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AN ANALYTICAL STUDY OF PROCESS PARAMETERS OF PACKAGING FILMS: A CASE OF U-FLEX LTD., NOIDA

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Abstract: Production and Process Industries' operations are quite cumbersome. Manufacturing processes tend to produce operational wastages due to various reasons, which can be reduced by identifying and eliminating those reasons. To meet out the customers' expectations and compliances of business world, vigilance during the production process is inevitable. Quality of Packaging Films produced through complex processes is affected by multiple variables. Traditional Statistical Process Control (SPC) methodologies are non-optimal to monitor and control these multiple variables as the effect of one variable can be confounded with the effects of other correlated variables. Further, the Univariate control charts are difficult to examine and analyze because of the large numbers of control charts of each process variable. An alternative approach is to construct a single multivariate T^2 control chart that minimizes the occurrence of false process alarms. This paper studies the application of Multivariate Statistical Process Control (MSPC) charts to monitor packaging film production process in a printing & packaging industry. T^2 diagnosis with Principal Component Analysis (PCA) is applied to analyze the critical process variables. Pareto Analysis is performed to identify the critical process variables for minimizing the rejections. Rewinder Tension and Line Tension are found to be the two most critical variables of the production process of packaging films.

Keywords: Packaging Films production process, MSPC, PCA, Pareto diagrams, Hotelling's T^2

1. INTRODUCTION

Modern technology is now an integral part of nation's society today with high-end package usage increasing rapidly. As consumerism is rising, rural India is also slowly changing into more of an urban society. The liberalization of the Indian economy, coupled with globalization and the influx of the multi-nationals, has improved the quality of all types of primary and secondary packaging. Also, industrialization and the expected emergence of the organized retail industry is fuelling the growth of the packaging industry. As people are becoming more health conscious, there is a growing trend towards well packed, branded products rather than the loose and unpackaged formats. Today even a common man is conscious about the food intake he consumes in his day-to-day life. The Indian packaging industry itself is growing at the rate of 14-15% annually. This growth rate is expected to double in the next two years. According to the Indian Packaging Institute, Indian Packaging industry is USD 14 billion and growing at more than 15%p.a. Manufacturing industries have to tackle the challenge of rising raw material prices. "Zero-waste" and "zero defects" approach may result up to 35% cut in raw material consumption in highly automated production lines. In this paper, packaging films manufacturing industry is studied where packaging films – the biaxially oriented polypropylene films (BOPP) - of different thickness (in microns) are produced. In the recent times, the packaging industry is facing a tough competition in the domestic as well as the global market with reference to quality and cost. While no stone is being left unturned to achieve the highest grades of qualities in poly-films production, we are trying for all avenues of quality controlling measures. Unless the plant competes in quality aspect, it will be difficult to sustain in the domestic as well as in the international market. The aim of this paper is to provide an insightful research and examination of the methodology and implementation of MSPC charts in the process of packaging films production at U-Flex Limited, Noida. Pareto Analysis is also carried out to identify the vital few process variables responsible for high rejections.

2. LITERATURE REVIEW

2.1 Statistical Process Control

Statistical Process Control has become an important approach for process industries since 1920s. The aim of SPC is to achieve higher product quality and lower production cost by minimizing the defects. In general, the statistical process control techniques help us to monitor the production process and to detect abnormal process behavior due to special causes. Once the special causes for abnormal process behavior are detected and further eliminated, the process can be improved, as well as the quality of the product. To monitor the production process W. A. Shewhart developed the statistical process control chart (see Shewhart [18]). This is also known as the Univariate Statistical Process Control (USPC) chart. Besides this, various other parameters viz. Control charts, Multivariate T^2 control charts, Pareto Analysis, R&R study, etc. constitute the cohort of SPC.

The standard assumptions in SPC are that the observed process values are normally, independently and identically distributed with fixed mean and standard deviation when the process is in control. Due to the dynamic behavior, these assumptions are not always valid.

In reality, manufacturing systems are often influenced by many known or unknown disturbances (Box and Kramer [1]). The modern production process is integrated and has become inevitably more complex because the number of process variables that need to be monitored has increased dramatically.

2.2 Multivariate T^2 control charts

Quality control problems originate when processes or products with two or more correlated quality variables are to be monitored or controlled. Hotelling [7] introduced a statistic which uniquely plots multivariate observations simultaneously. This statistic, appropriately named as the Hotelling's T^2, is a scalar that combines information from the dispersion and mean of several variables. Mason and Young [12] implemented multivariate statistical process control using Hotelling's T^2 statistic in the quality processes. Kourti [10] overviewed the latest developments in multivariate statistical process control (MSPC) and its application for fault detection and isolation (FDI) in industrial processes and expatiated the methodology and described how it is transferred to the industrial environment. Sharaf El-Din et al. [17] made a study on the application of Univariate and Multivariate control charts for quality improvement in steelmaking.

