Int. J. Agricult. Stat. Sci. Vol. 15, No. 1, pp. 401-408, 2019 ***ISSN : 0973-1903***

ORIGINAL ARTICLE

AN EMPIRICAL STUDY TO ANALYZE MANUFACTURING PROCESS USING PROCESS CAPABILITY INDICES IN PASWARA PAPERS LTD., MEERUT

Vivek Tyagi and Lalit Kumar*

Department of Statistics, N.A.S. College, Meerut - 250 002, India
Department of Statistics, Meerut College, Meerut - 250 002, India
E-mail: lalit.jindal@hotmail.com

Abstract: A manufacturing process is a unique combination of 4 Ms *viz.* manpower, methods, machines and materials in developing a product. Process capability indices have been used to provide quantitative measures of process potential and performances. High quality production assures advantages like cost saving, scrap reduction or remanufacturing, higher yield and increased customer satisfaction and market share. Process capability Indices like Cp, Cpk, Cpm and Cpmk are commonly used in industry to assess the ability of a process to meet specification limits on quality characteristics of interest. In modern manufacturing when product designs are complicated and consumers' requirements are changeable rapidly, multiple characteristics must be assessed simultaneously to improve product's quality and also to consider the correlation effects among different quality characteristics. The objective of this paper is to identify the critical variables of the whole process of paper manufacturing and to conduct process capability analysis (univariate and multivariate) to measure performance in a multistage manufacturing process by understanding the concepts, and methodologies of quality engineering techniques. The paper manufacturing has various stages namely pulping, screening, cleaning, deinking, refining, pressing, steam drying, bleaching, steam drying and size press. The results show that multivariate capability indices, MCpk for Cobb and RCT (CD), BF anf Paper Ash, significantly correlated, are 0.17 and 0.40 respectively.

Key words: Multiple regression, Multivariate process capability, Normal distribution, Multistage paper manufacturing.

1. Introduction

Process capability study is a part of SPC, that consists statistical tools developed from the normal curve and control charts with good engineering judgment to interpret and analyze the data representing a process. In manufacturing operation, there is the variability which is manifested in the product during the operations. Quantifying the variability with objectives and advantages of reducing it in the manufacturing process is the prime concern of the quality management. Process capability refers to the evaluation of how well a process meets specifications or the ability of the process to produce parts that conform to quality specifications. It ensures the process stability over time or the ability of the process to maintain a state of good statistical control. Before evaluating the process capability, the process must be shown under statistical control *i.e.* the process must be operating under the influence of only chance causes of variation and also ensures that the process data is normally distributed and observations are independent.

A process may produce a large number of units that do not meet the specifications, even though the process itself is in a state of statistical control (*i.e.* all the points on the X-bar and R charts are within the 3 sigma limits and vary in random manner). This may be due to lack of centering of the process mean in other words, the actual mean value of the parts being produced may be significantly different from the specified nominal value of the part. If this is the case, an adjustment of the machine to move the mean closer to the nominal value may solve the problem. Another possible reason for lack of conformance to specifications is that a statistically stable process may

Author for correspondence** ***Received *December 22, 2018* ***Revised*** *April 16, 2019* ***Accepted*** *May 02, 2019*

be producing parts with an unacceptably high level of common cause variation, even though the process is centered at the nominal value.

2. Review of Literature

In a complex process of multistage production, where variables are more to look upon, it becomes complex to comprehend and calculate. Process capability can be analyzed using univariate capability indices. But, sometimes, the variables are correlated, a multivariate process capability approach is then the alternative to analyze the process variables. Multivariate Process Capability Indices can be studied to analyze the correlated process variables. MPCIs can generally be divided into four different groups [Khadse and Shinde (2006)]. MPCIs groups are

a) based on the ratio of a tolerance region to a process region.

b) based on the probability of the non-conforming product

c) based on the Principal Component Analysis (PCA)

d) Others

A. Univariate Capability Indices

The process capability index Cp which determines whether a process is capable or not by calculating a unit-less value was introduced [Kane (1986)]. The index is expressed by

$$Cp = (USL-LSL) / 6\sigma \tag{1}$$

Here, in Cp, p stands for process. σ is the process standard deviation. USL denotes Upper Specification Limit while LSL represents Lower Specification Limit.

