JJMIE

Volume 15, Number 4, October. 2021
ISSN 1995-6665
Pages 319 - 328

Jordan Journal of Mechanical and Industrial Engineering

Establishing Process Capability Indices in a Sugar Manufacturing Industry – an Industrial Engineering Perspective

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Received February 12 2021 *Accepted September 2 2021*

Abstract

Quality of the product is a very important factor to any organization on which the future of the company depends. There are many tools available to check and control the quality of the product, and among them is the process capability study which is highly important. This work is an attempt towards applying the concepts of process capability principles pertaining to discrete manufacturing into the scenario of continuous process oriented industries. In this work, the process capability study is carried out in a sugar processing industry. Data pertaining to Critical-To-Quality parameters of sugar have been collected for several sugar samples. The reasons for the variability are identified and the necessary and corrective actions are suggested to overcome the variations in the sugar manufacturing process. A significant improvement is registered in the process capability indexes of CP and CPK for the identified Critical-To-Quality (CTQ) characteristics of sugar turbidity and minimum aperture. An increase of 7 folds is observed for the CPM value for the CTQ characteristic of minimum aperture. Thus, the process capability indexes are calculated and the capability of the process is determined based on their values.

Keywords: Quality Assurance; Process capability; Sugar processing; Statistical Process Control; ANOVA analysis; Critical-To-Quality (CTQ) characteristic;

1. Introduction

Industrial engineering principles are extensively applied in a wide domain of manufacturing as well as service sectors. Process capability study is one of such industrial engineering method which is extensively applied in discrete manufacturing industries. The preliminary process capability study is a logical and methodical procedure that examines the interactions of the potential causal factors for identification of the process deviations. Process run charts are employed to identify the outliers and detect the unnatural reasons (special causes) for variations until a condition of statistical control is reached. Natural variations because of common causes like wear of tool insert tip, can be identified and controlled, as they indicate a certain trend in run charts (increasing trend, or decreasing trend, or cyclic trend and so on). All in all, the process capability study anticipates the degree to which the process adheres to the client's prerequisites. In this work, study is carried out in a process based sugar manufacturing industry.

To measure the capability of the process quantitatively, certain indexes are used. They are of three types; one is the process potential capability index, another one is process performance capability index and the third one is the process capability index accounting for Taguchi's Loss Function. The formulae required for calculating the process capability indexes and their descriptions are given in the Table 1. The CTQ characteristics identified are the "sugar turbidity" and "minimum aperture" as they depict the process performance as well as the end product quality of the outcome of the sugar manufacturing process.

The parameter "turbidity" is a "smaller-the-better" type of characteristic, i.e., the lower the turbidity value, the better is the process capability. The lower bound (LSL) is taken to be an ideal value of "0" and the upper bound (USL) is taken to be a relative value of "100". Turbidity is a one-sided parameter with the process capability being higher when the values for turbidity obtained are more nearer to the ideal value of "0". Thus, the process performance capability index with respect to upper specification limit (C_{PKU}) is employed for measurement of the process capability of the Critical-To-Quality characteristic of turbidity. The higher the value of C_{PKU}, the better is the process with the turbidity values nearer to the ideal value of "0".

Whereas, the CTQ characteristic, the minimum aperture is a double sided value with optimal sieve size ranging between 0.3 (*LSL*) and 0.6 (*USL*) sieve size. Process capability index accounting for Taguchi's Loss Function, C_{PM}, is introduced and added for this double sided characteristic of minimum aperture, with a target value of $T=0.7$ sieve size.

The structure of the paper is as follows. Firstly, introduction to process capability indexes with respect to

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process manufacturing is discussed in the introduction section. This is followed by a comprehensive literature review. Data is collected for the CTQ characteristics of sugar turbidity and minimum aperture. This data collected is analyzed for the process capability in the data analysis section. Corrective actions have been applied for the process deviations and discussed in the results and discussions section. The conclusions have been derived in the conclusions sections followed by the list of references.

2. Literature Review

Quality Assurance tools and techniques like quality circles, TPM (Total Productive Maintenance), kaizen, JIT (Just-In-Time) are extensively used in the manufacturing sector [1]. Statistical analysis finds its application in a wide domain of areas[2].Statistical process control (SPC) is not only limited to manufacturing domain, but is also successfully applied in commercial bank's operation performance [3]. The concepts of process capability are successfully deployed into service sector of banking. Eric shao[4]proposed technique for identification, isolation and correction of assignable causes of a disturbance in manufacturing process, thus paving way for integration of SPC and EPC (Engineering process control). Balamurali and Usha[5]proposed a quick switching variables sampling system for deciding whether the component under inspection has to be accepted or rejected. This sampling system is limited to a quality characteristic with double specification limits and is based on the process performance capability index (CP_K). Kumaravadivel et al.[6]analyzed the casting process by Taguchi method and employed ANOVA analysis for determining the optimal process parameters and their contribution to process variations. Lee et al. [7]proposed a method to design control charts for detecting state changes as well as to rebuild manufacturing process model.

Adeoye et al.[8] conducted process capability study in a drug manufacturing company where they studied about the process deviations by employing control charts. Shinde et al. [9]investigated the significance of process capability indexes with respect to machines. It is inferred that the process capability examination can also be extended to machines or machine instruments, in addition to the manufacturing process analysis. S. Bangphan et al.[10] conducted process capability analysis by using SPC of rice polishing cylinder turning practice. John et al. [11]studied the process capability analysis by using curve fitting methods.

