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Statistical Process Capability Design to Improve Process Stability of a Molding Machine

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Abstract

Justification of production and manufacturing processes overtime, process capability in the concept of statistical control has been of great importance because it has promoted the production of products that satisfy the expectation of consumers. This paper aimed at promoting the adoption of quality process capability design in a bid to improve the process stability of a process and improve the process performance in the long run of production. In ensuring this, the technique of design of experiment is adopted using factorial design after which the capability analysis was carried out on the data on plastic containers produced by molding machines as deduced from the control X-bar and Range charts, it was established that the process was observed to be stable and in a state of statistical quality control and the plastic containers produced were observed to differ from one another as a result of variation on the part of the operators of the molding machines.

Keywords: Process capability design; Analysis of variance; Molding machine; Statistical quality control

Introduction

The taste of consumers for quality has evolved from time immemorial of a production processes. In satisfying quality, statistical methods have been adopted in promoting stability and capability of processes during this phase. Process capability analysis together with statistical process mechanism and design of experiments are statistical methods that have been used for decades with the goal to reduce the variability in industrial processes. The study of process capability in manufacturing industries has aided improvement in the production of products that are fit for purpose (quality). Moreover, use of statistical methods in industry is expanding by the introduction of quality management concepts specified as the Six Sigma program where statistical methods, including process capability analysis, are valuable parts. A process is a unique combination of tools, materials, methods and people occupied in producing a measurable output and involves a periodical of actions or operations influenced by several factors all contributing to its eventual outcome; an example is a manufacturing segment for automobile parts. All processes possess inherent statistical variableness which can be identified, evaluated and limited by statistical methods. Thus, in order to meet customer requirements, organizations must improve the quality by reducing variant in production processes because the lesser the variation in the process, the better the quality it provides. Process capability is the long-term performance level of the process after it has been brought under statistical control and it is determined by comparing the width of the process variation with the width of the specification limits and the inherent ability of a process to produce similar parts for a sustained period of time under a given set of conditions when operating in a state of statistical control. In specific, process capability deals with the uniformity of the process and it is often necessary to liken the process variation with the engineering or specification tolerances to determine the suitability of the process. The significance of process capability study is to isolate the inherent (random) variability which is always present from the assignable causes of variability which must be investigated. In a true process capability study, when there is exact observation of the process, inferences can be made about the stability of the process over time by directly controlling or monitoring data collection activity and understanding the time sequence of the data. Process capability is further defined as the spread within which most of the part values within a distribution will fall, generally described within plus or minus three standard deviation ($\pm 3\sigma$) and it involves the repeatability and consistence of a manufacturing process relative to customers' requirements. Process capability is a measurable attribute of a process to specification, which is commonly expressed as process capability index (C_{pk}) or as a process performance index (P_{pk}). This baseline definition enables us to compare process capability under actual manufacturing conditions with specification tolerances. Specifications or requirements are the numerical values within which the system is likely to operate, i.e. the minimum or maximum acceptable values. Process capability design is set up to see what the process is capable of doing under controlled conditions.

Capability analysis has been used in many facets of industrial processes. Capability study has been applied in the field of medicine, management for the evaluation of the best technique for management as well as to determine service operations for quality sustainability purposes. This capability study helps to create room for continuous improvement and development of products as well as improving the trust of customers in the company's products. Capability analysis is majorly summarized in indices; these indices can be monitored overtime to show how a system is changing. Capability indices that have been widely used in the manufacturing and industrial environment include C_p and C_{pk} explicitly and these indices provide a common metric to evaluate and predict the performance of a process.

In view of the deficiency in the study of process stability and capability in manufacturing industries within the country, this paper

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focuses on how quality process capability designs promote process stability of the production of plastic containers in a bid to improve the application of capability study in the manufacturing industry. The work is aimed towards promotion of quality process capability design in the production of plastic containers that will improve process stability of the process.

Several authors have worked on process capability design in a bid to improve on the process stability of a production process.

Sullivan [1] employed the concept of process capability studies using the knowledge of capability index C_p in the automobile industry to enhance stability of automobiles produced to engineering specifications.

