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Study the application of Multivariate Statistical Process Control (MSPC) charts to monitor packaging film production process in a printing & packaging industry

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Abstract:
The activities of the production and process industries are very laborious. For a variety of reasons, manufacturing processes frequently result in operational waste, which can be minimized by determining and removing the underlying causes. Vigilance during the production process is necessary to achieve consumer expectations and comply with business world regulations. A multitude of factors influence the quality of packaging films made using intricate techniques. Due to the possibility of confusing the effects of one variable with those of other associated variables, traditional Statistical Process Control (SPC) approaches are not the best means of monitoring and controlling these many variables. Furthermore, because each process variable has a huge number of control charts, Univariate control charts are challenging to evaluate and interpret. An alternative approach is to construct a single multivariate T^2 control chart that minimizes the occurrence of false process alarms. This study examines how the printing and packaging industries use Multivariate Statistical Process Control (MSPC) charts to track the production of packaging films. Principal Component Analysis (PCA) is used in T^2 diagnostics to examine the important process variables. To find the crucial process variables for reducing the rejections, Pareto analysis is used. It has been determined that the two most important factors in the packaging film production process are rewinder tension and line tension.

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

1. INTRODUCTION

The nation's society nowadays is deeply ingrained with modern technology, and the use of high-end packages is growing quickly. Rural India is gradually becoming more urbanized as consumerism increases. The quality of primary and secondary packaging has improved as a result of globalization, the liberalization of the Indian economy, and the entrance of multinational corporations. The packaging industry is expanding due to factors such as industrialization and the anticipated rise of organized retail. There is an increasing tendency away from loose and unpackaged forms and toward well-packed, branded products as people become more health aware.. Even the average man is aware these days of the amount of food he consumes on a daily basis. The packaging sector in India is expanding at a rate of between 14 and 15 percent each year. Within the next two years, this growth rate is anticipated to double. The Indian Packaging Institute estimates that the country's packaging market is worth $14 billion and is expanding at a rate of more than 15% annually. Growing costs for raw materials are a problem that manufacturing firms must deal with. In highly automated manufacturing lines, a "zero-waste" and "zero defects" approach may lead to a reduction in raw material usage of up to 35%. This study examines the packaging film manufacturing business, which produces biaxially oriented polypropylene films (BOPP) with varying thicknesses measured in microns. Regarding quality and price, the packaging business has recently faced fierce competition both domestically and internationally. We are exploring every possibility for quality control procedures, even as we strive to produce poly-films with the best possible grades of quality. It will be challenging for the factory to survive in both the domestic and foreign markets if it cannot compete on quality. This paper's objective is to present a perceptive analysis of the approach and application of MSPC charts in the packaging film production process 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

Since the 1920s, statistical process control has grown in importance for process industries. By decreasing faults, SPC seeks to increase product quality and decrease manufacturing costs. Statistical process control approaches, in general, aid in the monitoring of the production process and the identification of anomalous process behavior resulting from unique sources. Both the process and the product's quality can be enhanced after the unique reasons for the aberrant process behavior are found and removed further. W. A. Shewhart created the statistical

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process control chart (see Shewhart [18]) to monitor the production process. The Univariate Statistical Process Control (USPC) chart is another name for this. In addition, the SPC cohort is composed of a number of additional parameters, such as control charts, multivariate T2 control charts, Pareto analysis, R&R studies, etc. When the process is under control, the standard assumptions in statistical process control (SPC) state that the observed process values have a fixed mean and standard deviation and are normally, independently, and identically distributed. The dynamic nature makes these assumptions invalid in all cases.

Actually, a variety of known and unknown disruptions frequently have an impact on industrial systems (Box and Kramer [1]). Because there are so many more process variables that need to be monitored, the modern manufacturing process is interconnected and has unavoidably grown more complex.

