Improving Process Performance of Cotton Spinning by Using Statistical Process Control Techniques

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Abstract: Identifying the presence and understanding the causes of process variability are key requirements for well controlled and quality manufacturing. This pilot study demonstrates the introduction of Statistical Process Control (SPC) methods to the spinning department of a textile manufacturing company. The methods employed included X Bar and R process control charts as well as process capability analysis. Investigation for 29 machine processes identified that none were in statistical control. Recommendations have been made for a repeat of the study using validated data together with practical application of SPC and control charts on the shop floor and extension to all processes within the factory.

Keywords: *Capability analysis, Six Sigma Statistical Process Control, Variability.*

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1. INTRODUCTION

It has been recognized by the management of a cotton textile manufacturing company that the long term success of the business will rely on developing turnover and profitability by achieving penetration into high-added-value export markets. Discussions with potential export customers in Europe reveal that one of the critical requirements of all potential export partners in the target market is that there must be complete process integrity; all processes must be monitored and be fully controlled at all times. These process controls must be data-driven and not based on simple observation. Once standards have been agreed, the customer will expect that process control will ensure these standards are met for each and every delivery and that any product variability is maintained within very tightly defined limits. Initial observation of company's production processes showed scant evidence of standard work processes and also revealed high levels of rework and scrap. While routine sampling during production takes place throughout the

process of converting raw cotton into finished goods, it was unclear how effectively the resulting data were used to ensure good process control. All of these early observations indicated that any number of processes were likely not to be in full control. A sample of inspection data was analyzed and the results showed that there was a high level of variability which corroborated the suspicion that there is indeed likely to be a systemic problem of process control.

When aiming to improve any manufacturing enterprise or process, looking to industry best practice for guidance is generally held to be a valuable approach. Boeing Commercial Airplane Group is a company that has consistently demonstrated the highest levels of product and process integrity and is often cited as a benchmark for best practice within manufacturing. The Boeing Advanced Quality Systems Tools manual [1] lays down the guidelines and tools that the company uses to ensure that all aspects of production are in control and meet all the quality specifications stipulated. Examination of the Boeing

documentation shows that the company makes extensive use of Statistical Process Control (SPC) and Six Sigma principles to monitor and control their manufacturing processes and these two approaches also underpin a wide range of other tools employed.

1.1 Background and Literature

Statistical Process Control (SPC) is a mathematical model that measures the probability of the occurrence of an event in a stable system. It is an industry-standard methodology for measuring and controlling quality during the manufacturing process [2]. The use of SPC requires an understanding of how observed process variability data can be plotted and how this plot relates to the upper and lower specification limits set down for the process. These limits are determined according to the requirements of the customer or the product design. These limits are not to be confused with process control limits which are derived from the inherent characteristics of the process itself [3]. No matter how well controlled, all processes show variability from the process nominal value. In a stable system, where there are no other sources of variability, this is called common cause variation and the extent of that common cause variation will determine how capable the process is in relation to the manufacturing specification. The process that only has common cause variation is said to be in statistical control. The variability in a stable system can be plotted and the upper and lower control limits calculated.

Deming carried out extensive research using the funnel experiment, where the funnel is used as a model for a stable system. A funnel is placed on a fixed stand and marbles are dropped through the funnel towards a target. Deming demonstrated that, in a stable system subject only to common cause variation, the best results in the funnel experiment were achieved when the funnel was fixed and aimed at the target. Attempts to 'improve' results by responding to individual data points led to greater variability in the process [4]. The implication for manufacturing is that, if a process is subject to only common cause variation, once a machine is set up accurately according to effective guidelines, responding to individual data points in an attempt to improve outcomes only increases process variability rather than reducing it.

However, in the manufacturing context, other sources of variability beyond common cause can occur. This is called special or assignable variation. SPC can be used to identify when these other sources of variability are taking place.

Once common cause variation data for a system is known, the process capability indices, C_p and C_{pk} , can then be calculated by linking the common cause data with the product or component specification. The C_p index is the process spread relative to the component specification and the C_{pk} index is how close the process mean is to the centre of the upper and lower specification limits [1]. These indices indicate whether the system is indeed capable of meeting the manufacturing specifications that have been laid down for the product or process.

Deming states that truly understanding sources of variability is what will lead to improved product quality [5]. To analyse the variability of a process, quality data in the form of product or process measurements are obtained in real-time during manufacture. These data are then plotted on a graph alongside the pre-determined calculated control limits which reflect the common cause variation built into the system. If data fall outside these limits or are not randomly and evenly scattered around the mean it can be assumed that there are additional causes of variation, called special or assignable causes. When there are special causes of variation there is a likelihood of process scrap [6] with the resultant impact on productivity and profitability.