Taguchi [2] first introduced Taguchi capability value which was also a measure for estimating process capability with respect to target values. This method of capability analysis fits with his loss function approach. In cases where it is important to achieve a result when machining as close to the target value as possible, then the Taguchi capability index C_{pm} can be used. This concept of process capability design was used in machining systems.

Kane [3] further worked on process capability by introducing the capability index C_{pk}. This index was used to quantify process performance and takes into consideration cases where upper specification limits (USL) as well as lower specification limit (LSL) is relevant. He also investigated the test of hypothesis about process capability ratios and provided a table of sample sizes and critical values for C to aid in testing process capability. His work was also designed at obtaining the process capability estimate for a one sided specification. Measures of process capabilities were solely in terms of process variation and do not consider process location.

Refaie and Bata [4] proposed a procedure for assessing a measurement system and manufacturing process capabilities using Gage Repeatability (GR&R) designed experiments with four quality measures. The gage and part variance components are then estimated by conducting analysis of variance (ANOVA) on the GR&R measurement observations.

Van der Merwe and Chikobvu [5] considered process performance and developed a process potential index for average of observations from the new or unknown model. They derived theoretical and simulation results using Bayesian approach. They therefore removed the complexities of frequency distributions for measuring process performance by this approach.

Wang [6] developed a procedure for constructing multivariate process capability indices based on the principal component analysis (PCA) and Clements method for short-run production. PCA can identify correlations among multiple characteristics and determine independent components. This technique solves the problem of evaluating process quality performance with multiple quality characteristics in a short run production to help to meet the practical requirements of industry.

Chen, Huang and Huang [7] work on process capability as regards the construction of control chart of unilateral specification index C_{pl} and C_{pu} to monitor and evaluate the stability of process and process capability. This control chart contains upper control limit, lower control limit, upper warning limit, lower warning limit. This chart also supports a set of sensitizing rules for user to easily monitor the quality of process and the stability of the process.

Kaya and Kharaman [8,9] considered capability study involved using fuzzy set theory to add more information and flexibility to process capability analysis. The fuzzy formulation includes the development of C_p, C_{pk}, C_a, C_{pm}, C_{pmk} which are the most traditional used PCIs. The fuzzy PCA is developed when the specifications limits are represented by triangular or trapezoidal fuzzy numbers. The fuzzy process capability indices (FPCIs) are analyzed under the existence of correlation and hence, robust process capability indices are obtained. The fuzzy capability indices are improved for six-sigma approach.

Aslam et al. [10] worked on process stability and capability as regards to acceptance sampling. Their work was on the study of process capability as a justification of accepting or rejecting a lot or batch of a production process. In their work, three repetitive types of sampling plans using the generalized process capability index of multiple characteristics was adopted which included a repetitive sampling plan, a resubmitted sampling plan and a multiple dependent state repetitive sampling plan. The plan parameters of these sampling schemes are determined through the nonlinear optimization solution [10,11].

Research Methods

The basic goal of producers is to produce products with the aim of satisfying consumers' expectation in quality. For this research paper, it is aimed at promoting the adoption of quality process capability design in a bid to improve the process stability of a process and improve the process performance in the long run of production. In order to achieve this, technique of design of experiment is adopted using factorial design after which the capability analysis will be carried out on the data of plastic containers produced by molding machines and control X-bar and Range charts. Factorial design technique will be adopted for the experiment because we have two factors at various levels for the possible variability in the plastic containers produced. Hence, the process can be represented by an effect 2^k factorial model which is shown below:

$$y_{ijk}=\mu+\alpha_i+\beta_j+(\alpha\beta)_{ij}+\varepsilon_{ijk}$$

Where the model parameters $\alpha_i, \beta_j, (\alpha\beta)_{ij}$ and ε_{ijk} are all independent random variables that represent the effects of machines, effects of operators, effects of interaction of machines and operators, and random error respectively, μ is the overall mean and y_{ijk} is the response.

Sampling Technique and Tool for Analysis

A total number of 100 samples of secondary data on plastic containers produced by the molding machine are used for analysis, since the aim is to enhance production of plastic containers that are in-control (stable) and that are capable from the molding machine through quality process capability design. Therefore, the analysis of variance (ANOVA) and Factorial fit will be carried out using statistical package Minitab. This is done to identify the source of variability in the process and to test if factors (machines and operators) have individual or joint influence on the response of containers produced. After which variability that could result from various factors of production in the process will be controlled to ensure the improvement of production of plastic containers that satisfy quality.