Li et al. [11] considered Causation based T^2 decomposition for Multivariate Process Monitoring and Diagnosis. Zhang and Chang [21] proposed a new single control chart which integrates the exponentially weighted moving average (EWMA) procedure with the generalized likelihood ratio (GLR) test for jointly monitoring both the multivariate process mean and variability. Zhang et al. [22] suggested a new multivariate charting scheme for simultaneously monitoring the process mean vector and covariance matrix of a multivariate normal process by using a single chart. Shao et al. [15] demonstrated the combination of statistical process control with engineering process control with binomial distribution concept to effectively determine the starting time of a process fault and to avoid misinterpretation of signals.

To monitor the process mean in a short run, Celano et al. [2] proposed the CUSUM t-control chart and its economic design to overcome the problem of the preliminary estimation of the distribution parameters. Rama

Mohana Rao et al. [14] demonstrated the application of Multivariate Statistical Process Control (MSPC) charts to monitor hot metal production process in a steel industry. Here, T^2 diagnosis with Principal Component Analysis (PCA) was implemented to analyze the critical process variables. Sparks [16] used Hotelling T^2 control charts in some realistic problems and tried to give their solutions with practical examples. Yang et al. [20] studied Hotelling T^2 multivariate quality control charts for monitoring the turbine's performance and relative contribution of each attribute is calculated for the data points out of upper limits to determine the set of potential attributes. Henneberg et al. [5] showed an oil condition and wear debris evaluation method for ship thruster gears using T^2 statistics to form control charts from a multi-sensor platform. The proposed method considers the different ambient conditions by multiple linear regressions on the mean value as substitution from the normal empirical mean value.

2.3 Pareto Analysis

Pareto analysis is a statistical technique in decision making which is used for identifying and prioritizing a limited number of tasks that contribute a significant overall effect. It is one of the most robustly used and easy to implement method. Pareto analysis is a relatively easy methodology that is applied when trying to determine which tasks or factors in an organization will have the most substantial impact (see, Cervone [3]). It orders the data/factors in the decreasing order from the highest frequency of occurrences to the lowest frequency of occurrences. The total frequency is summed up to 100 percent. The *"vital few"* items occupy a significant amount (80 percent) of cumulative percentage of occurrences and the "useful many" occupy only the remaining 20 percent of occurrences, popularly known as the 80-20 rule, developed by Italian Economist Vilfredo Pareto (see also, Karuppusami and Gandhinathan [9]). The results of a Pareto analysis are typically depicted through a Pareto chart. The chart suggests the various factors under consideration in ranked order. The presentation of a Pareto chart is in the form of a bar graph in descending order and helps to predict easily which factors are vital few by providing a clear display through overcastting a line graph that intersects at 80 percent cumulative percentage and also helps in determining those factors which have least amount of benefits and vice-versa. In the case study of foundry industry by Perzyk [13], Pareto chart represents that the foundry staff should concentrate on reducing defects like 'sand inclusions' and 'gas holes', which make up to 72% of all the defects. Chandna and Chandra [4] analyzed forging operations that produce six cylinder crankshafts used in trucks and buses. Talib et al. [19] applied "Pareto Analysis" to sort and arrange the critical success factors (CSFs) according to the order of criticality for the implementation of total quality management (TQM). Joshi & Kadam [8] applied Pareto Analysis and cause effect diagram (CED) for minimization of defects in manual casting process in a foundry and presented the correct cause and correct remedial factors to improve quality level and productivity of the organization. Hossen et al. [6] implemented Pareto Analysis & CED to examine stoppage losses in a textile company. They revealed that idling and minor stoppage and breakdown losses are responsible for 89.3% of total stoppage losses.

3. OBJECTIVE

To analyze and monitor the process, estimation of Multivariate T^2 control chart along with Principal Component Analysis and Pareto Analysis is presented for U-flex Ltd, Noida.

4. METHODOLOGY

4.1 Pareto Analysis

For minimizing the occurrences of defects, the prioritization of defects will be done using Pareto diagrams in which "Vital Few" defects would be concentrated upon, contributing 70%-80% of the rejections. It will then be identified, during which process the critical defects are emanating.

4.2 Identification of responsible process (es) and variables

The practitioners should know what input variables need to be stable in order to achieve a stable output, and then these variables are rightly monitored. When the number of monitored variables is only 1 (N=1), then it is suggested to use the USPC control charts and when there are more than 1 (N>=2) variables then it needs to be examined whether these variables correlate with each other. Correlation coefficient can be used as a criterion to decide the strength of the correlation between variables.

