Although the residual charts have some advantages by using them for auto correlated processes, there are some problems due to the detection capability of the residual chart. Harris and Ross (1991) recognized that the CUSUM control chart and EWMA control chart for the residuals from a first-order autoregressive process may have poor capability to detect the process mean shift. Wardell et al. (1994) showed that Shewhart charts are not completely robust to deviations from the assumption of process randomness; namely when observations are correlated.

3. METHODOLOGY

3.1 ARIMA (p, q) Processes

The Autoregressive integrated moving average (ARIMA) time series models were used to remove autocorrelations to ensure process data is stationary and come up with the best model that gives process residuals. The Autoregressive integrated moving average ARIMA model is given by:

$$X_t = \emptyset_1 X_{t-1} + \emptyset_2 X_{t-2} + \cdots + \emptyset_p X_{t-p} + a_t + \theta_1 a_{t-1} + \theta_2 a_{t-2} + \cdots + \theta_q a_{t-q} \quad (1)$$

A process X_t is said to be stationary if for every t,

$$X_t - \emptyset_1 X_{t-1} - \emptyset_2 X_{t-2} - \cdots - \emptyset_p X_{t-p} = a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \cdots - \theta_q a_{t-q} \quad (2)$$

Where: $a_t \sim NID(0, \sigma^2)$

We plotted both the autocorrelation function (ACF) and the partial autocorrelation function (PACF) to identify the best ARIMA model capable of producing the IID residuals. ACF is given by:

$$\rho_k = \frac{Cov(X_k, X_{t-k})}{\sqrt{Var\, X_k \; . Var(X_{t-k})}} = \frac{\gamma_k}{\gamma_0} \quad (3)$$

And PACF is given by:

$$r_k = \frac{\frac{1}{N}\sum_{t=1}^{N-k}\left(X_t - \bar{X}\right)\left(X_{t+1} - \bar{X}\right)}{\frac{1}{N}\sum\left(X_0 - \bar{X}\right)} \quad (4)$$

3.2 I-MR Charts

The individuals and moving range (I-MR) chart is one of the most commonly used control charts for continuous data; it is applicable when one data point is collected at each point in time. The control limits are constructed by using the moving range of two successive observations as follows:

$$UCL = \bar{X} + 3\frac{\overline{MR}}{d_2} \quad (5)$$

$$CL = \bar{X}$$

$$LCL = \bar{X} - 3\frac{\overline{MR}}{d_2} \quad (6)$$

3.3 Cumulative Sum (CUSUM) Chart

Cumulative Sum (CUSUM) control charts show cumulative sums of subgroup or individual measurements from a target value. CUSUM charts can help to decide whether a process is in a state of statistical control by detecting small, sustained shifts in the process mean. To design the CUSUM control chart, estimates for the process standard deviation were computed, these were obtained from the I-MR charts. The CUSUM chart tracks the distance between the actual data point and the grand mean. Then, by keeping a cumulative sum of these distances, a change in the process mean can be determined, as this sum will continue getting larger or smaller. These cumulative sum statistics are called the upper cumulative Sum,

$$C_t^+ = \max\left[0, x_t - (\mu_0 + k) + C_{t-1}^+\right] \quad (7)$$

And the lower cumulative sum,

$$C_t^- = \max\left[0, (\mu_0 - k) - x_t + C_{t-1}^-\right] \quad (8)$$

Where x_t is the i^{th} observation of the process, k is the slack value or (reference value) which is often chosen about halfway between the target mean μ_0 and the out-of-control values of the mean say μ_1 for the upper CUSUM mean and μ_2 for the lower CUSUM mean. The critical size of the shift is determined by the following:

$$\mu_1 = \mu_0 + \delta_1\sigma, \quad (9)$$

$$\mu_2 = \mu_0 + \delta_2\sigma \quad (10)$$

Where μ_0 is the mean or target value, μ_1 is the upper shift mean, μ_2 is the lower shift mean, δ_1 is the upper critical shift, δ_2 is the lower critical shift and _ is the standard deviation of the process. The reference value K is half the magnitude of the shift, thus a value half way between the target μ_0 and the upper CUSUM mean μ_1, or the lower CUSUM mean μ_2. The reference value is a line, which if crossed, provides an early warning of a shift in the process mean. The upper and lower reference values K_1 and K_2 are calculated as follows:

$$K_1 = \frac{|\mu_1 - \mu_0|}{2} = \frac{\delta_1\sigma}{2} \tag{11}$$

$$K_2 = \frac{|\mu_2 - \mu_0|}{2} = \frac{\delta_2\sigma}{2} \tag{12}$$

The decision variable H, which acts as a control limits, must be created to determine the state of the process. The upper and lower decision variables H_1 and H_2 are calculated as follows:

$$H_1 = h_1\sigma \tag{13}$$

$$H_2 = h_2\sigma \tag{14}$$

Where h_1 and h_2 must be determined through the ARL approximated by the equation:

$$ARL = \frac{e^{-2\Delta b} + 2\Delta b - 1}{2\Delta^2} \tag{15}$$

for $\Delta \neq 0$, where $\Delta = \delta^* - k$ for C_t^+ and $\Delta = -\delta^* - k$ for C_t^-, $b = h + 1.166$ and $b = \frac{|\mu_1 - \mu_0|}{\sigma}$.

If $\Delta = 0$, one can use $ARL = b^2$The quantity δ^* represents the shift in the mean in the units of σ, for which the ARL is to be calculated. A two sided CUSUM is given by:

$$ARL = \left(\frac{1}{ARL_+} + \frac{1}{ARL_-}\right)^{-1} \tag{16}$$

3.4 Exponentially Weighted Moving Average (EWMA) Chart

Like the CUSUM chart, EWMA is suitable for detecting small process shifts. The EWMA is a statistic for monitoring the process that averages the data in a way that gives less and less weight to data as they are further removed in time. By the choice of weighting factor λ, the EWMA control procedure can be made sensitive to a small or gradual drift in the process. The EWMA statistic is defined as:

$$z_t = \lambda x_t + (1 - \lambda) z_{t-1} \tag{17}$$

with $0 \leq \lambda \leq 0$, $z_0 = \mu_0$, where z_t is the moving average at time t. If the observations x_t are independent random variables with variance σ^2, then the variance of z_t will be:

$$\sigma^2_{z_t} = \sigma^2 \left(\frac{\lambda}{2 - \lambda}\right)\left[1 - (1 - \lambda)^{2t}\right] \tag{18}$$

The control limits for EWMA Control Chart are:

$$UCL = \mu_0 + L_\sigma \sqrt{\frac{\lambda}{2 - \lambda}\left[1 - (1 - \lambda)^{2t}\right]} \tag{19}$$

$$CL = \mu_0 \tag{20}$$

$$UCL = \mu_0 - L_\sigma \sqrt{\frac{\lambda}{2 - \lambda}\left[1 - (1 - \lambda)^{2t}\right]} \tag{21}$$

3.5 ARL of EWMA Chart

There are two main approaches for computing ARL for an EWMA sequence. The first approach is based on the fact that ARL must satisfy the Fredholm integral equation. The second approach is based on the flexible and relatively easy to use Markov chain approach, originally proposed by Brook and Evans in 1972. In this study we used the second approach to calculate the ARL of the EWMA control chart. This procedure involves dividing the interval between LCL and UCL into

$p = 2m + 1$ subintervals of width 2δ, where $\delta = \frac{UCL-LCL}{2p}$. When the number of subintervals p is sufficiently large the finite approach provides an effective method that allows ARL to be effectively evaluated.