Data Analysis

Figure 1 presents the control charts which establish the statistical stability of the process. It is deduced from the figure that the process is in a state of statistical control. It was also observed for Range chart that the process is in a state of statistical control because the mean of the individual subgroups are within the upper and lower control limits

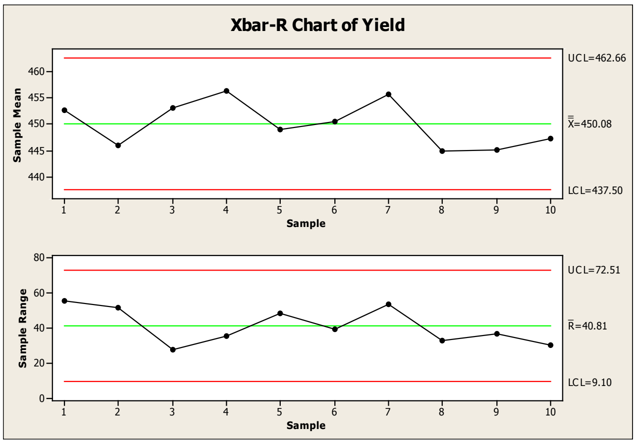

Figure 1: X-bar and R control charts for the plastic containers produced.

production (Table 1).

From Table 2, the p-value for the estimate of effects is greater than the significance level in the case of the machines as well as in the case of operators, inference can be drawn that there is a significant difference in the width dimension of the plastic containers produced as a result of the operation of the various machines as well as the various operators. It is also observed that there is a significant difference in the width of the plastic containers as a result of the joint operation of the machines and operators since the p-value is greater than the level of significance (Tables 1 and 2).

I proceeded to carry out the test for interaction between the two factors as was obtained that significant difference exist in the width of the containers due to joint operation of the machines and operators. From Table 2, conclusion can be drawn that there is no significant interaction between the machines and operators. Also, variability in the dimension of plastic containers produced result from the main effects of the operators and machines independently. This is established by the figure of main effects presented below:

It can be observed from Figure 2 that on the part of the machines, the mean of the respective subgroups are about the mean of the dimension of the plastic containers produced. Alternatively, on the part of the operators the mean of the respective subgroups is not about the mean of production. Therefore, it was deduced that the variability in the width of the plastic containers produced majorly results from the action of the various operators.

Table 3 as presented above shows the estimate of the coefficients of the parameters in the model of the factorial design.

Analysis of Variance (ANOVA)

Hypothesis to be tested

For machines

$H_{0:}$ $\mu_1=\mu_2=\ldots=\mu_{10}$ (There is no significant effect of the machine in variability of containers)

$H_{1:}$ $\mu_1\neq \mu_2\neq \ldots \neq \mu_{10}$ (There is a significant effect of the machine in variability of containers)

For operators;

$H_{0:}$ $\mu_1=\mu_2=\ldots=\mu_{10}$ (There is no significant effect of the operator in variability of containers)

$H_{1:}$ $\mu_1\neq \mu_2\neq \ldots \neq \mu_{10}$ (There is a significant effect of the operator in variability of containers) (Table 4)

In the analysis of variance to determine the factor responsible for maximum variability in the width of the plastic containers, Table 5 shows that on the part of the operators since the p-value <0.05, the null hypothesis is rejected and was deduced that there is a significant effect of the operators in the variability of the plastic containers that is, the operators are responsible for the maximum variability in the plastic containers produced. While on the part of the machines, since the p-value >0.05 we accept the null hypothesis and conclude that there is no significant effect of the machines in the variability of the plastic containers that is, the machines are not responsible for variability in the plastic containers produced. Hence, variability in the dimension of the plastic containers majorly results from the operation of the operators.

Figure 3 presents the interaction plot of the various machines as well as various operators. On the part of the individual machines, it was observed that the variability in the width of the containers occurred majorly from machine 1 and machine 10 produce containers that are about the mean of production. On the other hand, in the case of the

Estimated Effects and Coefficients for Yield (coded units)					
Term	Effect	Coef	SE Coef	T	P
Constant	-5.149	450.08	1.303	345.4	0.000
Machine	-6.305	-2.575	2.042	-1.26	0.21
Operator	-9.866	-3.153	2.042	-1.54	0.126
Machine*operator		-4.933	3.198	-1.54	0.126

Table 1: Factorial fit: yield versus machine, operator.