Values of Cp exceeding 1.33 indicate that the process is adequate to meet the specifications. Values of Cp between 1.33 and 1.00 indicate that the process is adequate to meet specifications but require close control. Values of Cp below 1.00 indicate that the process is not capable of meeting specifications. If the process is centered within the specifications and is approximately "Normal" then Cp = 1.00 results in a fraction nonconforming of 0.27%. It is also known as process potential. The limitation of Cp is that it does not measure the process performance in terms of the target value.

To consider the process location, Cpk was developed [Kane (1986)]. The magnitude of Cpk relative to Cp is a direct measurement of how much the process is off-centre. It assumes process output is normally distributed. However, this index does not consider whether the process location (μ), diverges from the target (T) or not.

$$Cpk = \min\left\{\frac{USL-\mu}{3\sigma}, \frac{\mu-USL}{3\sigma}\right\} \tag{2}$$

For processes only with the LSL, the Cpk is given by

$$Cpl = \frac{\mu-USL}{3\sigma} \tag{3}$$

and for processes with only USL,

$$Cpu = \frac{USL-\mu}{3\sigma} \tag{4}$$

Hence, $\quad Cp = (Cpl + Cpu) / 2 \quad (5)$

When the process is perfectly centered at the specification midpoint, then Cp = Cpk. Ideally, a Cpk nearer to 2 indicates that a process is good enough in capability aspect. Values greater than 1.33 indicates that a process is capable in short term and values less than 1.33 tells that the variation is either too wide compared to the specification or that the location of the variation is offset from the center of the specification. It may be a combination of both width and location.

Since Cp and Cpk indices do not account for the difference between the process mean and its target value.

Cpm index was flourished which counters the complication of difference between the process mean and its target value under the assumption that target is in the middle of the specification limits [Chan *et al.* (1988)].

$$Cpm = \frac{Cp}{\sqrt{1+\left(\frac{\mu-T}{\sigma}\right)^2}} \tag{6}$$

Here, T represents the target value of a quality characteristic.

Cpmk was developed which is a combination of Cpk & Cpm [Pearn *et al.* (1992)].

$$Cpmk = \min\left\{ \frac{USL-\mu}{3\sqrt{\sigma^2+(\mu-T)^2}}, \frac{\mu-USL}{3\sqrt{\sigma^2+(\mu-T)^2}} \right\} \quad (7)$$

Cpmk decreases or increases more rapidly than other indices (Cp, Cpk, Cpm) when µ gets departed from T or approaches to T.

B. Multivariate Capability Indices

A multivariate process capability index, Cpm, was proposed [Chan *et al.* (1991)] which is defined by

$$Cpm = \sqrt{\frac{nv}{\sum_{i=1}^{n}\left(\overline{X}-T\right)' A^{-1}\left(\overline{X}-T\right)}} \quad (8)$$

where, $\overline{X}$ is the mean of sample data.

T is the target value.

'v' is the number of quality characteristics

'n' is the number of observations

A^{-1} is the inverse of sample variance covariance matrix.

A multivariate capability index, $MCp^{(1)}$ was suggested [Pearn *et al.* (2007)]. It is expressed as

$$MCp^{(1)} = \frac{Vol(R1)}{Vol(R2)} = \frac{Vol(Modified\,Tolerance\,\mathrm{Re}\,gion)}{(\pi . x^2{}_{V,0.9973})^{v/2}\,|\Sigma|^{1/2}\left[\Gamma\left(\frac{V}{2}+1\right)\right]^{-1}} \quad (9)$$

where, R_1 is the largest ellipsoid centred at the target value completely within the original rectangular tolerance region, and R_2 is the ellipsoid that contains 99.73% of the multivariate normal distribution. The index $MCp^{(1)}$ is estimated by

$$\overline{MCp}^{(1)} = \frac{Vol(Modified\,Tolerance\,\mathrm{Re}\,gion)}{(\pi . x^2{}_{V,0.9973})^{v/2}\,|S|^{1/2}\left[\Gamma\left(\frac{V}{2}+1\right)\right]^{-1}} \quad (10)$$

As per the scope of this research paper, a multivariate capability index is calculated as

$$\text{MCpk} = Z / (k/2) \quad (11)$$

where, Z is the value of a standard normal random variable corresponding to the calculated DPM, and k is the multiple of sigma, normally k = 6 is considered. This index is interpreted as similar to Cpk in the univariate case.