J.Subramani et al. [12]studied the process performance using control charts for variables with known process capability indexes. Stefan et al.[13] gave the complete explanation of understanding process capability indexes, their classification and method of calculation. Details of both process capability indexes and process performance indexes were given. They concluded that process performance indexes are most efficient indexes to measure variability since process performance indexes are calculated by considering the standard deviation of entire data. Sharma and Rao have improved the production process capability of connecting rod [14] and crankshaft [15]production. Sharma et al.[16] have registered an improvement in the process capability indexes of CTQ characteristics of aluminium alloy wheel production. Sharma et al.[17] have established a relation between the process capability and the dimensional tolerances for the manufacture of the connecting rod component.Vannan and Vizhian[18]adopted the ANOVA analysis for analysing the coating parameters in the process of electroless coating. Mandahawi et al.[19] registered a significant process improvement in a paper manufacturing industry by following the DMAIC (Define-Measure-Analyze-Improve-Control) approach. Hypothesis formulation and testing the hypothesis forms a scientific method to judge, prove and register a process improvement. Mujbil Al-Marsumi[20] formulated and tested the hypothesis for obtaining significant process improvements in the Dairy Industry in Jordan. PederLundkvist[21] in his PhD dissertation established procedures for capability analysis in process industry.

Table 1. Formulae of process capability indexes

Index	Formula	Description
C_P	$\dfrac{Upper\ Specificaton\ Limit - Lower\ Specificaton\ Limit}{6\sigma}$	Process potential capability index
C_{PKU}	$\dfrac{Upper\ Specificaton\ Limit - Mean\ of\ process\ Limits}{3\sigma}$	Process performance capability with respect to upper specification limit. This measures the smaller-the-better type of characteristic. The larger the value of C_{PKU} the better is the characteristic.
C_{PKL}	$\dfrac{Mean\ of\ process\ Limits - Lower\ Specificaton\ Limit}{3\sigma}$	Process performance capability with respect to lower specification limit. This measures the larger-the-better type of characteristic. The larger the value of C_{PKL} the better is the characteristic.
C_{PK}	Minimum of $C_{PKU}$and C_{PKL}	Process performance capability index responsible for process centering.
C_{PM}	$\dfrac{Upper\ Specification\ Limit - Lower\ Specification\ Limit}{6\sigma_{CPM}}$ $where,\quad \sigma_{CPM} = \sqrt{\dfrac{\sum_{i=1}^{n}(x_i - T)^2}{(n-1)}} \quad where, T = T\arg et\ value$	Process capability index accounting for Taguchi's Loss Function

Jairo Munoz [22] studied the process capability of TIG welding process and applied the fuzzy logic theory for the uncertain data obtained during the TIG welding process. The quality inspection personnel have different individual opinions regarding the same weld quality. Such induced individual uncertainty can be addressed through fuzzy logic method which is a combination of possibilistic and probabilistic approached towards process capability. Baghbani et al. [23] implemented a fuzzy Process Failure Modes and Effects Analysis (PFMEA) in a sugar manufacturing set-up at Kurdistan. They identified as many as 49 potential failure modes and proposed solutions for starting with the highest Risk-Proirity-Number (RPN). Kustiyo and Arkeman[24] adopted the statistical methodology of reducing the process variation through a separate framework for identification of common causes and special causes for process deviations. They believed in the philosophy of Statistical Process Control approach for optimizing the sugar manufacturing process as a whole. Pearn and Chen [25] and Pearn et al.[26] have focused on the different process capability indexes including the CPM index accounting for the Taguchi's Loss Function. Mohan and Yadav [27] suggested process improvements in the sugar manufacturing process in the limelight of carbonation and phosphatation process. Aljebory and Alshebeb[28] registered an improvement in quality of a process oriented chemical industry through Statistical and Engineering process control.

This paper examines the process capability in a sugar manufacturing scenario. The structure of the paper is as follows. The first section of the paper starts with a brief introduction to process capability and formulae related to process capability indexes. This is followed by an exhaustive literature survey which comprehends the various works related to process capability and statistical process control. Data pertaining to multiple Crtitical-To-Quality parameters namely sugar turbidity and minimum aperture have been collected from sugar manufacturing process. The collected data is analyzed and validated through ANOVA analysis for suitability towards further process capability analysis. The results and discussion session summarizes the process capability indexes' values and generalizes that, the upper limit process performance index (C_{PKU}) is taken as the measure for smaller-the-better type of Critical-to-Quality characteristics respectively. Finally the paper ends with conclusion followed by the list of references cited in this paper.

3. Data Collection

In this study, data has been collected in a sugar processing industry**.** There are two important Critical-To-Quality (CTQ) characteristics in sugar manufacturing, namely, turbidity and minimum aperture that are used for determining process capability indexes. Out of total no. of samples collected, 75 samples of the parameter which describe the process in as-it-is state are given below. Some precautions must be taken before going to proceed for process capability analysis. They are that the collected data must be normally distributed. The collected data must be statistically stable.

3.1. Sugar Turbidity

Sugar turbidity is regularly assessed in sugar manufacturing plants. It represents the presence of suspended particles in sugar solution which is detected based on change in characteristics like wavelength and refractive index when light is diffused through the sugar solution with suspended particles[29]. Table 2 shows the continuous observations of turbidity.

3.2. Minimum aperture

Minimum aperture measures average grain size of the sugar crystal. The size of sugar crystals is determined when the crystals are passed through different sizes of multiple sieves. Coefficient of variation (CV) of sugar crystals size determines the consistency in homogeneity of crystal size. A Lower CV portrays a superior consistency while a high CV means a higher variation in sugar crystal sizes. A variation within 35% is generally desirable. Table 3 shows the continuous observations of this characteristic.