Multivariate T^2 control charts

When processes or products with two or more linked quality variables need to be monitored or regulated, quality control issues arise. Hotelling [7] presented a statistic that depicts multivariate observations simultaneously in a unique way. This scalar statistic, aptly called the Hotelling's T^2, integrates data from the dispersion and mean of multiple variables. Mason and Young [12] used Hotelling's T^2 statistic in the quality processes to apply multivariate statistical process control. Kourti [10] provided an overview of the most recent advancements in multivariate statistical process control (MSPC) and its use in industrial processes for fault detection and isolation (FDI). The author further elaborated on the technique and explained how it is applied in an industrial setting. A study on the use of univariate and multivariate control charts for quality improvement in steelmaking was conducted by Sharaf El-Din et al. [17].

Causation-based T2 decomposition was examined by Li et al. [11] for multivariate process monitoring and diagnosis. In order to simultaneously monitor the multivariate process mean and variability, Zhang and Chang [21] created a new single control chart that merges the generalized likelihood ratio (GLR) test with the exponentially weighted moving average (EWMA) approach. A new multivariate charting approach was proposed by Zhang et al. [22] to monitor the process mean vector and covariance matrix of a multivariate normal process simultaneously with a single chart. In order to accurately identify the beginning time of a process fault and prevent signal misinterpretation, Shao et al. [15] showed how to combine statistical process control with engineering process control using the binomial distribution approach.

Celano et al. [2] introduced the CUSUM t-control chart and its economic design to monitor the process mean in the short run and solve the issue of the preliminary estimation of the distribution parameters. The use of Multivariate Statistical Process Control (MSPC) charts to track the hot metal manufacturing process in the steel sector was illustrated by Rama Mohana Rao et al. [14]. In this case, the essential process variables were analyzed using Principal Component Analysis (PCA) in conjunction with T2 diagnostic. Sparks [16] attempted to provide solutions with real-world examples while utilizing Hotelling T2 control charts in a few realistic scenarios. In order to monitor the performance of the turbine, Yang et al. [20] examined Hotelling T2 multivariate quality control charts. To identify the set of potential attributes, the relative contribution of each attribute is calculated for the data points outside the upper bounds. A method for evaluating worn debris and oil quality for ship thruster gears was demonstrated by Henneberg et al. [5]. T2 statistics were used to create control charts from a multi-sensor platform. By doing numerous linear regressions on the mean value instead of using the standard empirical mean value, the suggested method takes into account the various ambient conditions.

Pareto Analysis

A statistical technique called Pareto analysis is applied in decision making to discover and rank a small number of tasks that have a major overall impact. It's one of the most widely utilized and simple methods to use. When attempting to ascertain which activities or elements within an organization will have the biggest influence, Pareto analysis is a rather simple technique to use (see, Cervone [3]). From the highest frequency of occurrences to the lowest frequency of occurrences, it arranges the data and factors in descending order. One hundred percent is the total frequency. The 80-20 rule, which was developed by Italian economist Vilfredo Pareto, states that the "useful many" only occupy 20% of all occurrences, while the "vital few" account for a significant amount (80%) of the cumulative percentage of occurrences (see also, Karuppusami and Gandhinathan [9]). A Pareto chart is commonly used to illustrate the outcomes of a Pareto study. The chart presents the several elements that are being considered in a prioritized order. A Pareto chart is presented as a bar graph that is sorted by decreasing order. It makes it easy to predict which factors are important few by overlaying a line graph that intersects at the 80 percent cumulative percentage. It also helps identify which factors have the least amount of benefits and vice versa. According to the Pareto chart in Perzyk's case study on the foundry business [13], the employees of the foundry should focus on minimizing defects such as "sand inclusions" and "gas holes," which account for 72% of all faults. The forging processes utilized to create the six cylinder crankshafts used in trucks and buses were examined by Chandna and Chandra [4]. For the purpose of implementing total quality management (TQM), Talib et al. [19] used "Pareto Analysis" to sort and arrange the key success factors (CSFs) in the order of criticality. Joshi & Kadam [8] provided the right cause and appropriate corrective elements to raise the organization's productivity and quality level while using Pareto Analysis and Cause Effect Diagrams (CED) to minimize faults in a foundry's manual casting process. 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

Pareto diagrams will be used to prioritize defects in order to reduce their frequency. The "Vital Few" faults, which account for 70%–80% of rejections, will be the focus of this process. After that, the process of identifying the important faults will begin.