4.3 Control limits construction (Normal Data 'Specific Time Period')
It is important to purge the preliminary data to obtain an in-control data. The data purging includes identifying and removing outliers and/or substitute missing data with an estimate. This in-control data plus / minus three sigma is established as a norm to monitor the future observations and to see whether it significantly deviates away from the norm. The out-of-control observations are removed to analyze the historic/future observations.

If we are sampling from a distribution with mean μ and standard deviation σ, the sample means from subgroups of n observations vary according to a distribution with mean and standard deviation given by: (Subgroups of size n) $\mu_{x\ bar} = \mu,\ \sigma_{x\ bar} = \sigma/\sqrt{n}$, and almost all subgroup means will lie within the 3-sigma limits: (3-sigma limits for subgroup means) $\mu_{x\ bar} \pm 3\ \sigma_{x\ bar}$. If we know the true values of μ and σ, we then use,

Upper Control Limit,

$$UCL = \mu_{x\ bar} + 3\ \sigma_{x\ bar}$$

Lower Control Limit,

$$LCL = \mu_{x\ bar} - 3\ \sigma_{x\ bar}$$

The new subgroup means outside this range would be considered to provide a signal that the process was out of control.

4.4 Analysis of historic/future observations

A period of historic/future observation with specific number of observations will be analyzed with T^2 generalized control chart and we see if any observation is out-of-control. The Hotelling's T^2 generalized statistic is calculated for each new observation based on the mean and the covariance matrix obtained from the in-control data set.

For the subgroup size $n = 1$, the Hotelling T^2 statistic is calculated as:

$$T^2 = (x - x\ bar)^T S^{-1} (x - x\ bar)$$

where, x is the observation vector, $x\ bar$ is the sample mean vector, and S^{-1} is the inverse of the covariance matrix.

control chart signals the out-of-control situation during the future observations. But it is not known which variable or set of variables is responsible for it. MSPC diagnosis is useful to identify those variables.

For analyzing data, MINI TAB, STATISTICA and SPSS software are used by us in this paper.

4.5 Diagnosis of critical variables
An out-of-control situation occurs while using USPC control charts, then the responsible variable(s) will reveal easily. While using the T^2 control chart, the diagnosis of responsible variable(s) of an out-of-control situation will require more analysis. The contribution of each variable to the out-of-control observation can be determined by using the Principal Component Analysis.

5. OVERVIEW OF PRODUCTION PROCESS AT U-FLEX LTD., NOIDA

5.1 Biaxially Oriented Polypropylene Films - BOPP
The Film Business at U-Flex produces over 68,000 tonnes per annum (TPA) of BOPP films on its three state-of-the-art lines. These films come in the thickness range of 8 – 75 microns and are available in plain, heat-sealable, metallisable, matte, pearlised, cavitated, overwrap, white opaque and specialty film

grades variety. As far as the performance properties of BOPP are concerned, the following parameters are judged:

- Good mechanical strength;
- Good chemical resistance;
- Good dimensional stability;
- Excellent barrier against moisture;
- Superior optical clarity;
- One or both side heat sealable;
- Good stiffness;
- Resistance to tear and abrasion

Most commercially available BOPP films are multi-layer films such as three layers, five layers and seven layers. The three-layer film, for example, the middle of the core layer is generally homo-polymer polypropylene (PP), providing excellent mechanical properties, two outer layers of copolymer PP, to provide better sealing performance.

1. Raw material is treated to dry the moisture content of the raw materials which affects the degree of degradation of the film and the film on the bubble and hence the production of the BOPP film. Especially the co-extruded film and the surface layer raw materials contain many hygroscopic additives which make it necessary to subject the raw materials to dry processing, in order to remove the high water content of these raw materials.
2. Extruded cast homo-polymer copolymerized PP is extracted by the extruder, chill rolled in the cast, so that the three co-extruded PP film is subjected to rapid cooling due to which the molecular chain do not have sufficient time to orderly arrange themselves in the process of solidification. The purpose of this operation is to reduce the PP before the degree of crystallinity in order to improve the toughness of the film, so that the film is not easily ruptured and can bear higher tensile stresses.
3. Winding volume- this volume contains 7% - 10% of the total volume of the polymer and the winding tension decreases with increasing diameter so as to ensure that the film acquires the capability of good contraction, otherwise, the great stress caused by shrinkage of the film will cause the film to be deformed, or even stick together, rendering it unusable.