Table 2. Observations for Turbidity

S.No.	Level-1	Level-2	Level-3	S.No.	Level-1	Level-2	Level-3
1	120	136	95	14	84.9	83.4	85.2
2	98.2	98.4	96.2	15	83.4	126	68.5
3	86.6	86.6	84	16	70.3	89	88
4	79.5	72.4	86	17	84	68.5	65
5	114	94	81	18	86	85.2	89
6	81	87.3	86	19	88	80.6	78
7	80	80	88	20	86.5	84	80
8	65	80.6	80.6	21	71	79	79
9	89	88	86.5	22	81	80	70.3
10	78	73	71	23	78	78	88
11	80	84	81.7	24	83	89	81
12	85.5	82	83	25	80	65	81.7
13	79	78	82.6				

4. Data Analysis

4.1. Hypothesis formulation for ANOVA analysis

For analyzing the observations of the Critical-To-Quality characteristics, the observations must be analyzed whether they are significantly different or not. This is done through ANOVA analysis. Firstly the Hypothesis must be formulated and tested subsequently[30]. The following hypothesis are to be tested:

Null Hypothesis **- H_0: $\mu_i = \mu$** for all i = 1,2,3

Alternate Hypothesis **- H_1:$\mu_i \neq \mu$**for somei= 1, 2, 3

where$\mu_i$is the population mean for level i and **μ** is the overall grand mean of all levels

Each level consists of 25 measurement readings with a total of three such levels (Table 2 and Table 3).

4.2. Turbidity

4.2.1. ANOVA Analysis for turbidity

The data pertaining to turbidity is tabulated in Table 2. The statistical calculations for turbidity are summarized in Table 4 and the ANOVA table is depicted in Table 5.

For 95% confidence levels, the probability level ***"p"*** is of a significance of 0.05. For this value of ***"p"*** the critical value for the rejection region is $F_{CRITICAL(p,K-1,N-K)}$ i.e., $F_{CRITICAL(0.05,2,72)}$ and is obtained to be 3.1239. Thus,

$F_{STATISTIC} < F_{CRITICAL}$

Hence, the null hypothesis is accepted. If the judgment from ANOVA is in favor of the null hypothesis, then it suggests that the result is not significantly different, and, $\mu_i \approx \mu$ for all i = 1,2,3. Therefore, a *post hoc* test is not a requisite. Hence the data is statistically stable and ready for performing process capability study.

Table 3. Observations for Minimum Aperture

S.No.	Level-1	Level-2	Level-3	S.No.	Level-1	Level-2	Level-3
1	0.98	1.07	1.07	14	1.09	0.94	1.19
2	1	1	1.3	15	1.19	1.14	1.13
3	1	1.1	1	16	0.9	0.9	0.94
4	1	1.2	1.1	17	0.99	0.8	0.98
5	1.09	1.09	1.04	18	1.01	1.18	1.07
6	1.07	1.07	1.18	19	1.09	1.22	1.3
7	0.82	0.8	0.8	20	0.94	1.18	1.08
8	0.8	0.94	0.94	21	1.01	0.8	0.82
9	1.04	0.94	1.01	22	1.15	1.19	1.01
10	1.01	1.08	1.15	23	1.16	1.09	1.16
11	1.08	1.16	1.16	24	1.13	1.07	1.14
12	1.06	1.16	1.3	25	0.94	1.22	1.3
13	1.3	1.22	1.2				

Table 4. Statistical calculations for turbidity

S.No.	Statistical calculation	Level-1	Level-2	Level-3
1	n (Number of observations)	25	25	25
2	$\sum X$ (sum of observations)	2111.9	2148	2055.3
3	μ_i(Mean of observations)	84.476	85.92	82.212
4	$\sum X^2$ (sum of squares)	181760.21	190337.74	170326.97
5	σ(Standard Deviation)	11.824	15.5209	7.5184
6	μ (Grand mean)	$[(\mu_1 + \mu_2 + \mu_3) / 3] = 84.203$		

Table 5. ANOVA table for turbidity

Source	SS	df	MS	
Between-treatments	174.6675	2	87.3337	F = 0.59923
Within treatments	10493.572	72	145.7441	
Total	10668.2395	74		

4.2.2. Process capability and control study for turbidity

Figure 1 shows that the control chart of both $\overline{X}$ and R chart for turbidity is lying in between the UCL and LCL. There are no outliers seen in this chart.

Now it is seen that the process capability curve is skewed towards right i.e., towards Upper Specification Limit (USL). This is depicted in Figure 2 below.

Thus, the process is found to be incapable for achieving the sugar of expected turbidity levels, as the turbidity is a smaller-the-better type of characteristic.

The following are the corrective actions suggested to overcome this problem. If the suspended particles are present in the sugar juice, then, this impacts the productivity of steps in the refining cycle. Clarification is the process where these suspended particles are eliminated. Here, a blend of lime, activated carbon, and a clarifying agent, are imparted to the sugar juice. Firstly, the activated carbon eliminates flavonoids and natural acids which when normally present in the sugar results in a bad flavour. Next, the kind of clarifying agent used depends on whether the raw material is a sugar stick or sugar beet. Turbidity investigation on the sugar juice is the measure for the effectiveness of the clarification process. A lower turbidity shows adequate clarification done. pH meters have capacity to show readings to indicate juice turbidity for optimal usage of the clarifying agents. More care has been taken than the usual during these processes so that turbidity levels can be reduced.