4.2 Identification of responsible process (es) and variables

It is imperative for practitioners to ascertain which input factors must remain constant to attain a stable output, and then appropriately monitor these variables. It is advised to utilize USPC control charts when there is only one (N=1) variable being monitored; if there are more than one (N>=2) variables, it is necessary to determine whether the variables are correlated. The correlation coefficient is a useful metric for determining how strongly variables are correlated.

4.3 Control limits construction (Normal Data 'Specific Time Period')

To get an in-control set of data, it's critical to remove the preliminary data. Outliers are found and eliminated as part of the data cleansing process, and any missing data is replaced with an estimate. The purpose of establishing this in-control data plus or minus three sigma as a norm is to keep an eye on upcoming observations and determine if they considerably depart from it. To examine the past and future observations, the out-of-control observations are eliminated.

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

Using a T^2 generalized control chart, a period of past and future observations with a predetermined number of observations will be examined to see whether any observations are out of control. Every time a new observation is made, the Hotelling's T^2 generalized statistic is computed using the covariance matrix and mean 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

If an out-of-control scenario arises when utilizing USPC control charts, the variable(s) in question will become evident. Further analysis will be needed to identify the causative variable or variables in an out-of-control situation when utilizing the T^2 control chart. The Principal Component Analysis can be used to ascertain each variable's contribution to the out-of-control event.

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

5.1 Biaxially Oriented Polypropylene Films - BOPP

Using three cutting-edge lines, the Film Business at U-Flex manufactures more than 68,000 tonnes of BOPP films annually (TPA). These films are available in plain, heat-sealable, metallisable, matte, pearlized, cavitated, overwrap, white opaque, and specialty film grades. Their thickness ranges from 8 to 75 microns. Regarding BOPP's performance properties, the following metrics are evaluated:

- 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

The majority of BOPP films that are sold commercially are multi-layer films with three, five, or seven layers. In a three-layer film, for instance, the two outside layers are usually copolymer polypropylene (PP), which improves sealing performance, and the center layer is often homo-polymer polypropylene (PP), which offers outstanding mechanical qualities.

- The raw materials are dried to reduce their moisture content, which has an impact on the rate of film degradation, the film on the bubble, and ultimately the creation of BOPP film. Since various hygroscopic additives are included in raw materials, especially in the co-extruded film and top layer, dry processing is required to eliminate the raw materials' high water content.

- Cast that was extruded the extruder extracts the homo-polymer copolymerized polypropylene (PP) and chill rolls it in the cast. This causes the three co-extruded PP films to cool down quickly, preventing the molecules from having enough opportunity to arrange themselves in an ordered manner during the solidification process. In order to increase the film's toughness and its ability to withstand higher tensile stresses, the goal of this operation is to decrease the PP before the degree of crystallinity.

- Winding volume: this volume makes up 7% to 10% of the polymer's total volume. The winding tension decreases as the diameter increases to ensure that the film can undergo good contraction; otherwise, the film's great stress from shrinkage will cause it to become deformed or even stick together, making it useless.

5.2 Blown Film Extrusion*

The majority of plastic films used in the packaging sector are produced using the method of film (tuberular film) extrusion. The procedure entails "bubble-like" expansion after a plastic is extruded via a circular die. The following are the main benefits of using this method to manufacture film:

- 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 - Then, two nip rolls that are positioned high above the die (whose height varies depending on the needed cooling) pull it upward from the die. The gauge of the film is altered by varying the speed of these nip rollers. If the bubble is laid flat, the nip rollers flatten it into a double layer of film; alternatively, the gusseted boards can be used to make a film with gussets.