5.2 Blown Film Extrusion*

Film (Tubular film) extrusion is the process by which most plastic films are made for the packaging industry. The process involves extrusion of a plastic through a circular die, followed by "bubble-like" expansion. The principal advantages of manufacturing film by this process include the ability to:

- Produce tubing (both flat and gusseted) in a single operation.
- Regulation of film width and thickness by control of the volume of air in the bubble, the output of the extruder and the speed.
- Eliminate end effects such as non uniform temperature that can result from flat die film extrusion.
- Capability of biaxial orientation (allowing uniformity of mechanical properties).
- Blown Film Extrusion can be used for the manufacture of co-extruded, multi-layer films for high barrier applications such as food packaging.

***Source: U-Flex, Noida**

RAW MATERIAL
↓
PROCESSING
↓
NIP ROLLS
↓
AIR RING

Figure 1: Flowchart for Blown Film Extrusion

Raw Material - Raw material or polymer in the form of small beads or pellets.

Processing– The pellets are fed from a hopper into the barrel of the extruder. The polymer enters the feed throat and comes into contact with screw. At the front of the barrel the molten plastic leaves the screw.

Nip Rolls - It is then pulled upwards from the die by a pair of nip rolls, high above the die (the height of which depends on the amount of cooling required). Changing the speed of these nip rollers changes the gauge of film. The nip rolls flatten the bubble into a double layer of film, if lay flat or gusseted film can be formed using the gusseted boards.

Air Ring - Around the die there exists an air ring. The air ring cools the film as it travels upwards.

The historical process data, of approximately 100 days, is considered under this study and a total of 1000 observations (200 samples) are analyzed. The various inputs for packaging film production process are Line Tension (Kg/cm^2), Nip Pressure (Kg/cm^2), Un-winder Tension (Kg/cm^2), Re-winder Tension (Kg/cm^2), Melting Point (^{0}C), Color L (CIE), Color b (CIE), Dust content (ppm), Oligomer (%), Intrinsic Viscosity (I.V.) (dl/g), End group (meq/Kg), Moisture content (w/w%), Ash content (ppm), etc.

The packaging film with lower ash content and I.V. is required for the production of quality poly-films. For the production of quality packaging films, it is essential to identify and optimize raw materials quality and machine operating conditions. To reduce the abnormality of poly- films, the machine is supposed to operate in optimized conditions along with the following compositions of raw material:

M/c parameters:

Line Tension: 62, Nip Pressure: 270, Un-winder Tension: 90, Re-winder Tension: 72

Raw Material parameters:

Intrinsic Viscosity (at 25^{0}C): 0.610-0.645, End Group: 45 max, Moisture Content: 0.40 max, Ash content: 400 ppm.

6. RESULTS & DISCUSSION

6.1 Process Investigation and Identification of critical process variables

Generally, not all quality attributes and process variables are equally important. Some of them may be very important (critical) for quality of the product performance and some of them may be less important. Monitoring a large number of variables is not efficient. Only the critical quality characteristics should be selected and monitored as the critical variables are directly related to the rejection criteria. The practitioners should know what input variables need to be kept stable to achieve a stable output and then these variables are appropriately monitored. To identify the same, we must take into account that which defects are significantly contributing in rejections or downgrading. The Pareto Analysis should be carried out to identify the vital few defects; relevant critical variables can be segregated. Fig 2 shows the Pareto Analysis for the data under study:

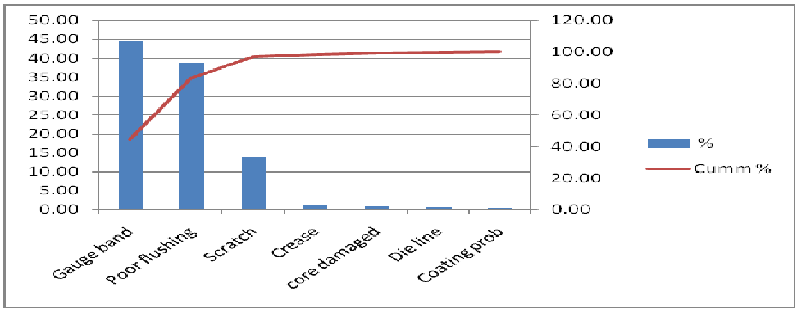

Figure 2: Pareto Analysis to identify vital few defects

Here, the Pareto Analysis reveals that merely two particular defects viz. gauge band and poor flushing are significantly contributing, approximately 90%, to the rejection or downgrading the material. The critical process variables of the process, pertaining to the quality, are identified by consultation with the Senior Heads of Production and Quality Departments. Accordingly, Line Tension (Kg/cm^2), Nip Pressure (Kg/cm^2), Un-winder Tension (Kg/cm^2), Re-winder Tension (Kg/cm^2), I.V. (dl/g), End group (meq/Kg), Moisture content (w/w%), Ash content (ppm) are identified as the critical process variables (p – value < 0.05) to find out dependency and relationship between them, which may influence the quality of the manufactured polypropylene film.

