Application of the Advanced Quality Improvement Techniques: Case Study

Vidosav Majstorovic[1], Tatjana Sibalija[2]

[1] Faculty of Mechanical Engineering, University of Belgrade, Kraljice Marije 16, 11 000 Belgrade, Serbia
[2] Faculty of Engineering International Management, European University, Carigradska 28, 11 000 Belgrade, Serbia

{vidosav.majstorovic@sbb.rs, tsibalija@gmail.com}

Abstract. Implementation of the advanced cost-effective methodologies for product and/or process quality improvement is an effective mean to fulfil or exceeds customer's expectations. This paper presents the analysis of a performance of automatic enamelling process for a non-normal data distribution, conducted within the six sigma project implemented in a production system. Drawing on the process analysis results, process optimisation was performed using location and dispersion modelling. It proved its effectiveness in determining the significant effects of process factors on the response mean and variation, and in obtaining the optimal factors setting of the observed single-response process.

Keywords: process performance analysis, non-normal distribution, process parameters optimisation, location and dispersion modelling.

1 Introduction

The challenge in today's competitive markets is to be on the leading edge of producing high quality products at minimum costs. The implementation of the advanced quality improvement programs, such as six sigma, could help in improving company's competitiveness which is a key issue in a fast-moving global industry. Six sigma is a disciplined approach for process and/or product quality improvement, based on customer quality requirements. It takes users away from 'intuition-based decisions' to 'fact-based decisions'. For the existing system, six sigma is deployed according to DMAIC (Define-Measure-Analyse-Improve-Control) procedure. This paper deals with a case study performed in a Serbian cookware production system with the aim to reduce waste and cost of poor quality (COPQ) and improve the process sigma level, using six sigma methodology. In section 2, steps of define and measure stages were presented in brief, followed by detailed presentation of the process performance analysis for non-normally distributed data. In the improvement phase, the usage of location and dispersion modelling for the process parameters optimisation was shown. The discussion regarding the significance and effectiveness of the used techniques was also presented. Section 3 provides the concluding remarks on the applied techniques.

2 Six Sigma Application

This study illustrates parts of a six sigma project conducted according to DMAIC. In the define stage, IDEF0 method was used to map the system, showing detailed presentation of main processes, sub-processes and activities. Pareto analysis was developed to rank the defect types detected in the automatic enamelling process. The major defects were mainly related to the product characteristic - pot enamel thickness. Then, Ishikawa diagrams were used to analyse main causes of major defects, showing that the most problematic sub-process is base enamelling [1]. In order to verify the measuring system, the detailed measuring system analysis (MSA) was performed in the measure stage (Figure 1). The gage R&R study was conducted to calculate the equipment variation (repeatability), operator variability (reproducibility) and variation of pot enamel thickness (part-to-part variation). Since operators and equipment caused less than 20% of the total variation and the gage bias was statistically insignificant, the measuring system was accepted for the measurement and process analysis [2].

2.1 Process performance analysis for non-normally distributed data

Capability studies are used to predict the overall ability of a continuous distribution process to make products within the required specifications. Process capability analysis entails comparing the performance of a process against its specifications, thus enabling analysis of previous and current performance, and benchmarking. Process capability and performance indices were widely investigated as means of summarizing process performance [3], [4]. Several recent studies were dedicated to capability and performance indices [5], [6]. The simplest capability index Cp presents the ratio of the specification width to the natural tolerance spread of a process. To incorporate the measure of process location, Cpk index was created [3], [4], considering how well the process spread is located about the target and the specification limits. The interpretation of the capability indices implies the following assumptions [3]: process stability; representative samples; normality; independences of observations. Capability indices show what is achievable rather than what is currently being achieved. As a response to this, the process performance indices Pp and Ppk were developed. Performance indices are calculated using the same formulae as for capability indices. However, performances indices do not assume that the process is in-control or is normally distributed and they use all of the data collected (both points in- and out-of-control). The process performance indices make used of the within sample standard deviation including both common and special cause of variation. Therefore, they provide a more realistic assessment of what is actually being produced [3]. It is more realistic to use Pp and Ppk than Cp and Cpk as the process variation cannot be tempered with by inappropriate subgrouping. The essential assumptions for the capability indices use are that the process is stable and the output is normally distributed.