Analysis of variance for yield (coded units)						
Source	DF	Seq SS	Adj SS	Adj MS	F	P
Main Effects	2	675	675	337.5	1.99	0.143
2-Way interactions	1	403.9	403.9	403.9	2.38	0.126
Residual error	96	16300.5	16300.5	169.8		
Total	99	17379.4				

Table 2: Factorial fit: analysis of variance.

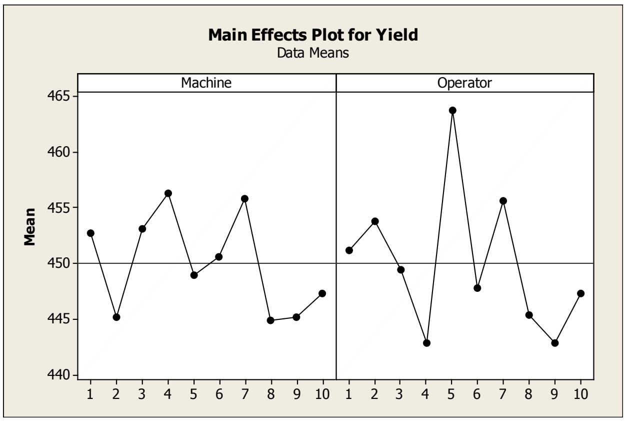

Figure 2: Main effects plot for yield.

Estimated Coefficients for Yield using data in uncoded units	
Term	**Coef**
Constant	449.711
Machine	0.767677
Operator	0.639192
Machine*Operator	-0.2436

Table 3: Factorial fit: estimated coefficients for yield.

Factor	Type	Levels	Values
Machine	random	10	1, 2, 3, 4, 5, 6, 7, 8, 9, 10
Operator	random	10	1, 2, 3, 4, 5, 6, 7, 8, 9, 10

Table 4: Hypothesis.

Analysis of Variance for Yield					
Source	**DF**	**SS**	**MS**	**F**	**P**
Machine	9	1709.7	190	1.24	0.283
Operator	9	3721.5	413.5	2.7	0.009
Error	81	12417.8	153.3		
Total	99	17849			

Table 5:ANOVA: yield versus machine, operator.

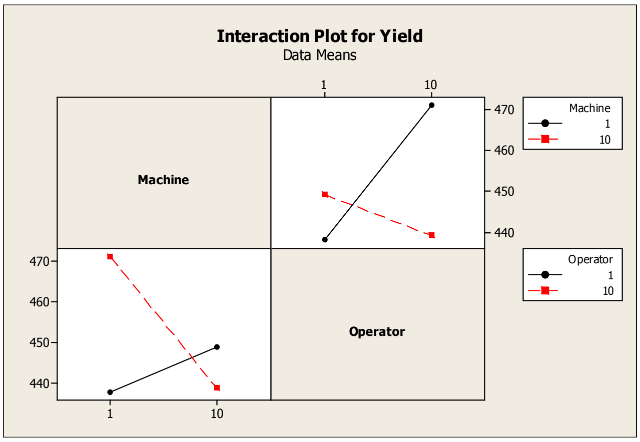

Figure 3: Interaction plot for yield.

operators it was observed that operator 10 is majorly responsible for the production of containers that vary from one another, while operator 1 produces containers that are about the mean of the production.

Process capability analysis

Process capability analysis is shown in Figure 4.

Computation for X-bar chart

Centre line (CL)=$\bar{\bar{X}}$

Upper control limit (UCL)=$\bar{\bar{X}} + A_2 \bar{R}$

Lower control limit (LCL)=$\bar{\bar{X}}$ - $A_2 \bar{\bar{X}}$

Where: A_2=0.32 and $\bar{\bar{X}}$ and $\bar{R}$ are estimated as:

$$\bar{\bar{X}} = \frac{\sum_{i=1}^{10} \bar{X}i}{10} = \frac{4500.8}{10} = 450.08$$

$$\bar{\bar{R}} = \frac{\sum_{i=1}^{10} \bar{R}i}{10} = \frac{408.1}{10} = 40.81$$