It is also necessary to examine the sample adequacy and multi co-linearity among these variables. Kaiser-Meyer-Olkin Measure (KMO) and Bartlett's Test of Sphericity are carried out using SPSS 20 for sample adequacy and multi-co-linearity among the critical variables respectively. Table 1 exhibits the results of the same. Since KMO value here is 0.563 (which is greater than 0.50) it shows that the sample is adequate. Also, the p-value of Bartlett's Test of sphericity is 0.000 (which is less than 0.05) and it shows that the variables do have a co-linearity i.e. have correlation among them.

Coefficient of correlation between variables is a good indicator to know the extent of relation among the variables. The correlations among the process variables are generated with the help of STATISTICA 10 statistical software. Table 2 shows the correlation among the process variables generated from the data.

Table 1: KMO & Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.563
Bartlett's Test of Sphericity	Approx. Chi-Square	365.464
	df	28
	Sig.	.000

Table 2: Correlations among Critical Process Variables of BOPP production

Variable	LINE TENSION	NIP PRESSURE	UNWINDER	REWINDER	I.V.	END GROUP	MOISTURE CONTENT	ASH CONTENT
LINE TENSION	1.0000	.1361	-.0913	-.0390	-.0501	-.0040	-.0142	-.0109
	p= ---	p=.000	p=.004	p=.217	p=.113	p=.898	p=.654	p=.730
NIP PRESSURE	.1361	1.0000	-.2326	.1190	-.0363	.0894	-.0350	.0365
	p=.000	p= ---	p=.000	p=.000	p=.251	p=.005	p=.269	p=.248
UNWINDER TENSION	-.0913	-.2326	1.0000	-.0886	.0324	.0581	.0804	-.0378
	p=.004	p=.000	p= ---	p=.005	p=.306	p=.066	p=.011	p=.232
REWINDER TENSION	-.0390	.1190	-.0886	1.0000	-.0036	.1038	-.1364	.0818
	p=.217	p=.000	p=.005	p= ---	p=.909	p=.001	p=.000	p=.010
I.V.	-.0501	-.0363	.0324	-.0036	1.0000	-.4323	.0920	.1190
	p=.113	p=.251	p=.306	p=.909	p= ---	p=0.00	p=.004	p=.000
END GROUP	-.0040	.0894	.0581	.1038	-.4323	1.0000	-.0647	-.1452
	p=.898	p=.005	p=.066	p=.001	p=0.00	p= ---	p=.041	p=.000
MOISTURE CONTENT	-.0142	-.0350	.0804	-.1364	.0920	-.0647	1.0000	-.0934
	p=.654	p=.269	p=.011	p=.000	p=.004	p=.041	p= ---	p=.003
ASH CONTENT	-.0109	.0365	-.0378	.0818	.1190	-.1452	-.0934	1.0000
	p=.730	p=.248	p=.232	p=.010	p=.000	p=.000	p=.003	p= ---

From the Table 2, it is observed that Line Tension is having weak positive correlation with Nip Pressure and very weak negative correlations with Un-winder Tension, Re-winder Tension, I.V., End Group, Moisture content and Ash content. Nip Pressure shows weak positive correlations with Re-winder Tension, End Group and Ash content but shows weak negative correlations with Un-winder Tension, I.V. and Moisture content. Un-winder Tension shows weak positive correlations with I.V., End Group and Moisture content but shows weak negative correlations with Re-winder Tension and Ash content. Re-winder Tension reveals positive correlations with End group and Ash content but shows weak negative correlations with I.V. and Moisture content. I.V. shows weak positive correlations with Moisture content and Ash content but having moderate negative correlation with End Group. End group has weak negative correlations with Moisture content and Ash content. Moisture content has weak negative correlations with Ash content. Since the p-values are smaller than 0.01, this indicates that there is sufficient evidence that the correlations are significant at 1% level of significance.

6.2 Control limit construction

A set of data containing observations on 200 samples are analyzed using the X-Bar chart with customary plus/ minus three sigma control limits to identify the critical observations. The individual control charts for the critical process variables are shown in Figure 3 through Figure 10.

X-Bar charts of Line Tension, Re-winder Tension and Moisture content are shown in Fig. 3, Fig. 6 and Fig. 9 respectively. From these figures, it is observed that the sample observations (167,183,187) for Line Tension, the observations (164,183,185) for Re-winder Tension and the observation (164) for Moisture content fall outside the control limits, implying an unstable process. X-Bar charts of other critical variables viz. Nip Pressure, Un-winder, I.V., End group and Ash content are shown in Fig. 4, Fig. 5, Fig. 7, Fig. 8 and Fig. 10 respectively. From these figures we observe that the process is falling within the specification limits thus implying a stable process.