3. Paswara Papers Ltd., Meerut: A Case

A. Collection and Storage

The unused or scrap papers from home, schools or office are being collected through various vendors and being stored into warehouses until needed. Successful recycling requires clean recovered paper. It must be free from contaminants, such as food, plastic, metal, wax and other trash, which make paper difficult to recycle. Finally, forklifts move the paper from the warehouse to large conveyors.

B. Pulping and Screening

The paper is being sent by conveyor to a big vat called a pulper, which contains water and chemicals. The pulper chops the recovered paper into small pieces. Heating the mixture breaks the paper down more quickly into tiny strands of cellulose (organic plant material) called fibers. Eventually, the old paper turns into a mushy mixture called pulp. The pulp is forced through screens containing holes and slots of various shapes and sizes. The screens remove small contaminants such as bits of plastic and globs of glue. This process is called screening. At this stage, the consistency of the pulp remains 4.5-5 gm/ 100 ml and Schopper-Riegler degree (^{0}SR) ranges from 23 to 26.

C. Cleaning

Mills also clean pulp by spinning it around in large cone-shaped cylinders. Heavy contaminants like staples are thrown to the outside of the cone and fall through the bottom of the cylinder. Lighter contaminants collect in the center of the cone and are removed. This process is called cleaning.

D. Deinking

Sometimes the pulp must undergo a "pulp laundering" operation called deinking (de-inking) to remove printing ink and "stickies" (sticky materials like glue residue and adhesives). Small particles of ink are rinsed from the pulp with water in a process called washing. Larger particles and stickies are removed with air bubbles in another process called floatation. During floatation, pulp is fed into a large vat called a floatation cell, where air and soap like chemicals call surfactants are injected into the pulp. The surfactants cause ink and stickies to loosen from the pulp and stick to the air bubbles as they float to the top of the mixture. The inky air bubbles create foam or froth which is removed from the top, leaving the clean pulp behind.

E. Refining

During refining, the pulp is beaten to make the recycled fibers swell, making them ideal for papermaking. If the pulp contains any large bundles of fibers, refining separates them into individual fibers. If the recovered paper is colored, color stripping chemicals remove the dyes from the paper. At this stage, the consistency of the pulp remains 3.5-4 gm / 100 ml and Schopper-Riegler degree (^{0}SR) ranges from 27 to 30.

Now the pulp is mixed with water and chemicals to make it 99.5% water. This watery pulp mixture enters the head-box, a giant metal box at the beginning of the paper machine, and then is sprayed in a continuous wide jet (with the help of moulds) onto a huge flat wire screen which is moving very quickly through the paper machine. On the screen, water starts to drain from the pulp, and the recycled fibers quickly begin to bond together to form a watery sheet.

F. Pressing

Successively, pulpy (watery) sheet is pressed through a series of felt-covered press rollers which squeeze out excess water since at this stage it contains 72% of moisture. After three successive pressing, watery sheet remains with 49% of moisture.

G. Drying (Steam)

The sheet, which now resembles paper, passes through a series of heated metal rollers (steam inside) which dries the paper. At this stage, sheet remains with 11% of moisture.

Now the sheet is mixed with starch powder and alum to maintain the pH level and to provide the surface size. At this stage, it consists 32% of moisture. Thereafter, again passes through the steam dryers which dry the sheet up to with 6.5 to 7.5% of moisture.

H. Paper Reel (Mother Roll)

Finally, the finished paper is wound into a giant roll and removed from the paper machine. The roll of paper is cut into smaller rolls, or sometimes into sheets, before being shipped to a converting plant where it will be printed or made into products such as envelopes, paper bags, or boxes.