4. DATA ANALYSIS AND DISCUSSION

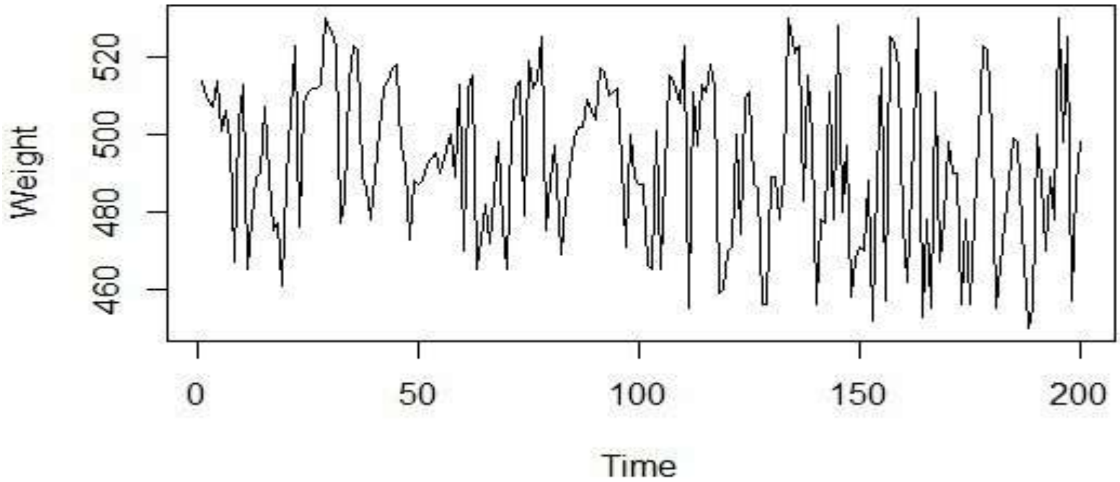

Fig 1: Time Series Plot of net weight

Figure 1 shows a time series plot of net weight of contents of Super Saver beans. An Augmented Dickey-Fuller (ADF) test was also applied to test for the presence of a unit root in the time series. The ADF test on the original data provided evidence of the absence of a unit root in the data meaning to say that the data is stationary.

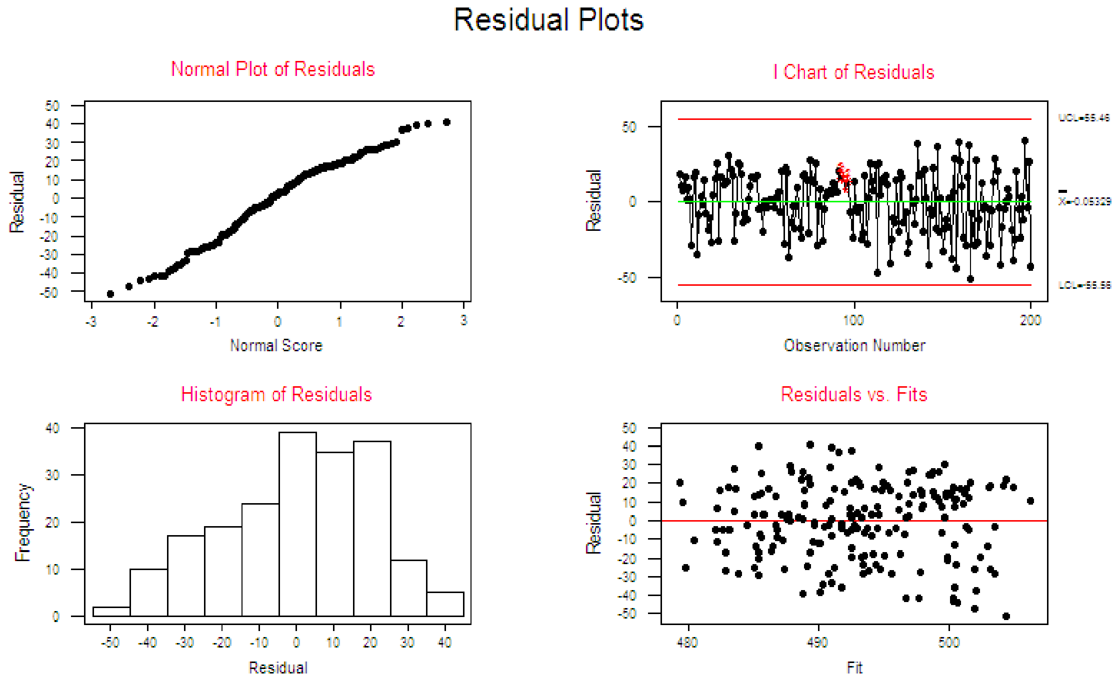

Fig 2: Residual Plots obtained from ARIMA (2, 0, 1) Model

Referring to figure 2; the individual charts of residuals indicate that the residuals have constant location and scale. All Data points are in control. Plot of residuals against fitted values are shapeless and therefore the randomness assumption holds. The histogram of residuals is approximately normal indicating that the residuals are normally distributed. From the 4 plot above it can be safely concluded that these residuals are adequate to be monitored for process quality by control charting techniques.