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.

To produce superior poly-films, packaging film with a lower ash content and I.V. is needed. The quality of raw materials and machine operating parameters must be identified and optimized for the manufacturing of high-grade packaging films. The following raw material compositions, when combined with the machine operating under optimal conditions, are intended to reduce the abnormality of poly-films:

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

In general, not every process variable and quality parameter has the same weight. A portion of them might be less significant, while others might be crucial for the product's performance quality. Keeping an eye on a lot of different factors is inefficient. Since the critical variables are directly related to the rejection criteria, only the critical quality features should be chosen and tracked. In order to obtain a stable output, practitioners should be aware of which input factors must remain constant. These variables should then be properly monitored. We need to consider which faults are substantially causing rejections or downgrading in order to identify the same.

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:

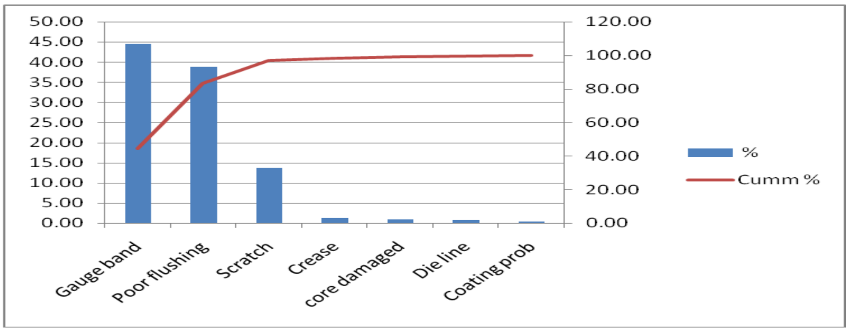

Figure 2: Pareto Analysis to identify vital few defects

Here, the Pareto Analysis shows that only two specific defects—the gauge band and inadequate flushing—are responsible for about 90% of the material's rejection or downgrade. Senior Heads of the Production and Quality Departments consult in order to determine the process's essential variables that affect quality. 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.

Examining the multico-linearity and sample adequacy of these variables is also essential. SPSS 20 is used to perform the Bartlett's Test of Sphericity and the Kaiser-Meyer-Olkin Measure (KMO), which measure multi-co-linearity among the important variables and sample adequacy, respectively. The same's results are displayed in Table 1. This example's KMO score of 0.563, which is higher than 0.50, indicates that the sample size is sufficient. Furthermore, the Bartlett's Test of Sphericity p-value of 0.000 (less than 0.05) indicates that there is co-linearity, or correlation, between the variables.

The degree of relationship between the variables can be determined using the coefficient of correlation between them. 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 TENSION	REWINDER TENSION	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= ---

Table 2 shows that there is very little negative correlation between Line Tension and I.V., End Group, Moisture content, and Ash content, and very little positive correlation between Line Tension and Nip Pressure. Weak negative connections are seen with Un-winder Tension, I.V., and Moisture content, although weak positive correlations are seen with Re-winder Tension, End Group, and Ash content. faint negative connections are seen between Re-winder Tension and Ash content, although faint positive correlations are seen between Un-winder Tension and I.V., End Group, and Moisture content. Rewinder Tension exhibits mild negative connections with I.V. and Moisture content, but positive correlations with End group and Ash content. I.V. has a moderately negative association with the End Group but weakly positive relationships with the Moisture and Ash contents. The end group's moisture and ash contents have weakly negative relationships. There is a modest negative association between the content of moisture and ash. There is enough data to conclude that the correlations are significant at the 1% level of significance because the p-values are less than 0.01.