SPC is a management tool. In itself, it does not control the process but it serves as a monitoring function to indicate when variability due to assignable causes is taking place [4]. The primary tool of SPC is the control chart. There are two basic types of control charts. The first is called a univariate control chart. It is a graphical display employed when only one quality characteristic is being assessed. The second, referred to as a multivariate control chart, is a graphical display of a statistic that summarizes or represents more than one quality characteristic [7]. Within these two primary groups there are various options to choose from, dependent on the specific nature of the data to be examined [1].

SPC is based on understanding sources of variability in manufacturing systems, and relies on a Gaussian plot of the relevant process data. The area under the standard bell-shaped Gaussian curve has a theoretical value of 1, although in practice this value is approximately 0.9973 or 99.73% of the population, assuming limits of 3 standard deviations either side of the nominal value or mean. The use of three standard deviations has regularly been an accepted industry norm. However, many companies believe that these limits are too wide and have in recent years adopted Six Sigma methodology, where the confidence limits are set at 6 standard deviations from the mean or nominal value. At this level, 99.9997% of data points need to lie within acceptable limits [8].

Six Sigma, developed by Motorola in 1986, is a methodology the company uses to reduce the variability of their manufacturing process. This was a clear requirement resulting from their programme of ongoing research of customer requirements and expectations [8].

Six Sigma follows a structured approach, building on Deming's Plan, Do, Check, and Act cycle [5], [9] and the principles of SPC. It is a systematic series of iterative steps for gaining valuable knowledge and for the continual improvement of the product and process. It requires a whole-team approach and incorporates many of the tools commonly used in "lean" systems, especially the extensive array of problem solving techniques [7].

Six Sigma uses the acronym DMAIC as a way of itemizing the key steps:

D defines the problem. This requires a concise problem statement that all of the team understands. M defines measures, what is measured, and how that measure will improve value to the customer. A defines the analysis phase where the collected data are statistically analyzed to reveal patterns in the data. It defines the improvement phase based on the data. This is where team problem solving techniques are important to develop a new way of working based on the data. C defines the control where systems are put in place to ensure that any improvements are sustained and form the basis of the next level of improvement [7].

Many practitioners have now added an R at the start of the process to define the recognition of opportunities for improvement. This could

include possible feedback from customers or from customer complaints [8].

As previously stated, the term Six Sigma makes reference to a process where outputs are expected to be within 6 standard deviations from the mean. This means that 99.9997% of the area of the Gaussian curve, and the data points within it, are within acceptable limits. In practice, this means that a manufacturing process would only have 3.4 defects in a million activities [10]. Whilst there are few companies that achieve this extraordinary level of performance, it is considered a target that companies can and should aspire to.

2. METHODOLOGY

2.1 Statistical Process Control & Process Capability Analysis

Whilst adopting the Six Sigma methodology could be a long term aim for the firm, it is clear that the understanding of Six Sigma and its implementation would be too difficult to achieve currently. However, it is understood that there are significant benefits that could be accrued by adopting SPC analysis as a method of detecting assignable variation in the processes within the factory and this is likely to be within the capabilities of the company. It was therefore decided that SPC and its related tool, the standard control chart, would be the most appropriate approach to use at this stage. Selecting a suitable control chart is dependent on the nature of the data to be collected. The initial processes to be observed occur within the spinning department. They are continuous processes, with two to five samples of product taken on a regular basis. As a result, using the Boeing protocol for chart selection, the most suitable control charts to use for monitoring these spinning processes are the X Bar & Range charts [1], [7].

The X Bar chart requires the calculation of the sample average, and then the average of the sample averages, X Double Bar. The range (R) is calculated for each sample group and then the average taken of all the sample ranges. Having obtained results for X Double Bar and R Bar, the upper and lower control limits can then be calculated. The results of all these calculations can then be plotted to give a chart form.

The formulae required for X Double Bar Chart compilation are:

Control limits:

$$UCL = \bar{\bar{X}} + A_2 \bar{R}$$

$$LCL = \bar{\bar{X}} - A_2 \bar{R}$$

Centre lines:

$$\bar{\bar{X}} = \frac{\sum \bar{X}}{k}$$

(where k = number of sub-groups).

Plot points:

$$\bar{X} = \frac{\sum X}{n}$$

The formulae required for R Chart compilation are:

Control limits:

$$UCL_R = D_4 \bar{R}$$

$$LCL_R = D_3 \bar{R}$$

Centre lines:

$$\bar{R} = \frac{\sum R}{k}$$

(where R = range of subgroup measurements and k = the number of sub-groups).

A₂ D₃ and D₄ (see Equations 1, 2, 5 and 6) are standard scaling constants required for the application of the SPC model. They are required to standardize data dependent on sample batch size. The following values were extracted from the Boeing AQS manual [1].