I. Defects

As the paper production is a very critical process, there is more vulnerability of defects which can either reject or downgrade the paper quality. In this process,

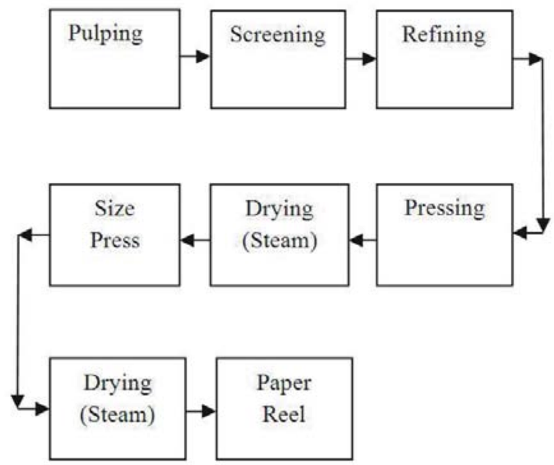

Fig. 1: Production stages of kraft paper at Paswara Papers Ltd.

following are the defects that can put a hindrance from quality point of view.

i. Wax
ii. Spots
iii. Tar coal
iv. Holes
v. Moisture
vi. Shade variation

J. Pulp Testing Parameters

Parameter	Specification
a. Degree SR	16 - 20
b. Consistency (Weight / 100mL)	3% - 4%

4. Objective

The objective of this study is to identify the critical process variables of paper manufacturing process and to measure their capability indices (univariate and multivariate).

5. Research Methodology

Observed data (500 samples) of 3 months has been collected from the shop floor of Paswara Papers Ltd, Meerut. Normality tests have been carried out for various measured variables using Jarque Bera Test. Transformation function, Inverse DF, has been used to normalize the data variables.

Using the technique of multiple regression, critical variables have been identified and Univariate Capability Indices have been computed. Multivariate Capability index has also been computed for highly correlated variables.

For analysis and computation purposes, STATISTICA 10 and STATGRAPHICS 18 software have been used.

6. Result & Findings

Table 1 shows the Jarque Bera statistic along with p-values for the process variables. The variables are not normally distributed since p-values for all the variables are less than 0.05 except Cobb (p-value 0.07) and Ply Bond (p-value 0.68).

As the variables are not normal, data got transformed to normal using Inverse DF. Table 2 depicts the Jarque Bera statistic along with p-values for the process variables (transformed). The variables are now normally distributed since p-values for all the variables are more than 0.05.

Table 1: Jarque Bera Normality Test for collected variables.

Jarque Bera	Collected Data of the process variables								
	GSM	BF	Cobb	RCT (CD)	Bulk	Caliper Thickness	Ply Bond	Paper Ash	Moisture
JB Test Statistic	19.40	24.61	5.43	32.32	37.01	33.28	0.77	14.32	16.16
p-value	0.00	0.00	0.07	0.00	0.00	0.00	0.68	0.00	0.00

Table 2: Jarque Bera Normality Test for transformed variables.

Jarque Bera	Transformed Data (Normalized) of the process variables								
	GSM	BF	Cobb	RCT (CD)	Bulk	Caliper Thickness	Ply Bond	Paper Ash	Moisture
JB Test Statistic	1.35	5.41	2.18	5.77	1.22	4.99	1.55	4.11	4.80
p-value	0.51	0.07	0.34	0.06	0.54	0.08	0.46	0.13	0.09

A. Descriptive Statistics

The average values for the variables have been computed along with range and standard deviation. GSM, Cobb and Ply Bond show the high standard deviation as 4.88, 2.98 and 6.14 respectively, as compared to other variables. Table 3 depicts the same.

Table 3: Descriptive Statistics of the process variables.

Variables	N	Mean	Minimum	Maximum	St. Dev.
GSM	500	143.78	132.64	155.18	4.88
BF	500	19.00	18.19	19.70	0.39
Cobb	500	42.19	36.13	50.46	2.98
RCT (CD)	500	1.06	0.63	1.31	0.14
Bulk	500	1.45	1.36	1.57	0.04
Caliper Thickness	500	0.21	0.20	0.22	0.01
Ply Bond	500	226.34	212.19	240.61	6.14
Paper Ash	500	7.25	6.89	7.73	0.20
Moisture	500	6.73	6.24	7.11	0.16

B. Multiple Regression Analysis

Among 9 variables under consideration, GSM has been considered as dependent variable and others as independent variables.

Table 4 shows the results of fitting a multiple linear regression model to describe the relationship between GSM and 8 independent variables.

Table 4: Multiple Regression Model.