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		
LINE TENSION	.586	.127
MOISTURE CONTENT	.549	.005
ASH CONTENT	.123	1.016
SAMPLE NO 167: Component Score Coefficient Matrix		
LINE TENSION	1.239	.461
ASH CONTENT	.461	1.239
SAMPLE NO 176: Component Score Coefficient Matrix		
UNWINDER TENSION	.530	-.146
REWINDER TENSION	.079	.607
MOISTURE CONTENT	-.062	.507
ASH CONTENT	.584	.144
SAMPLE NO 183: Component Score Coefficient Matrix		
LINE TENSION	1.491	.745
REWINDER TENSION	.745	1.491
SAMPLE NO 185:		

Component Score Coefficient Matrix		
REWINDER TENSION	0.000	1.000
ASH CONTENT	1.000	0.000
SAMPLE NO 187: **Component Score Coefficient Matrix**		
LINE TENSION	-.098	1.014
REWINDER TENSION	1.014	-.098

The component score coefficient matrices of the critical variables of the critical samples are displayed in Table 3. The one or ones with the highest scores are determined by calculating the normalized PCA scores. The overall average contribution of each variable is displayed on the chart in Figure 3. The research shows that there is autocorrelation in the data.

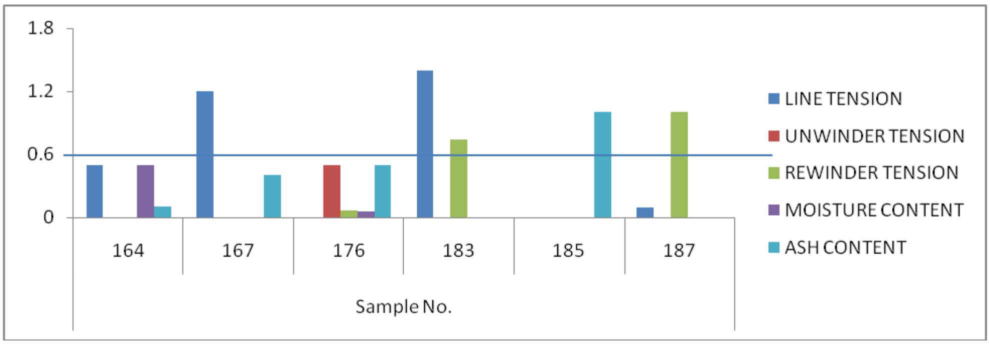

Figure 3: Overall average contribution of critical process variables

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

Table 4 displays the diagnosis of the out-of-control observations for possible process variables. According to the table, Re-winder Tension is indicated as being out-of-control in the MSPC chart for observations 176 and 187, but it is indicated as being under control in the USPC chart. Rewinder Tension is shown as being out of control in both MSPC and USPC for observation 183. In both MSPC and USPC, Line Tension is shown as being out-of-control for observations 167, 183, and 187.

8. CONCLUSION

We use the PCA technique in this case study to decrease measurement redundancy by reducing the number of essential process variables to potentially responsible factors. These results show that USPC and MSPC are clearly different from one another. The process's contribution of ash content must be managed by increasing the material granules' crystallinity. The process variables for line tension and rewinder tension are found to be the most important and crucial ones, and they both call for increased attention. This can be accomplished by changing the PLC parameters more regularly, and the machine needs to have regular maintenance performed on it. Careful interpretation of the relationship between the variables is necessary. 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

It has proven difficult and frequently impossible to articulate in practice to manage the dynamic behavior of process variables in a process. Conventional statistical process control methods are employed in certain industries, but they are ineffective for tracking the dynamic behavior of the important variables. Others rely on their judgment and expertise. Use of MSPC charts is advised when more than one quality characteristic needs to be tracked in order to prevent misleading signals that arise from utilizing a USPC chart for each variable. This essay investigates the issues with USPC process monitoring variables. When multiple variables are connected with one another in a complicated process, it might be challenging to interpret an out-of-control signal and identify the impact of these factors when monitoring simultaneously with MSPC charts. Additional research is required. In these circumstances, we advise doing a thorough investigation utilizing PCA.

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