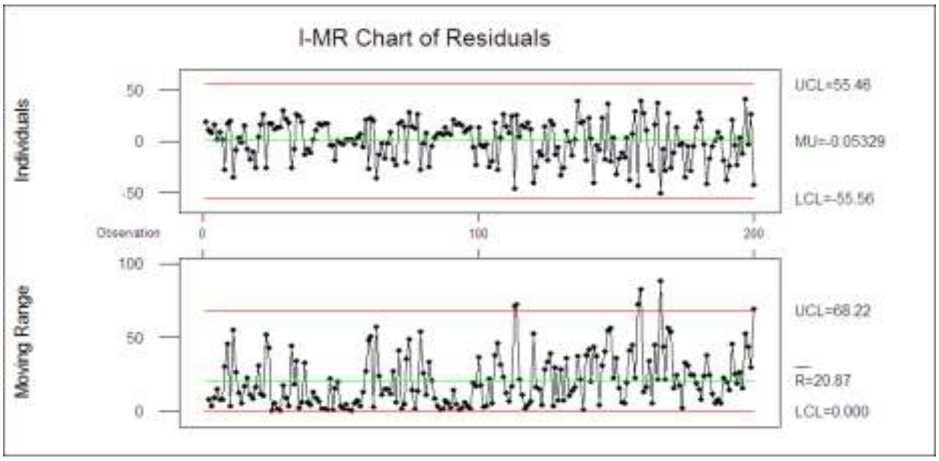

Fig 3: I-MR Chart for residuals

The I-MR chart in figure 3 shows that the process is not stable, the individuals chart show that all the data points are in control and The Moving range chart displays five disturbances in the process and these out of control signals are shown at 113,158,159,166 and 200.Therefore the process requires further investigation. From the I-MR charts we can estimate the standard deviations for the packaging process and use them to chart CUSUM charts.

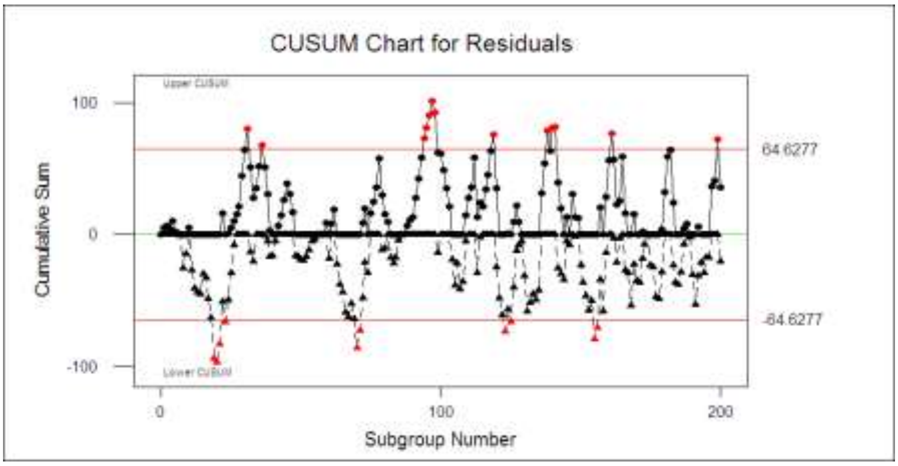

Fig 4: CUSUM Chart for residuals

Figure 4 shows the CUSUM chart for packaging process data using h and k values as determined using Anygeth.exe. The values obtained are $h = 4.4688$, $k = 0.594$, $\sigma = 0.789$, $and\ \Delta = 0.5$. For the CUSUM chart, the in-control ARL was set to 14 days. As such, one would expect to see about one false alarm every 14 days. This says that when a process is in control one expects an out-of-control signal (false alarm) each 14 runs. That is, the scheme will give a false alarm with probability of 1/14. The CUSUM chart generated produced out of control signals at: 19,20,21,23,31,36,70,71,94,95,96,97,98,119,123,125,138,140,141,155,156,161,199.

The EWMA chart was used as a control chart technique to determine whether the packaging process was in control or not. Figure 5 shows the EWMA control chart based on the parameter $\lambda = 0.2$. The EWMA chart detects out of control signals at 19,20,31,94,95,96,97. Therefore, the process is not in control.