Parameter	Estimate	StandardError	T-Statistic	P-Value
GSM	50.9785	13.8805	3.67266	0.0003
BF	1.65907	0.496844	3.33923	0.0009
Cobb	-0.314727	0.0600053	-5.24499	0.0000
RCT (CD)	10.7619	1.13191	9.50775	0.0000
Bulk	-76.7021	4.6255	-16.5825	0.0000
Caliper Thickness	286.609	29.9665	9.56432	0.0000
Ply Bond	0.0360913	0.0251235	1.43655	0.1515
Paper Ash	11.932	0.789873	15.1062	0.0000
Moisture	2.93735	0.88639	3.31383	0.0010

R-squared = 74.0988%

Adjusted R-squared = 73.6768%

Standard Error of Est. = 2.5042

Mean absolute error = 1.86847

Durbin-Watson statistic = 2.10563 (P = 0.8810)

The equation of the fitted model is:

GSM = 50.9785 + 1.65907*BF - 0.314727*Cobb + 10.7619*RCT(CD)-76.7021*Bulk + 286.609*Caliper Thickness + 0.0360913*Ply Bond + 11.932*Paper Ash + 2.93735*Moisture

Since the p-value in the ANOVA table (Table 5) is less than 0.05, there is a significant relationship between the variables at the 95.0% confidence level.

Table 5: Analysis of Variance.

Source	Sum of Squares	Df	Mean Square	F-Ratio	P-Value
Model	8808.71	8	1101.09	175.58	0.000
Residual	3079.08	491	6.27103		
Total	11887.8	499			

The R-Square statistic indicates that the model as fitted explains 74.0988% of the variability in GSM. The adjusted R-square statistic, which is more suitable for comparing models with different numbers of independent variables, is 73.6768%.

The standard error of the estimate shows the standard deviation of the residuals to be 2.5042. The mean absolute error (MAE) of 1.86847 is the average value of the residuals. The Durbin-Watson (DW) statistic tests the residuals to determine if there is any significant correlation based on the order in which they occur in your data file. Since the p-value is greater than 0.05, there is no indication of serial autocorrelation in the residuals at the 95.0% confidence level.

In the view to simplify the model, notice that the Ply Bond has the highest p-value, 0.1515. Since the p-value is greater or equal to 0.05, that term is not statistically significant at the 95.0% or higher confidence level. Hence, Ply Bond can be removed from the model.

Table 6 shows estimated correlations between the coefficients in the fitted model. These correlations can be used to detect the presence of serious multi-collinearity, *i.e.*, correlation amongst the predictor variables. In this case, there are 2 correlations (between two variables) with absolute values greater than 0.5 (not including the dependent variable). COBB and RCT (CD) have the correlation -0.5431 while BF and PAPER ASH have the correlation 0.5415.

C. Capability Indices

Table 7 shows the computation of various univariate capability indices *viz.* Cp, Cpk, Cpm and Cpmk of the quality variables of multistage production processes of paper manufacturing.

D. Multivariate Capability Analysis

Multivariate capability indices compare the joint performance of the 2 variables to their specification limits. MCpk is an index similar to CP or CPK in the univariate case. Normally, it is desirable that MCpk be greater than or equal to 1.33. DPM measures the number of non-conforming items per million. Z is an index that equates the percentage of items out of spec to the value of a standard normal distribution. Z values of 4 or greater are desirable.

The Sigma Quality Level (SQL) is a metric used by companies applying Six Sigma techniques to quantify the level of quality in their processes. Average companies usually achieve a Sigma Quality Level of approximately 4 (assuming a 1.5 sigma drift in the means over time). Sigma Quality Levels of 6 or higher correspond to world class quality performance.

Case 1: Data variables: COBB & RCT (CD)

Number of complete cases: 500

Table 8 shows the percentage of items beyond a set of multivariate specification limits. In this case, the estimated frequency of non-conformities with respect to at least one of the two variables equals 300022 per million.

Table 9 shows Multivariate capability index (MCpk) as 0.17. DPM estimates that 300022 out of every million

Table 6: Correlation matrix for coefficient estimates.