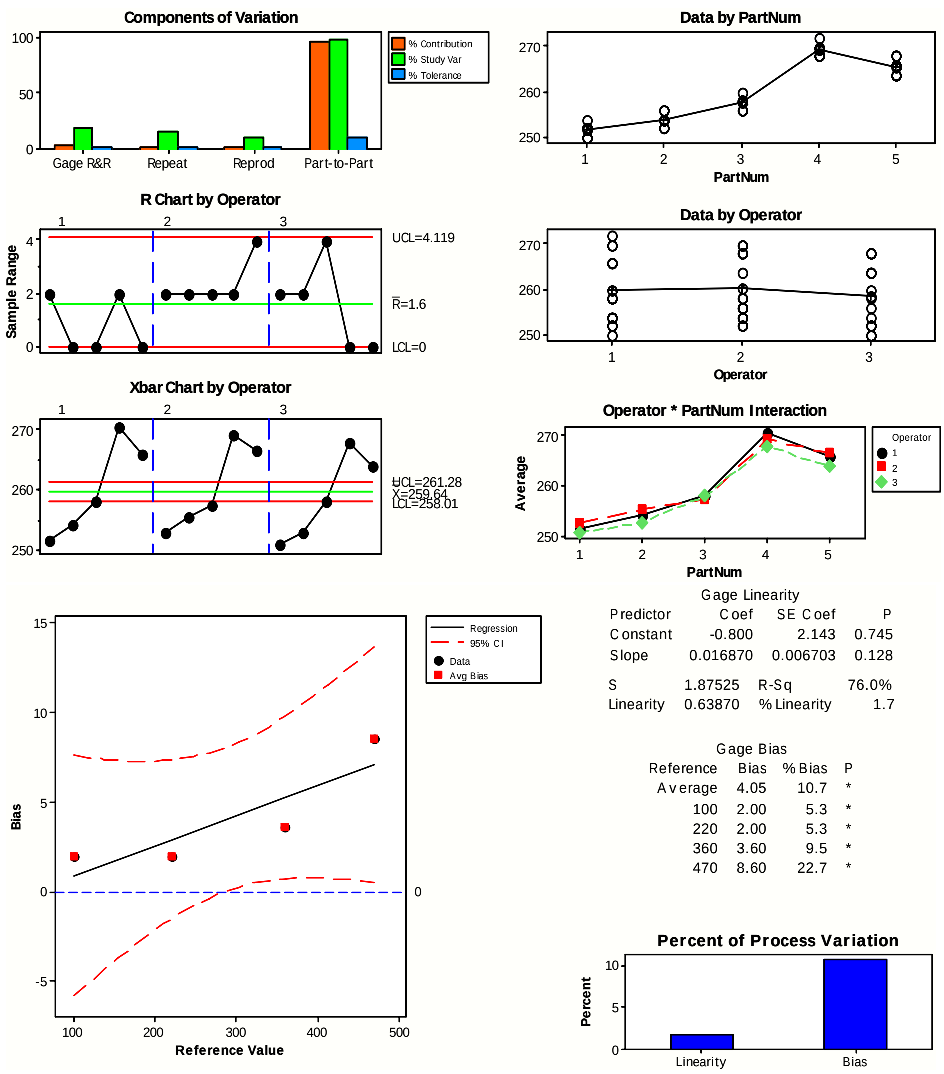

Fig. 1. Details of MSA: gage R&R (up) and linearity and bias study (down)

When the distribution is non-normal, capability indices calculated using conventional methods could often lead to erroneous conclusions. If the capability indices based on the normal assumption are used to deal with non-normal observations, the values of the capability indices may be incorrect and quite likely misrepresent the actual process and product quality [4]. For non-normal distributions, by replacing the unknown 6σ distance by *Up - Lp* calculated based on the available sample data using the estimates of the mean, standard deviation, skewness and kurtosis, a natural tolerance is [4], [5]:

$$Tolerance_{natural} = \mathrm{Up} - \mathrm{Lp} = \mathrm{X}_{0.99865} - \mathrm{X}_{0.00135} \tag{1}$$