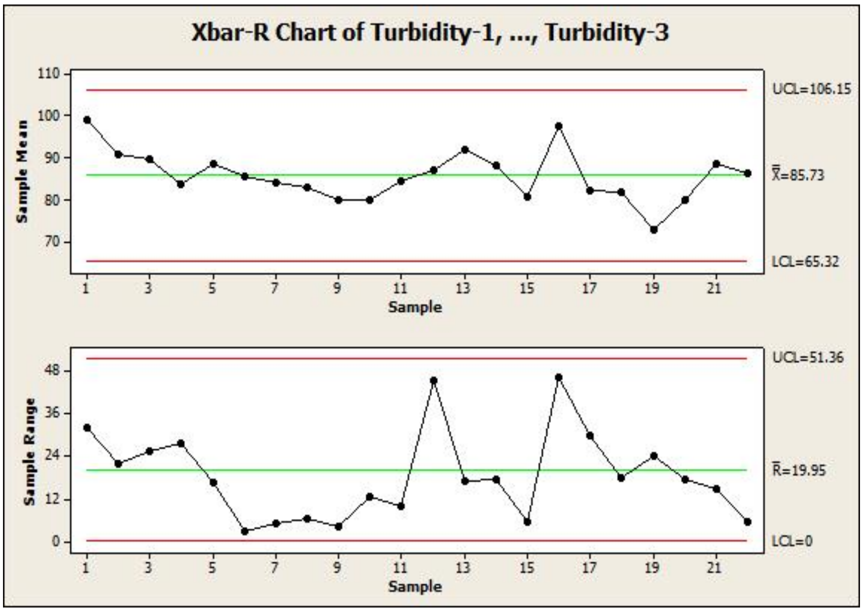

Figure 1: $\overline{X}$ and R chart for Turbidity.

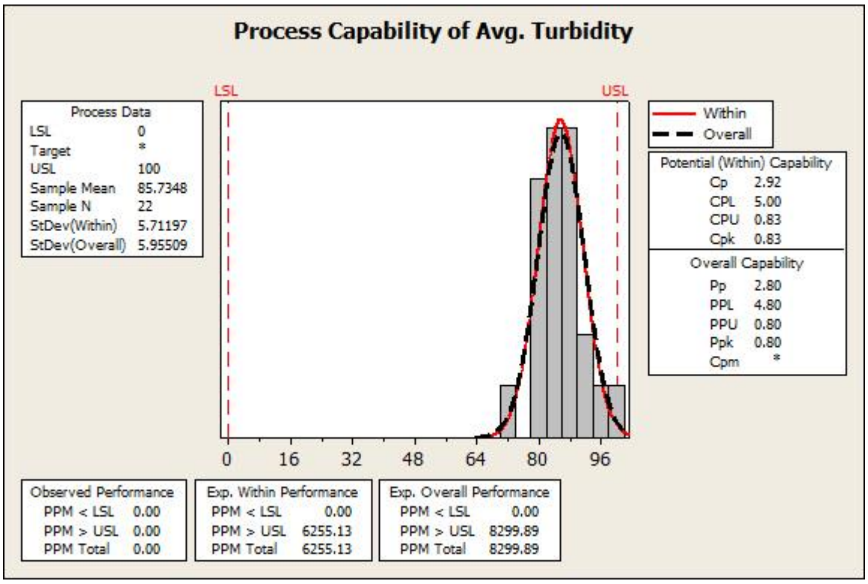

Figure 2: Process capability analysis of turbidity

The process run charts are employed after taking corrective actions, so that the process shall not deteriorate. Figure 3 shows the run chart of turbidity after taking corrective action.

The C_{PKU} index is applicable to turbidity, as it is a smaller-the-better type of characteristic. Hence, From Table 1 it is clear that C_{PKU} is given by the formula:

$$C_{PKU} = \frac{USL - \overline{X}}{3\sigma} = \frac{100 - 26.45758}{3 \times 7.181799} = \frac{73.54242}{21.5454} = 3.41337 \quad (1)$$

Thus, after taking the corrective action, there is an increase in C_{PKU} from 0.43856 to 3.4133.

4.3. Minimum aperture

Minimum aperture is the optimum size of the sugar crystal that is generally suggested for industrial use. For analyzing the observations of minimum aperture, firstly the observations must be analyzed whether they are significantly different or not. This is done through ANOVA analysis.

4.3.1. ANOVA analysis for minimum aperture

The data pertaining to minimum aperture is tabulated in Table 3. The statistical calculations for minimum aperture are summarized in Table 6 and the ANOVA table is depicted in Table 7.

For 95% confidence levels, the probability level ***"p"*** is of a significance of 0.05. For this value of ***"p"*** the critical value for the rejection region is $F_{CRITICAL(p,K-1,N-K)}$ i.e., $F_{CRITICAL(0.05,2,72)}$ and is obtained to be 3.1239. Thus,

$F_{STATISTIC} < F_{CRITICAL}$

Hence, the null hypothesis is accepted. If the judgment from ANOVA is in favor of the null hypothesis, then it suggests that the result is not significantly different, and, $\mu_i \approx \mu$ for all i = 1,2,3. Therefore, a *post hoc* test is not a requisite. Hence the data is statistically stable and ready for performing process capability study.