	GSM	BF	Cobb	RCT (CD)	Bulk	Caliper Thickness	Ply Bond	Paper Ash	Moisture
GSM	1.0000	-0.7553	0.3107	-0.1802	0.1145	0.0154	-0.2820	-0.6250	-0.5031
BF	-0.7553	1.0000	-0.2519	0.0741	-0.4918	0.0325	0.1030	**0.5415**	0.1681
Cobb	0.3107	-0.2519	1.0000	**-0.5431**	-0.1579	-0.2730	-0.1002	-0.1324	0.0476
RCT (CD)	-0.1802	0.0741	-0.5431	1.0000	0.1159	0.2667	-0.2590	0.0264	0.1423
Bulk	0.1145	-0.4918	-0.1579	0.1159	1.0000	-0.2317	-0.3099	0.0320	-0.0611
Caliper Thickness	0.0154	0.0325	-0.2730	0.2667	-0.2317	1.0000	-0.2157	-0.2808	-0.3400
Ply Bond	-0.2820	0.1030	-0.1002	-0.2590	-0.3099	-0.2157	1.0000	-0.0722	0.2791
Paper Ash	-0.6250	0.5415	-0.1324	0.0264	0.0320	-0.2808	-0.0722	1.0000	0.0161
Moisture	-0.5031	0.1681	0.0476	0.1423	-0.0611	-0.3400	0.2791	0.0161	1.0000

Table 7: Capability Indices of the variables.

Variables	LSL	NOMINAL	USL	Cp	Cpk	Cpm	Cpmk
GSM	130.00	143.75	150.00	1.09	0.68	0.68	0.42
BF	18.00	19.00	20.00	1.09	1.08	0.85	0.85
Cobb	35.00	42.16	45.00	0.65	0.37	0.56	0.31
RCT (CD)	0.90	1.06	1.50	0.89	0.48	0.71	0.38
Bulk	1.20	1.45	1.80	3.93	3.28	2.58	2.16
Caliper Thickness	0.19	0.21	0.22	1.15	0.83	0.98	0.71
Ply Bond	200.00	226.30	250.00	1.64	1.55	1.36	1.28
Paper Ash	7.00	7.25	9.00	1.98	0.50	1.67	0.42
Moisture	6.50	6.73	7.50	1.16	0.54	1.06	0.49

Table 8: Estimation of Defects Per Million.

Variable	Observed Beyond Spec.	Estimated Beyond Spec.	Estimated DPM
Cobb	22.0%	18.0986%	180986.
RCT (CD)	15.0%	13.003%	130030.
Joint	37.0%	30.0022%	300022.

Table 9: Multivariate Capability Indices.

Index	Estimate*
MCpk	0.17
DPM	300022.
Z	0.52434
SQL	2.02434

*Based on 6.0 sigma limits. The Sigma Quality Level includes a 1.5 sigma drift in the means.

items will violate one or more of the specifications. Z-value is computed as 0.52434 while SQL (Sigma Quality level) is measured to be 2.02434.

Fig. 2 depicts the Capability plot that displays the fitted multivariate normal distribution for Cobb and RCT (CD) variables.

In Fig. 2, the shaded blue (dark) area corresponds to locations where both the variables are within the specification limits whereas, the shaded in red (light) area corresponds to locations where one or both variables are out of specifications.

Case 2: Data variables: BF & PAPER ASH

Number of complete cases: 500

Table 10 represents the percentage of items beyond a set of multivariate specification limits. In this case, the estimated frequency of non-conformities with respect to at least one of the two variables equals 113263 per million.

Table 11 shows Multivariate capability index (MCpk) as 0.40. DPM estimates that 113263 out of every million items will violate one or more of the

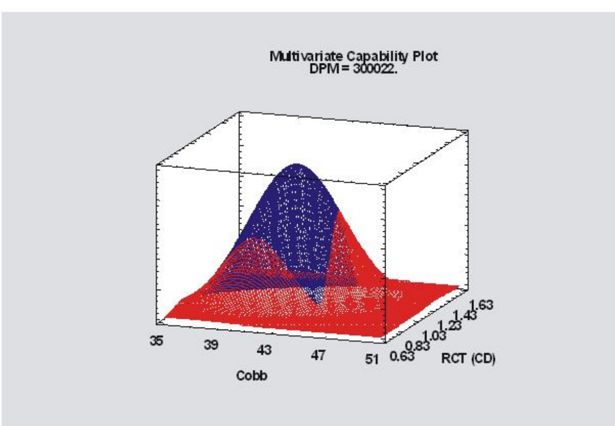

Fig. 2: Multivariate Capability Plot between Cobb & RCT (CD)

Table 10: Estimation of Defects Per Million.