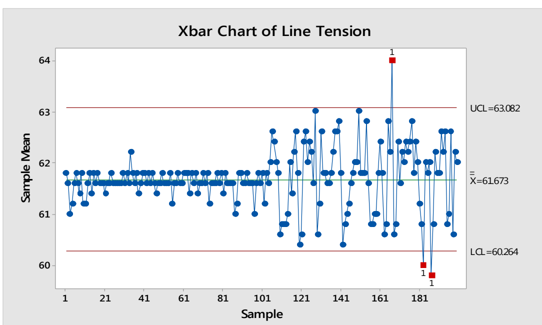

Figure 3: X-Bar Chart of Line Tension

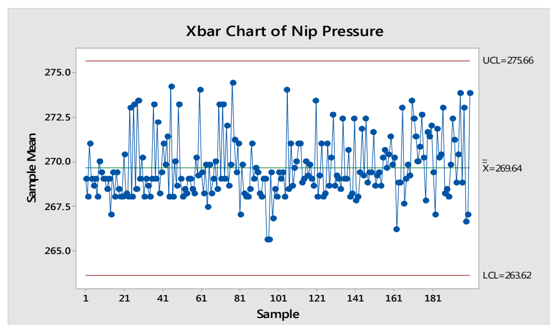

Figure 4: X-Bar Chart of Nip Pressure

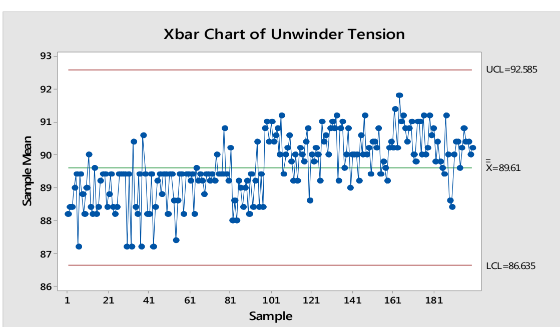

Figure 5: X-Bar Chart of Un-winder Tension

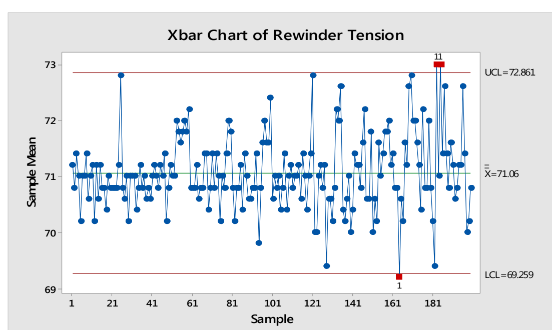

Figure 6: X-Bar Chart of Re-winder Tension

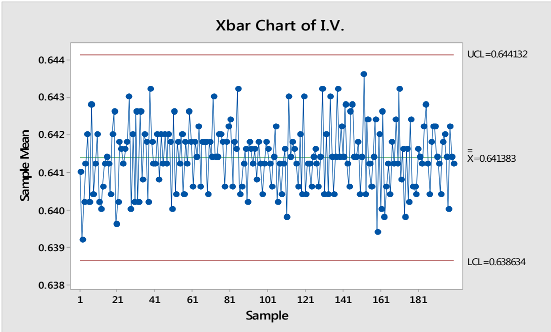

Figure 7: X-Bar Chart of I.V.