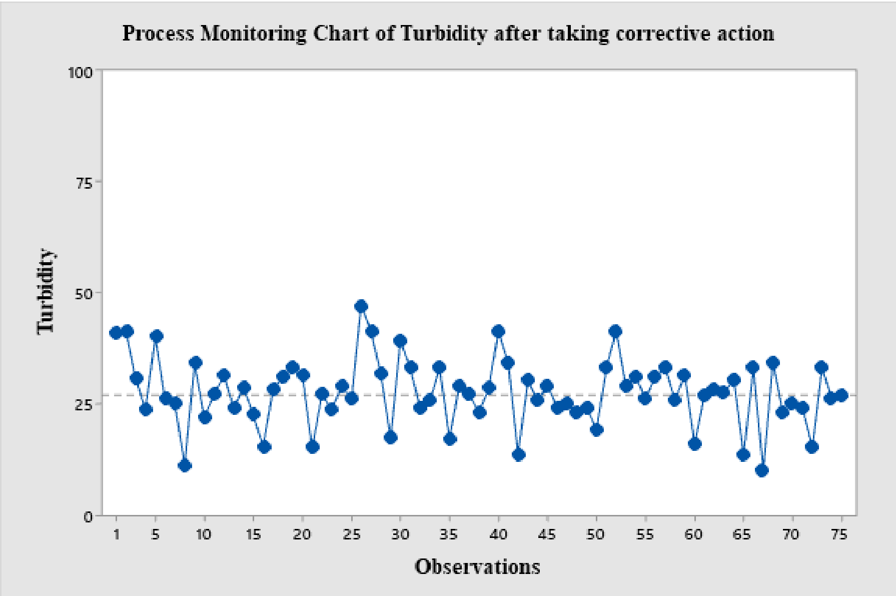

Figure 3. Process run chart for turbidity post corrective action

Table 6. Statistical calculations for minimum aperture

S.No.	Statistical calculation	Level-1	Level-2	Level-3
1	n (Number of observations)	25	25	25
2	∑X (sum of observations)	25.85	26.56	26.79
3	μ_i(Mean of observations)	1.034	1.0624	1.0716
4	$\sum X^2$ (sum of squares)	27.0223	28.665	29.2335
5	σ(Standard Deviation)	0.1106	0.1366	0.1479
6	μ (Grand mean)	$[(\mu_1 + \mu_2 + \mu_3) / 3] = 1.056$		

Table 7. ANOVA table for minimum aperture

Source	SS	df	MS	
Between-treatments	0.0192	2	0.0096	F = 0.54603
Within treatments	1.2664	72	0.0176	
Total	1.2856	74		

4.3.2. Process capability and control study for minimum aperture

Figure 4 shows that the control chart of both $\overline{X}$ and R chart for minimum aperture is lying in between the UCL and LCL. There are no outliers seen in this chart.

$$C_P = \frac{USL - LSL}{6\sigma} = \frac{0.9 - 0.6}{6 \times 0.129935} = \frac{0.3}{0.779612} = 0.384807 \tag{2}$$

$$C_{PKU} = \frac{USL - \overline{X}}{3\sigma} = \frac{0.9 - 1.063733}{3 \times 0.129935} = \frac{-0.16373}{0.389806} = -0.42004 \tag{3}$$

$$C_{PKL} = \frac{\overline{X} - LSL}{3\sigma} = \frac{1.063733 - 0.6}{3 \times 0.129935} = \frac{0.463733}{0.389806} = 1.189652 \tag{4}$$

C_{PK} = Minimum of $C_{PKU}$and C_{PKL}= - 0.42004. (5)

Consider a process Target Value of aperture size of T = 0.70 which is on the lower side of aperture size. Then, we have the CPM value calculations as follows:

$$C_{PM} = \frac{USL - LSL}{6\sigma_{CPM}} \quad where, \quad \sigma_{CPM} = \sqrt{\frac{\sum_{i=1}^{n}(x_i - T)^2}{(n-1)}} \quad where, T = T\arg et\ value \tag{6}$$

Thus,

$$C_{PM} = \frac{0.9 - 0.6}{6 \times 0.682276} = 0.073$$

Thus the C_P value is 0.4,C_{PK}value is -0.42004 and C_{PM}value is 0.073

Now it is seen that the process capability curve is completely skewed towards right with the process mean extending outside the Upper Specification Limit (USL). This shows an incapable manufacturing process which requires a corrective action. This is depicted in Figure 5 below.

Thus the process is found to be incapable for achieving the sugar of expected minimum aperture levels. The following are the corrective actions suggested to overcome this problem. Coefficient of variation (CV) is a method of portraying the accuracy of the measurements. Lower Coefficient of Variation describes a superior consistency while a high coefficient of variation means an inconsistent size of sugar crystal with more variation. A Coefficient of variation of below 35% is preferred for crystals of sugar. Commonly, sugar crystals of coarser size are easier to separate through the centrifuging screen and constitute a superior yield. Fine sugar crystals on the other hand, pass through the sieve and again mix-up with the mother liquor which must be solidified once more, thus minimising the recovery rate. The dissolvability of finer crystals of sugar is more when compared to larger crystals of sugar, thus, making the finer crystals more preferred and costlier. Therefore, in order to strike a balance in the size of sugar crystal, the sugar factories manufacture medium sized crystals (neither large nor small) of the sieve size of 350 to 400 micro-meters aperture size.