Table 1. Standard Scaling Constants Used for Calculation of X Bar and R Charts

Sample sub group size	A ₂	D ₃	D ₄
1	2.66	0	
2	1.88	0	3.267
3	1.023	0	2.575
4	0.729	0	2.282
5	0.577	0	2.115

Although there are a number of specialist software tools that could be used to analyse the data e.g. Minitab, R, etc., it was decided that Excel should be used as it is straightforward to use, readily available both at the university and factory, and requires little additional training, particularly at the company in question.

It was also decided to extend the initial analysis to include process capability analysis. This analysis allows a manufacturer to assess whether the key characteristics of the process are sufficient to meet the demands of the manufacturing specification. At the heart of process capability analysis is the generation of Cp and Cpk indices. These indices show the process spread of the natural variation within a process (based on six standard deviations either

side of the mean) relative to the upper and lower manufacturing specification limits. Cp reflects the spread of data and Cpk reflects how close the process mean is relative to the centre between the upper and lower specification limits. The specification limits may be design-defined or customer-defined [1]. To calculate the process capability indices the following formulae can be used.

$$Cp = (USL - LSL)/6\sigma$$

$$Cpk = \text{Min} [(USL - \bar{X})/3\sigma, (\bar{X} - LSL)/3\sigma]$$

-) The Cp and Cpk indices can give an indication of how many defective parts per million will be anticipated through operation of the current system. The Boeing AQS system supplies the following chart which links Cp values to expected defect rates [1].

Table 2. Cp Values to Expected Defect Rates

Cp	Parts per million defective
0.50	133,614
0.75	24,449
1.00	2,700
1.10	967
1.20	318
1.30	96
1.40	27
1.50	7
1.60	2
1.70	0.34
1.80	0.067
1.90	0.012
2.00	0.0018

Figure 1a. R chart for Ring Spinning Machine 7

Figure 1b. X Bar chart for Ring Spinning Machine 7

Figure 2a. R chart for 2nd drawing process, shift C, machine 2

Figure 2b. X bar chart for 2nd drawing process, shift C, machine 2

Although there is a degree of risk assessment required in setting the individual acceptable limit for any particular process or product, a widely accepted minimum acceptable Cp value in industry is 1.30 - 1.33.

2.2 Specific Methods

In order to test the application of SPC methods to textile manufacture, it was decided to begin with a pilot study in the spinning department. Spinning is the process that takes cotton fibre, prepares the fibre and then spins it into yarn which can then go on to other processes within the factory. As part of the firm's routine quality assurance programme, samples are taken regularly for all stages of the spinning process and historical data have been retained. It was decided that for this first pilot phase the inspection data already collected (historical data) would be used. This would allow an indication of the extent of process variability to be obtained before further detailed analysis will be undertaken. It would enable the team to select the best approach for a more detailed future investigation.

Data from a total of 29 machine processes were analyzed. As the factory operates on three shifts, where there were sufficient data, the analysis examined each machine for each of the three shifts. For others where fewer data points were available, the analysis looked at data for the process or machine, aggregated over the three shifts.

The measures taken are in the form of weight in grams for a standard length of output. This allows a calculation of the count (measure of fineness) of the resulting spun yarn (Nm). Samples are taken regularly by the factory's quality department team. The corresponding data is captured on manual data collection sheets.

The historical data from these sheets were collated by the researchers, X Bar, R, Cp and Cpk were calculated and the results were converted into electronic (Excel) form for generation of the control charts.

3. RESULTS

For brevity, of the 29 machine processes examined, we will present here the results from just two (Ring Spinning Machine 7; 2nd Drawing Process, shift C machine 2) as the method is the same for all and the outputs will be similar. The control chart for any process that is stable and in statistical control should show data points, all of which lie within the upper and lower control limits and which are randomly centered round the mean. When assessing any individual control chart it is useful to have clear guidelines for deciding whether the process is in control or not. Celone and Buckley [11] list the following control chart features that would immediately suggest that a process is not in control:

7 consecutive data points on one side of the mean, 7 consecutive data points consistently increasing or decreasing, cycling even within control limits; and Any single point outside the control limits.

Using Celone and Buckley's guidelines, the results from Ring Spinning Machine 7 clearly show a process that is out of control. Even though data points are within the control limits, the R chart (Fig. 1a) has more than 7 consecutive data points below the mean and shows signs of cycling above and below the centre line. The X Bar chart (Fig 1b) also shows signs of cycling and although no data point in this chart lies outside of either control limit, there are data points that lie very close to these limits.

The results from 2nd Drawing Process, shift c machine 2 also show a process that is out of control. The Range chart data points (Fig 2a) are within the control limits but data points alternate above and below the centre line

which, on its own, might suggest further investigation is necessary. However the X Bar chart (Fig 2b) shows very strong evidence of lack of process control with signs of cycling and many data points lying way outside of control limits.