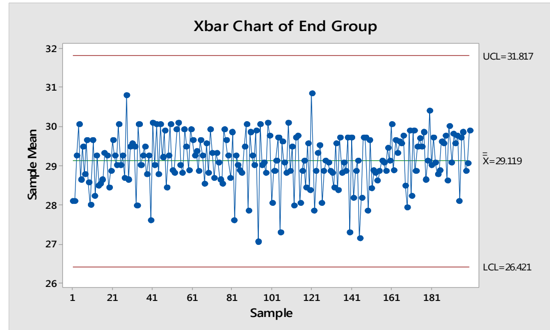

Figure 8: X-Bar Chart of End Group

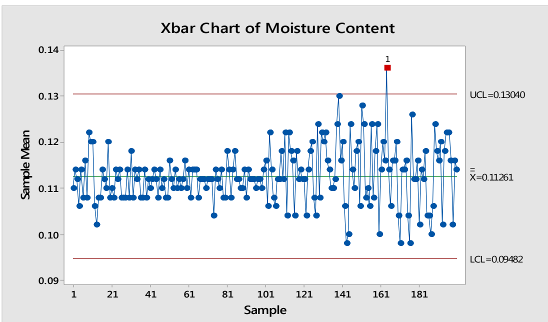

Figure 9: X-Bar Chart of Moisture Content

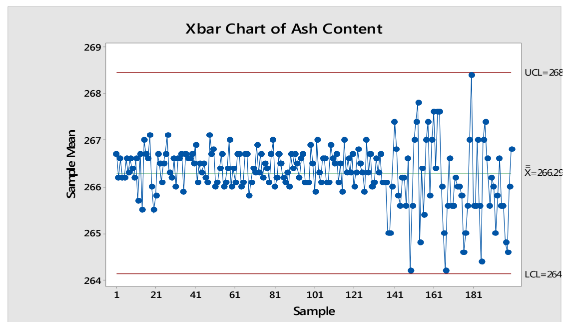

Figure 10: X-Bar Chart of Ash Content

These UPSC control charts are necessary to identify the out-of-control observations and to establish the norms to monitor the future observations.

6.3 Hotelling T^2 Control Chart Construction

The T^2 control chart is also constructed (Fig. 11) to see whether any observation containing a problematic relationship between the parameters exits. A view of the Fig.11 at once reveals that there is an indication of out-of-control of six observations (164, 167, 176, 183, 185 and 187) all of which fall outside the control limits.

Still it is not known which variable or set of variables is responsible for throwing the process out-of-control and hence PCA is adopted to identify contribution of each of the critical process variables.

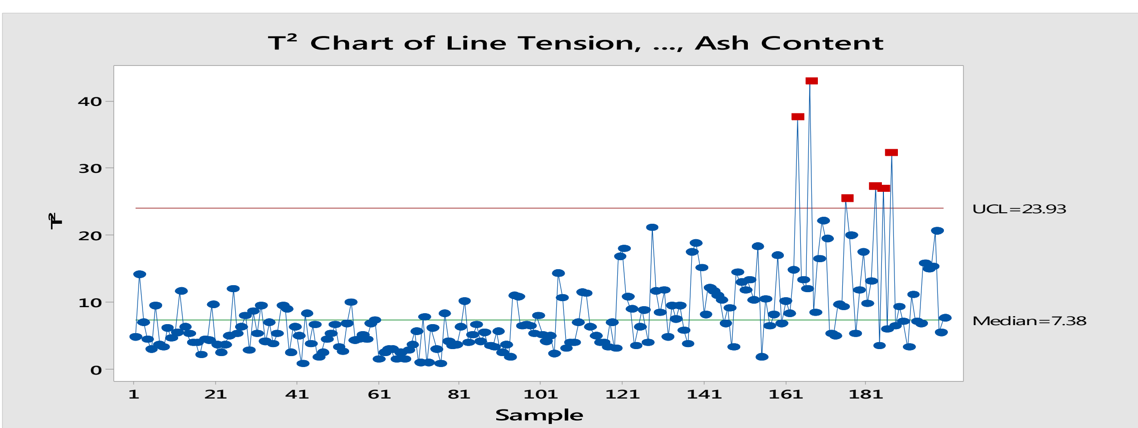

Figure 11: T^2 Generalized variance chart for the critical process variables.

7. FINDINGS

T^2 diagnosis is carried out with Principal Component Analysis. Principal Component Analysis is a variable reduction procedure.

Table 3: Component Score Coefficient Matrices of critical variables of critical samples

SAMPLES	**Component**	
	1	**2**
SAMPLE NO 164 : Component Score Coefficient Matrix		
LINETENSION	.586	.127
MOISTURECONTENT	.549	.005
ASHCONTENT	.123	1.016
SAMPLE NO 167: Component Score Coefficient Matrix		
LINETENSION	1.239	.461
ASHCONTENT	.461	1.239
SAMPLE NO 176: Component Score Coefficient Matrix		
UNWINDERTENSION	.530	-.146
REWINDERTENSION	.079	.607
MOISTURECONTENT	-.062	.507
ASHCONTENT	.584	.144
SAMPLE NO 183: Component Score Coefficient Matrix		
LINETENSION	1.491	.745
REWINDERTENSION	.745	1.491
SAMPLE NO 185: Component Score Coefficient Matrix		
REWINDERTENSION	0.000	1.000
ASHCONTENT	1.000	0.000
SAMPLE NO 187: Component Score Coefficient Matrix		
LINETENSION	-.098	1.014
REWINDERTENSION	1.014	-.098

Table 3 shows the component score coefficient matrices of critical variables of critical samples. Normalized PCA scores are calculated to see which one(s) has/have higher scores. Fig.13 shows the chart of overall average contribution of each variable. The analysis indicates that the data are auto correlated.