Variable	Observed Beyond Spec.	Estimated Beyond Spec.	Estimated DPM
BF	0.0%	1.06186%	10618.6
Paper Ash	11.2%	10.4919%	104919.
Joint	11.2%	11.3263%	113263.

Table 11: Multivariate Capability Indices.

Index	Estimate*
MCpk	0.40
DPM	113263
Z	1.20936
SQL	2.70936

*Based on 6.0 sigma limits. The Sigma Quality Level includes a 1.5 sigma drift in the means.

specifications. Z-value is computed as 1.20936 while SQL (Sigma Quality level) is measured to be 2.70936.

Fig. 3 depicts the Capability plot that displays the fitted multivariate normal distribution for BF and Paper Ash variables.

In Fig. 3, the shaded blue (dark) area corresponds to locations where both the variables are within the specification limits whereas, the shaded in red (light) area corresponds to locations where one or both variables are out of specifications.

6. Conclusions & Suggestions

Table 7 depicts Cp more than 1 for all the quality variables under study except cobb (Cp = 0.65) and RCT (CD) (Cp = 0.89), shows that the process is capable and 99.73% process region is within the tolerance limit. To overcome the limitation of Cp, not considering the process mean location, Cpk has been computed. However, this index does not consider the divergence of μ from the target, T. Hence, Cpm and Cpmk have been calculated for the variables. Cpm for bulk, ply bond, paper ash and moisture are 2.58, 1.36, 1.67 and

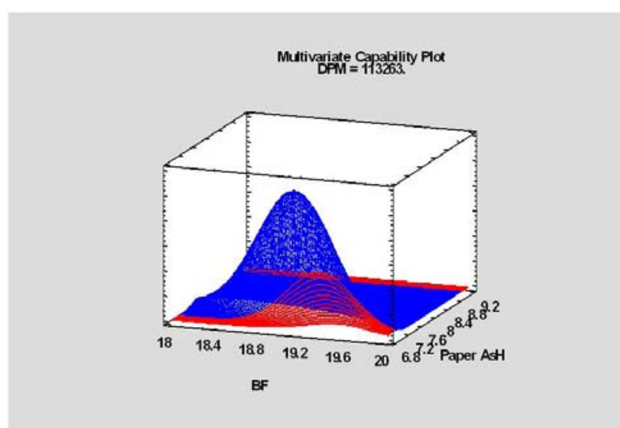

Fig. 3: Multivariate Capability Plot between BF & Paper Ash.

1.06 respectively while Cpmk for bulk and ply bond are 2.16 and 1.28 respectively.

As far as multivariate capability index is concerned for significantly correlated variables, Cobb-RCT (CD) and BF-Paper Ash, it has been calculated as 0.17 and 0.40 respectively.

The most critical processes of paper manufacturing are pulping, screening, refining and heat treatment processes. Apart from good quality input raw materials, CAPA should be implemented in the processes. The selection of parameters of the processes and heat treatment process should be improved upto the benchmark level. The PLCs and testing machines should be calibrated at some periodic level.

Acknowledgement

Authors are highly grateful to the Editor and anonymous reviewer for their fruitful comments which led to much improvement in the paper.

References

Chan, L.K., S.W. Cheng and F.A. Spring (1991). "A multivariate measure of process capability," in *Journal of Modeling and Simulation*, **11(1),** 1-6.

Chan, L.K., S.W. Cheng and F.A. Spring (1988). "A new measure of process capability: Cpk," in *J. Qual. Technol,* **20,** 162-175.

Kane, V.E. (1986). "Process capability indices," in *Journal of Quality Technology,* **18**,11.

Khadse, K.G. and R.L. Shinde (2006). Multivariate process capability using relative importance of quality characteristics in The Indian Association for Productivity, Quality and Reliability (IAPQR). *Transactions,* **31(2)**, 85-97.

Pearn, W.L., S. Kotz and N.L. Johnson (1992). "Distributional and inferential properties of process capability indices," in *J. Qual. Technol,* **24,** 216-233.

Pearn, W.L., B.M. Hsu and M.H. Shu (2007). "Measuring process capability based on Cpmk with gauge measurement errors," in *Quality and Reliability Engineering,* **23(5),** 597-614.