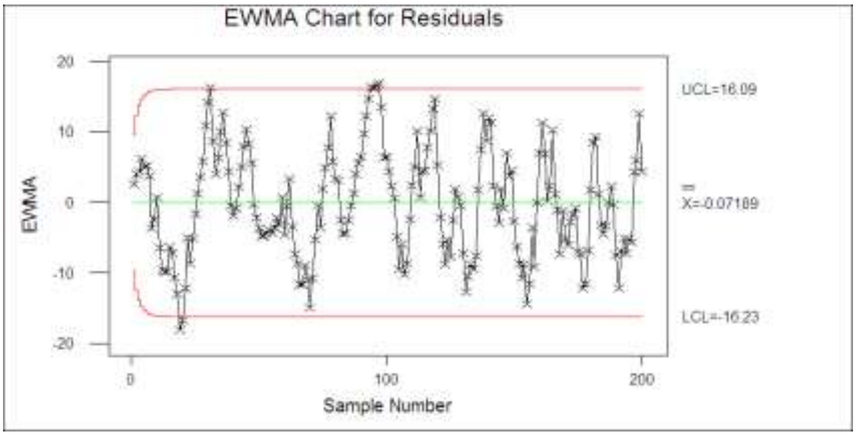

Fig 5: EWMA Chart of residuals

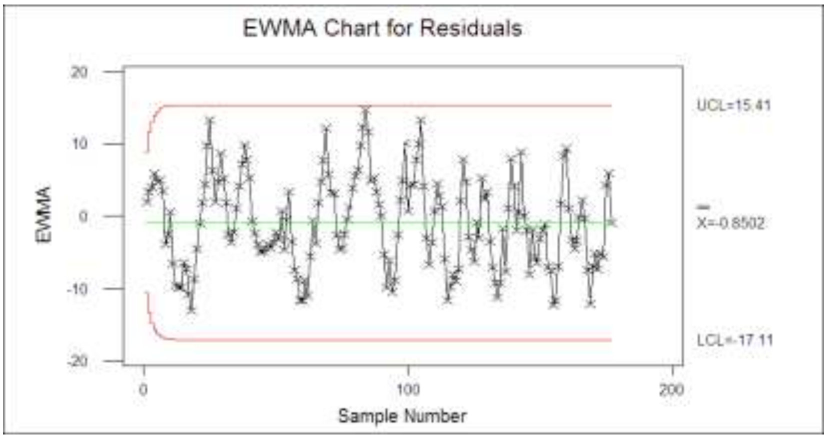

Fig 6: Revised EWMA Chart

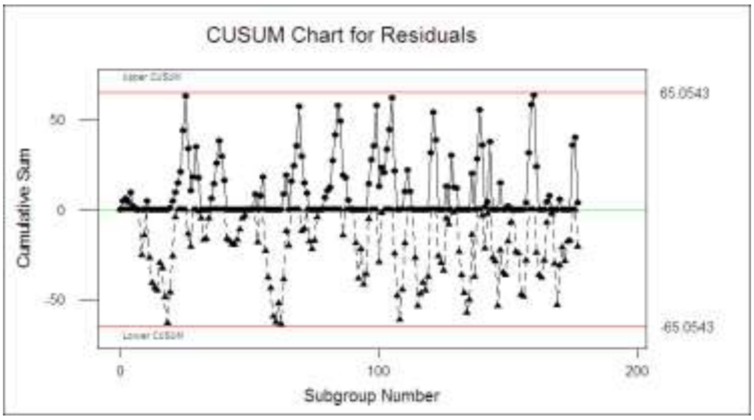

Fig 7: Revised CUSUM Chart

Fig 6 and fig 7 show the revised EWMA and CUSUM charts respectively after the elimination of all out – of – control signals. That is removing all packaging with the corresponding out – of – control points indicated above (fig 4 and fig 5).

5. CONCLUSION

As in the many modern applications of statistical process control charts, the autocorrelation has an important effect on data and it should be considered. When the data are auto correlated the wrong decisions can be made about uncontrolled number of process variables. If there is any autocorrelation between the consecutive observations, it should be taken into account during the process. Both the CUSUM and the EWMA control chart techniques were very capable of detecting small mean shifts in the packaging process data when correctly set up to analyze the data. The instability of the process is believed to be attributed to the fact that employees in the packaging department are not as skilled as they are expected to be in their job area. It is also believed that during the packaging process, the packagers do not pay particular attention to the measurement scale indicated by huge deviations from the process mean. The Average Run length of 14 days suggests that the process is bound to fail every 14 days.

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