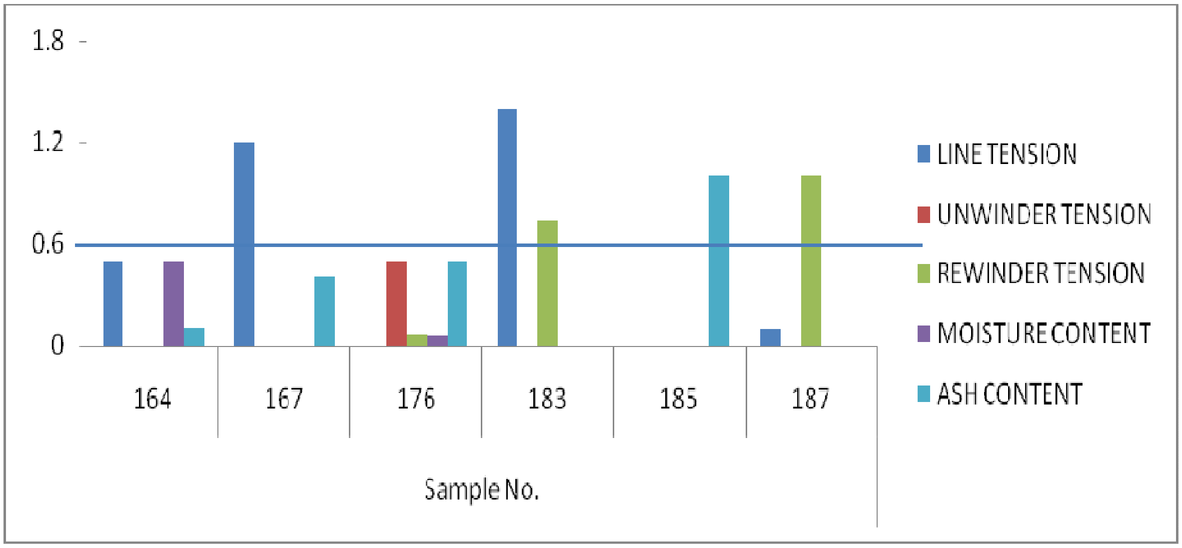

Figure 12: Overall average contribution of critical process variables

Table 4: Diagnosis of critical process variables

S. No.	Observation Number	Signaled by MSPC	Potential problematic variables(s)	Signaled by USPC
1	164	Out of control	Line Tension Moisture Content Ash content	In control Out of control In control
2	167	Out of control	Line Tension Ash content	Out of control In control
3	176	Out of control	Un-winder Tension Re-winder Tension Moisture content Ash content	In control In control In control In control
4	183	Out of control	Line Tension Re-winder Tension	Out of Control Out of control
5	185	Out of control	Ash content	In control
6	187	Out of control	Line Tension Re-winder Tension	Out of control In control

Diagnosis of the out-of-control observations for potential process variables are shown in Table 4. From the table, it is noticed that for 176 and 187 observations, Re-winder Tension is signaled out-of-control in MSPC chart, the same was signaled in control in USPC chart. For observation 183, Re-winder Tension is signaled out-of-control in both MSPC and USPC. For the observations 167, 183 and 187, Line Tension is signaled out-of-control in both MSPC and USPC. Ash content is signaled out-of-control in MSPC charts for observations 164,167,176 and 185 but is signaled in control in USPC charts.

8. CONCLUSION

The PCA technique is applied by us in this case study and it reduces the number of critical process variables to potentially responsible variables to reduce the redundancy in measuring. These findings indicate a clear distinction between USPC and MSPC. Ash content contribution in the process needs to be controlled by improving the crystallinity of the material granules. Re-winder Tension and Line Tension process variables come out to be the significant critical variables and both of them require more vigilance. The same can be achieved by adjusting the PLC parameters more frequently and maintenance operations of the machine must be carried out at regular intervals. The relationship among the variables must be interpreted with caution. The sample used by us is a very small proportion and further research studies with much larger sample sizes would be required to ensure appropriate generalization of the findings of this study. The current study can be used as an input for further cause-and-effect analysis in the process in a detailed manner.

9. SUGGESTIONS

The control of dynamic behavior of process variables in a process has been challenging and often inexpressible in practice. Some industries use conventional statistical process control techniques which are not valid for monitoring the dynamic behavior of the critical variables. Others rely on experience and guesswork. When there is more than one quality characteristic which is to be monitored, it is advisable to use MSPC charts to avoid false signals associated with using USPC chart for each variable. This paper explores the problems in process monitoring variables in USPC. In some complex processes, when more number of variables are correlated with each other, monitoring simultaneously with MSPC charts having the problem of interpreting an out-of-control signal and detecting their contribution is difficult and needs further investigation. In such situations, we recommend using PCA for detailed study.

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