The process run charts are employed after taking corrective actions, so that the process shall not deteriorate. Figure 6 shows the run chart of minimum aperture after taking corrective action. The USL of minimum aperture is 0.9 and the LSL is 0.6. Hence, From Table 1 it is clear that C_P and C_{PK} is given by the formula:

$$C_P = \frac{USL - LSL}{6\sigma} = \frac{0.9 - 0.6}{6 \times 0.043817} = \frac{0.3}{0.262902} = 1.14111 \tag{7}$$

$$C_{PKU} = \frac{USL - \overline{X}}{3\sigma} = \frac{0.9 - 0.731733}{3 \times 0.043817} = \frac{0.168267}{0.131451} = 1.280072 \tag{8}$$

$$C_{PKL} = \frac{\overline{X} - LSL}{3\sigma} = \frac{0.731733 - 0.6}{3 \times 0.043817} = \frac{0.131733}{0.131451} = 1.002148 \tag{9}$$

C_{PK} = Minimum of $C_{PKU}$and C_{PKL} = 1.002148 (10)

$$C_{PM} = \frac{USL - LSL}{6\sigma_{CPM}} \quad where, \quad \sigma_{CPM} = \sqrt{\frac{\sum_{i=1}^{n}(x_i - T)^2}{(n-1)}} where, T = T\arg et\ value \tag{11}$$

Thus,

$$C_{PM} = \frac{0.9 - 0.6}{6 \times 0.095219} = 0.525$$

Thus, after taking the corrective action for minimum aperture , there is an increase in C_P from 0.3848 to 1.1411 and increase in C_{PK} from -0.4200 to 1.00214 and C_{PM} has increased from an initial value of 0.073 to 0.525, which records an increase of 7 folds.