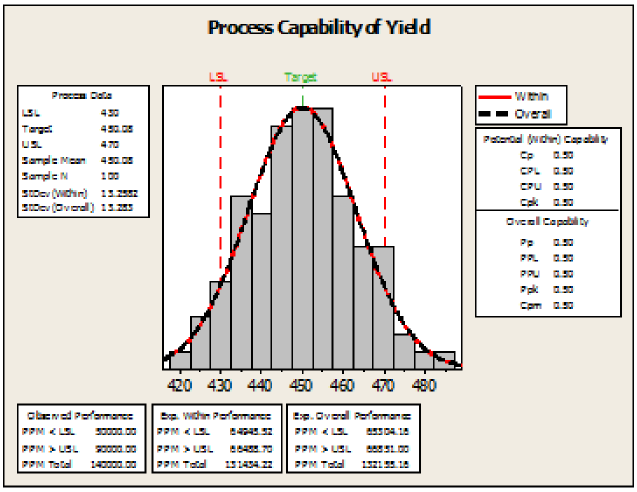

Figure 4: Process capability of yield.

Hence the control limits are estimated as:

CL=$\bar{\bar{X}}$ =450.08

UCL=$\bar{\bar{X}}$ + $A_2 \bar{R}$ =450.08 + (0.32) 40.6=463

LCL=$\bar{\bar{X}}$ - $A_2 \bar{R}$ =450.08 – (0.32) 40.6=437

Computation for R chart

From the above table, $d_{4=}$1.777, $d_{3=}$0.223 and

Centre line= $\bar{R}$ $_=$40.81. Hence, the control limits are estimated as:

Upper control limit (USL)=$d_4 \bar{R}$ =1.777 * 40.81=72.51

Lower control limit (LCL)=$d_3 \bar{R}$ $_=$0.223 * 40.81=9.10

Analysis of the process capability using the company's specification limits:

USL=470

LSL=430

Therefore, the estimate of the process capability for the individual 10 subgroups is:

$$C_p = \frac{USL - LSL}{6};$$

where the values process capability indices for all the subgroups are estimated as: (Table 6).

It is observed that for all of the subgroups, the process was observed to be incapable in all the cases since all the C_p values are lesser than 1.

Furthermore, the overall process capability indices for the process are obtained by:

$$C_p = \frac{USL - LSL}{6} = \frac{470 - 430}{6\ (3032\ )} = 0.50$$

Also, the capability index C_{pk} is calculated as:

$$C_{pk} = \min\left[\frac{\bar{X} - LSL}{3\sigma}, \frac{USL - \bar{X}}{3\sigma}\right]$$

Where: $\bar{X}$ =450.08, LSL=430, USL=470 and σ=13.32

X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}
0.426	0.427	0.742	0.685	0.469	0.486	0.448	0.656	0.639	0.721

Table 6: Values for process capability.

$$C_{pk} = \min\left[\frac{450.08-430}{3(13.32)}, \frac{470-450.08}{3(13.32)}\right]$$

$C_{pk=}$min [0.50, 0.50]

C_{pk}=0.50

From the process capability plot for the plastic containers produced, it is observed that the process is not capable since the C_p=0.50<1 and the C_{pk}=0.50<1 and the process is also observed not to perform since process performance index P_p=0.50<1 even though the process is in a state of statistical control (Appendix 1).

Conclusion

As it was deduced from the control X-bar and Range charts in the analysis of this paper, it was established that the process was observed to be stable and in a state of statistical control. From the analysis carried out and the results obtained, the plastic containers produced were observed to differ from one another as a result of variation on the part of the operators of the molding machines. Therefore, conclusion can be drawn from the analysis that the process requires improvement to promote the process capability and process performance of the process in the long run of production in other to meet the required specification of customers as regards the plastic containers produced. Moreover, it was obtained that the specification limits of the company were off-centered since the capability index (C_p) was greater than the centering capability index (C_{pk}). Hence, improvement on the training of operators in respect of the use of the molding machines might be required since it is observed that the variability in the width of plastic containers resulted from the various operators. The variability on the part of the machines irrespective of operators is not significant since the plastic containers by the various machines are observed to be about the mean of production.

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