In examining the control charts for all 29 machine processes it was concluded that none of the processes was in statistical control. In looking at the process capability analysis indices, for Ring Spinning Machine 7 the Cp and Cpk indices calculated were 0.54 and 0.28 respectively. Both are clearly and significantly below the industry norm of 1.30 – 1.33 and indicate that, even without variation attributable to assignable causes, the current process is not capable of meeting the design specification for the process. In all of the 29 machine processes examined, Cp calculated values were less than 1.00.

4. DISCUSSION

Superficial examination of the raw data sheets compiled in the laboratory of the factory would suggest that the machines are largely running within acceptable parameters. However the analysis of the 29 data sets obtained from the firm's quality team would indicate that, according to SPC calculations, none of the machine processes is in statistical control. The immediate implication is that SPC methods should be introduced to help identify process variability which ultimately impacts on product quality. However, the current analysis does not indicate from where the inherent variability is derived.

Firstly, it is possible that the measurements on which this analysis is based are themselves faulty as pre-existing data from the factory was utilized and the sampling and measuring procedures were not validated. If there are measurement errors then machine adjustments will be made based on incorrect information which will introduce process variability and loss of control.

Secondly, the common cause variability inherent within the system could be such that the system, even without any extra sources of variability, is not capable of meeting the manufacturing specifications laid down. Indeed, calculated Cp and Cpk values would indicate that this could be a significant factor. The machinery in use within the organisation is

modern, recently installed and from manufacturers that have a worldwide reputation for producing high quality equipment. It is unlikely therefore that the machinery itself would be incapable of producing to the manufacturing specifications lay down. However, there are consumables within the system which may be a source of variability, and the operators of the machinery may not be skilled in setting up the machinery so that it runs effectively and in control.

Thirdly, it is likely that there are assignable causes which underlie at least part of the variability of the system. Potential sources of this variation could include factors such as humidity and temperature, both of which may have an impact on cotton fibre. It is also possible that outputs of processes which are out of control that become inputs of subsequent processes can bring with them assignable variation that then becomes compounded. Once again a human element in assignable cause variation must also be considered. From observation on the factory floor, it is suspected that workers are adjusting machines on the basis of single data points. This would not be unexpected as, apart from the raw data collection sheets and experience of working with the machines on a daily basis, machine operators do not have access to statistical or other tools to allow them to make truly data-driven decisions.

5. CONCLUSIONS

The initial evidence shows that all processes measured are out of statistical control, although the sources of variability have not yet been established. It is recognized that at this stage the research group has neither defined individual sources of variability nor arrived at any solutions. However SPC tools have been used to highlight that there is an issue with process variability and that the current practice of process correction based on single data point observations without any SPC analysis is only adding to the instability of the process and increasing process variability. In order to find the source of the error or errors, further investigation of all process steps is required. It is only when the sources of variability in all process steps have been identified and clearly understood can the root causes of the problem be fixed.

6. RECOMMENDATIONS

Subsequent research must seek to pin down and understand the sources of variation within all process steps within the firm's operations. In order to rule out data collection artifacts, it would be necessary to repeat the current investigation but using new data. These data would need to be collected under the supervision and monitoring of the research team, with the calibration of all measuring equipment and the development of a standardized process of taking and calculating the results in order to establish measurement integrity. This will require training as the concept of standard work within the factory processes will be new to most if not all operators.

It is suggested that an SPC control chart is designed and set up, initially for one or two processes, with the chart located at the machine where it is visible to all workers in that section. Measurements will be taken in line with current procedures and the results plotted on the control chart. Relevant workers will require intensive training in order to understand the nature of common cause variability and the criteria that must be met in order that data should trigger process intervention. When this tool and method of controlling the process has been fully understood it is suggested that the SPC approach should be implemented across all processes within the factory.

It is also understood that collecting and analysing data is only the first step and there will be a requirement to set up a range of tools and methodologies to identify causes of variability and non-compliance and to continue to improve the process. Some of these methodologies and tools will require the setting up of well-trained experienced cross-functional teams who are capable of analysing the problem root causes and suggest suitable solutions [8].

There are many tools that can be used to identify problems and link them to solutions which would be helpful in subsequent research. For example, Failure Mode and Effect Analysis (FMEA) would enable researchers (or management) to analyse and assess the risks within each individual process step that can impact process variability and process integrity. The selection of and implementation of these tools is outside the scope of this paper and will

be the subject for further research and subsequent publications. Ultimately, the ideal would be for the company to achieve the capability and skills to work towards Six Sigma levels of process integrity. This current programme of research could represent important early steps in defining the problems and nominating suitable measures, the first two stages in the Six Sigma DMAIC system model.

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