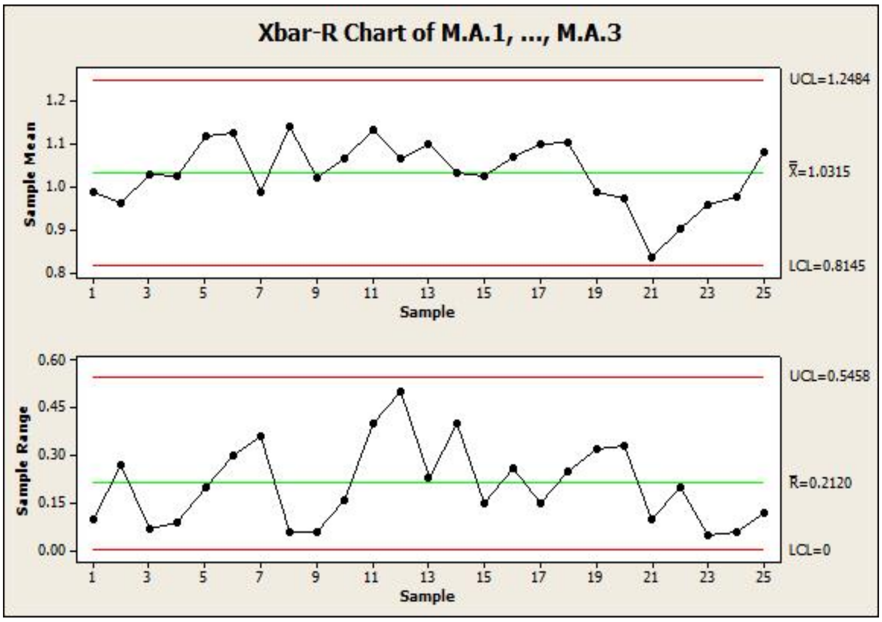

Figure 4. $\overline{X}$ and R chart for Minimum aperture

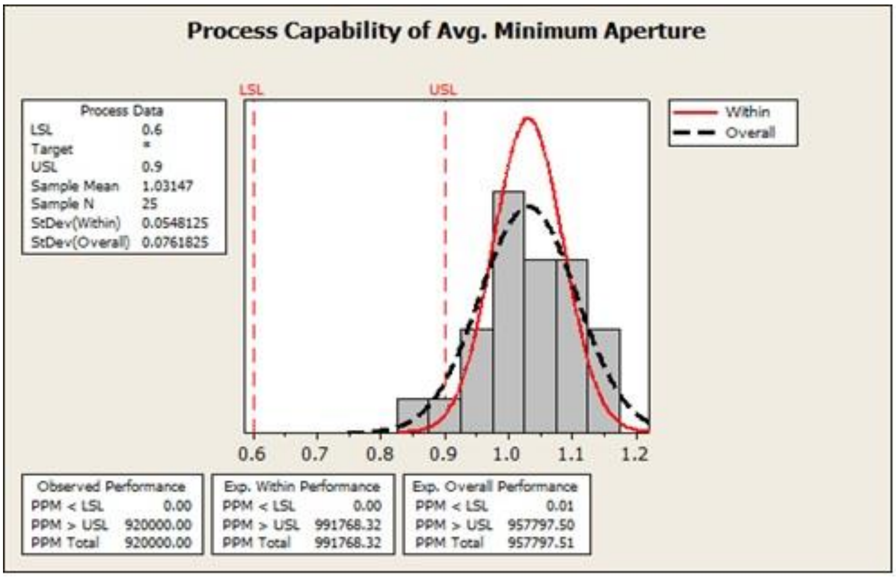

Figure 5. Process capability analysis of minimum aperture

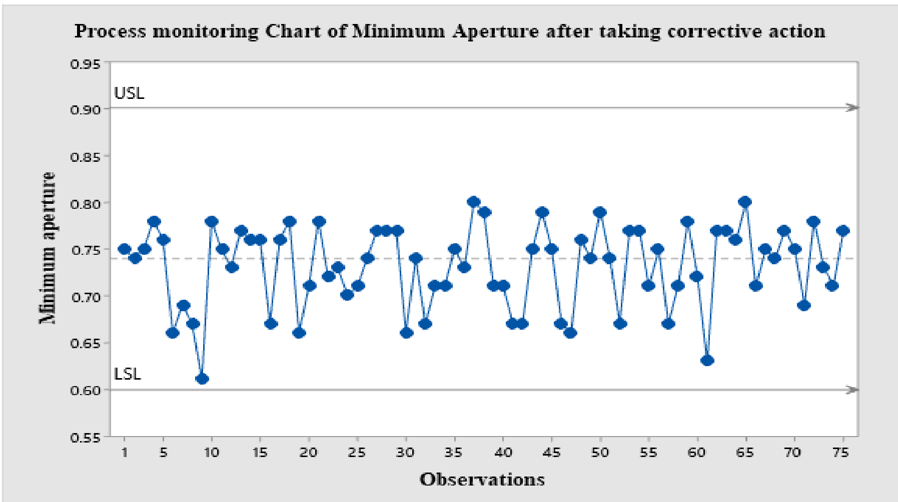

Figure 6. Process run chart for minimum aperture post corrective action

5. Results and Discussions

5.1. The process capability indexes' values

Based on the formulae of capability indexes depicted in Table 1, the final process performance capability indexes for the critical-to-quality characteristics are consolidated in the tabular format in Table 8.

Table 8. Final Process Capability indexes

S.No.	CTQ characteristic	Type of CTQ	C_P	C_{PKU}	C_{PKL}
1	Turbidity	Smaller-the-better	2.32	3.41	1.22
2	Minimum Aperture	Double sided characteristic	1.14	1.28	1.002

6. Discussion

It is observed from initial studies that for Turbidity (which is smaller-the-better type characteristic) and Minimum aperture (which is double sided type characteristic), the capability indexes are smaller than 1.0. For achieving a target value of the capability index to be more than 1.0 following are the corrective actions taken:

- Clarification process is intensified for raising the CP_{KU} levels of turbidity
- The coefficient of variation is preferably kept to a value of less than 35% for raising the $C_P$and CP_K levels of Minimum Aperture

Thus, this work horizontally deploys the concept of process capability pertaining to discrete manufacturing industries into a continuous process production scenario. The characteristics pertaining to continuous process industries are one-sided and are either a larger-the-better characteristic or smaller-the-better characteristic. In such a situation, the process performance capability index upper limit *(CP_{KU})* is dedicated for smaller-the-better and process performance capability index lower limit *(CP_{KL})* is dedicated for larger-the-better characteristics. The greater the index value, the better is the Critical-To-Quality characteristic.

It is observed from Table 8 that for the CTQ characteristic of Turbidity, the process performance capability index upper limit *(CP_{KU})* is to be considered as Turbidity is a smaller-the-better type of characteristic. It is evident that for turbidity the final CP_{KU} = 3.41 after implementing the corrective action of intensifying the clarification process. On the other hand, the Minimum Aperture is a double sided CTQ Characteristic. Hence for Minimum Aperture the smaller value among the CP_{KU} and CP_{KL} is to be considered. Thus, for Minimum Aperture, the final process performance capability index CP_K = 1.002. Considering for a target value $T = 0.7$ for minimum aperture, this study has witnessed around a 7 folds increase of the value of $C_{PM}$from an initial value of 0.07 to a final value of 0.525 post corrective action. Therefore, after implementing the corrective actions, the process performance indexes for the CTQ characteristics of "Turbidity" and "Minimum Aperture" are both obtained as greater than the value of 1.0.

In this way, the process capability concepts are successfully applied to a process oriented industry.

Future scope of this work can be extended to other quality assurance parameters like Sucrose content, Moisture Content, Dextran content, Conductivity Ash and SO_2 content for performing process capability studies.

7. Conclusions

Nowadays all organizations are craving to maintain good quality in their products and services to survive in this high competitive world. Though there are many tools to improve and scrutinize the quality of the product, SPC (Statistical Process Control) and process capability analysis have carved a niche importance.

In this study, sugar industry was chosen for the process capability study. Quality parameters of sugar were collected for required number of samples. To get the trust worthy results in process capability analysis, control charts for all quality parameters were drawn and checked whether the collected data is stable or not. Process performance capability indexesC_{PKU} and C_{PKL} were considered as a measure for smaller-the-better and larger-the-better critical-to-quality characteristics. Process capability indexes for CTQ parameters were calculated and process capability histograms were drawn. As the process for producing with the turbidity and minimum aperture within specification limits is incapable, corrective actions were suggested to make process capable. Process capability index accounting for Taguchi's Loss Function, C_{PM}, is introduced and added for this double sided characteristic of minimum aperture, with a target value of $T=0.7$ sieve size. A significant increase in C_{PM} from an initial value of 0.073 to a final value of 0.525 is observed, which records an increase of 7 folds.

Thus, the concept of process capability pertaining to discrete manufacturing processes is extended to continuous process oriented industry like sugar manufacturing. Hence, the procedures adopted in this work can be horizontally deployed onto other process dominant industries like pharmaceuticals, cement and refinery, where the process characteristics are predominantly one-sided of either smaller-the-better or of larger-the-better nature.

References

[1] J. A. Farooquiea and A. B. Mohapatrab, "Japanese manufacturing techniques and practices: an Indian perspective," Jordan Journal of Mechanical and Industrial Engineering, Vol. 3,No. 3, 2009,

[2] R. H. Fouad and A. Mukattash, "Statistical process control tools: a practical guide for Jordanian industrial organizations," Jordan Journal of Mechanical and Industrial Engineering, Vol. 4,No. 6, 2010, 693-700.

[3] M.-C. Tsai and C. Ou-Yang, "Improving a commercial bank's operation performance through statistical process control," Journal of the Chinese Institute of Industrial Engineers, Vol. 27,No. 3, 2010, 226-236.

[4] Y. E. Shao, "The identification techniques that result from using an integrated SPC-EPC control system," Journal of the Chinese Institute of Industrial Engineers, Vol. 15,No. 2, 1998, 179-184.

[5] S. Balamurali and M. Usha, "Optimal designing of variables quick switching system based on the process capability index C pk," Journal of Industrial and Production Engineering, Vol. 31,No. 2, 2014, 85-94.

[6] A. Kumaravadivel, U. Natarajan, and C. Ilamparithi, "Determining the optimum green sand casting process

parameters using Taguchi's method," Journal of the Chinese Institute of Industrial Engineers, Vol. 29,No. 2, 2012, 148-162.
[7] S.-P. Lee, D. S.-H. Wong, C.-I. Sun, W.-H. Chen, and S.-S. Jang, "Integrated statistical process control and engineering process control for a manufacturing process with multiple tools and multiple products," Journal of Industrial and Production Engineering, Vol. 32,No. 3, 2015, 174-185.
[8] A. Adeoye Akeem, "Process Capability Analysis as a Means of Decision Making in manufacturing company," International Journal of Advanced Research in Computer Science & Technology (IJARCST), Vol. 1,No. 1, 2013, 15-18.
[9] J. Shinde and R. Katikar, "Importance of process capability and process performance indices in machine tool," International Journal of Research in Engineering & Applied Sciences, Vol. 2,No. 2, 2012, 1211-1217.
[10] S. Bangphan, P. Bangphan, and T. Boonkang, "Process Capability Analysis by Using Statistical Process Control of Rice Polished Cylinder Turning Practice," International J. of Mechanical, Aerospace, Industrial, Mechatronic and Manufacturing Engineering, Vol. 8,No. 12, 2014, 2037-2043.
[11] J. J. Flaig and F. Khorasani, "Process capability analysis using curve fitting methods," Global Journal of Research In Engineering, 2013,
[12] J. Subramani and S. Balamurali, "Control charts for variables with specified process capability indices," International journal of probability and statistics, Vol. 1,No. 4, 2012, 101-110.
[13] S. Steiner, B. Abraham, and J. MacKay, "Understanding process capability indices," Waterloo, Ontario, 1997,
[14] G. Sharma and P. S. Rao, "Process capability improvement of an engine connecting rod machining process," Journal of industrial engineering international, Vol. 9,No. 1, 2013, 1-9.
[15] G. Sharma and P. S. Rao, "A DMAIC approach for process capability improvement an engine crankshaft manufacturing process," Journal of Industrial Engineering International, Vol. 10,No. 2, 2014, 1-11.
[16] G. Sharma, P. S. Rao, and B. S. Babu, "Process capability improvement through DMAIC for aluminum alloy wheel machining," Journal of Industrial Engineering International, Vol. 14,No. 2, 2018, 213-226.
[17] G. Sharma, P. S. Rao, and B. S. Babu, "Process-based tolerance assessment of connecting rod machining process," Journal of Industrial Engineering International, Vol. 12,No. 2, 2016, 211-220.
[18] S. E. Vannan and S. P. Vizhian, "Statistical Investigation on Effect of Electroless Coating Parameters on Coating Morphology of Short Basalt Fiber," Jordan Journal of Mechanical and Industrial Engineering, Vol. 8,No. 3, 2014,
[19] N. Mandahawi, R. H. Fouad, and S. Obeidat, "An application of customized lean six sigma to enhance productivity at a paper manufacturing company," Jordan Journal of Mechanical and Industrial Engineering, Vol. 6,No. 1, 2012, 103-109.
[20] M. Al-Marsumi, "Total quality management in the top rank of the dairy industry in Jordan,"Jordan Journal of Mechanical and Industrial Engineering, Vol. 3,No. 1, 2009, 47-58.
[21] P. Lundkvist, "Experiments and Capability Analysis in Process Industry," Luleå tekniska universitet, 2012.
[22] J. Munoz, "Process capability analysis using fuzzy sets theory," in Applications of Fuzzy Logic Technology, 1993, pp. 212-223.
[23] S. Iranzadeh, "Investigating the relationship between RPN parameters in fuzzy PFMEA and OEE in a sugar factory," Journal of Loss Prevention in the Process Industries, Vol. 60,2019, 221-232.
[24] A. Kustiyo and Y. Arkeman, "Design for improvement of sugar factory performance based on statistical thinking," in IOP Conference Series: Earth and Environmental Science, 2019, p. 012033.
[25] W. Pearn and K. Chen, "Making decisions in assessing process capability index Cpk," Quality and reliability engineering international, Vol. 15,No. 4, 1999, 321-326.
[26] W. Pearn, M. Shu, and B. Hsu, "Testing process capability based on Cpm in the presence of random measurement errors," Journal of Applied Statistics, Vol. 32,No. 10, 2005, 1003-1024.
[27] N. Mohan and M. Yadav, "Carbonation and Phosphatation Process for Refined Sugar Production: A Comparative Evaluation," in Sugar and Sugar Derivatives: Changing Consumer Preferences, ed: Springer, 2020, pp. 225-240.
[28] K. M. Aljebory and M. Alshebeb, "Integration of Statistical and Engineering Process Control for Quality Improvement (A Case Study: Chemical Industry-National Chlorine Industries)," Ind. Eng, Vol. 8,No. 4, 2014, 243-256.
[29] F. Carpenter and V. Deitz, "Status of Sugar Colour and Turbidity Measurements," Journal of the American Society of Sugar Beet Technologists, Vol. 12,1963, 326-347.
[30] A. Khalili and K. Subari, "Understanding the linkage between soft and hard total quality management: evidence from Malaysian manufacturing industries," 2013,