where: *Up* and *Lp* estimate the 99.865 and the 0.135 percentile, respectively, to imitate the normal distribution property that the tail probability that the process is outside $\pm 3\sigma$ limits from the average equals 0.27%; $X_{0.00135}$ and $X_{0.99865}$ are values that meet the conditions: $P(X<X_{0.00135})=0.00135$, and $P(X<X_{0.99865})=0.99865$, respectively. Values $X_{0.99865}$ and $X_{0.00135}$ are the *z*-values of the non-normal cumulative distribution curve at the 99.865 % point and the 0.135 % point, respectively. The distance between the 99.865th and 0.135th percentiles is equivalent to 6σ spread in the normal case. The process median is presented by the 50th percentile for the non-normal distribution, which is equivalent to the average value for normal distribution. The relations above were concluded from Clements' method of determining percentiles based on Pearson family of distribution. Clements developed a method for capability indices calculation for non-normal distributions, utilising Pearson curves to provide accurate estimates of $X_{0.0013}$, $X_{0.50}$ and $X_{0.99865}$, and based on the skewness and kurtosis assessment [4].
Since the process performances calculation does not require the assumption that the data are normally distributed, it makes sense to evaluate process performance indices in discussing the actual process for non-normal data. Based on the relation (1), the process performance indices for non-normal distribution could be formulated as:

$$Pp = \frac{USL - LSL}{X_{0.99865} - X_{0.00135}}, \quad Ppk = \min\left\{\frac{USL - X_{0.50}}{X_{0.99865} - X_{0.50}}; \frac{X_{0.50} - LSL}{X_{0.50} - X_{0.00135}}\right\} \tag{2}$$

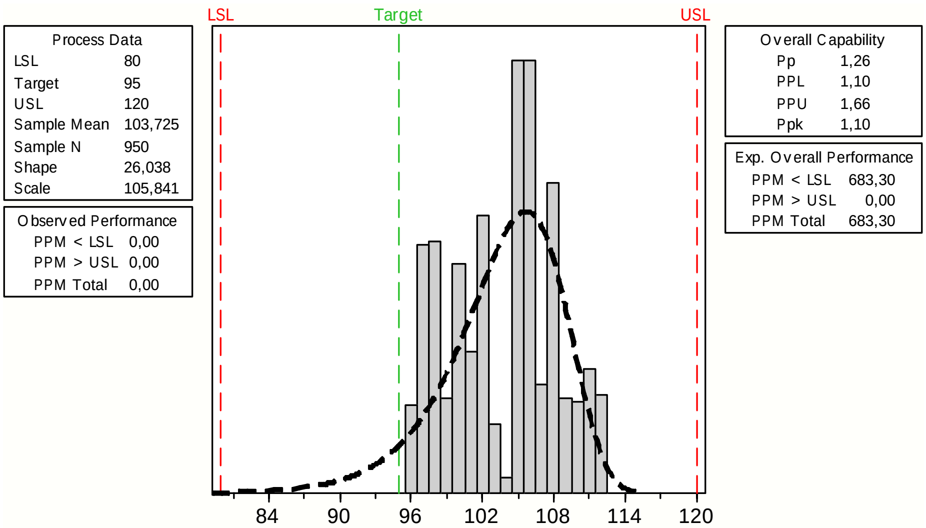

Fig. 2. Performance of the base enamelling process for a Weibull distribution

In the observed six sigma project, as a part of Statistical Process Control (SPC) implementation, the analysis of the base enamelling process was performed using $\overline{X}, R$ control chart and process capability and performance analysis. Specification limits for base enamel thickness are: LSL÷USL=80÷120µm; the specified target value is 95 µm.

After concluding that the process is statistically stable, process probability plot showed that the process data are not normally distributed. Several probability plots for different non-normal distributions were tested, and the Weibull distribution is found the best one to fit the actual process data. The Anderson-Darling goodness-of-fit test and p-value test were used to evaluate the hypothesis that the Weibull distribution provides the best fit. Capability plot for Weibull distribution showed that the actual overall process tolerance interval is contained within the specification interval. Figure 2 presents the base enamelling process performance for a Weibull distribution. The process capability estimation was performed using the overall process performance indices calculated using relation (2). Pp value of 1.26 shows that the process is capable of producing at least 99.74 % of conforming parts. Since Pp is greater than Ppk and PPU is greater that PPL, the process median is off the target and closer to USL. This clearly indicates the location problem. The non-conformance rate is estimated as 683 parts per million.

2.2 Process parameters optimisation using location and dispersion modelling

If the process is not capable of producing virtually all conforming products, it is necessary to improve process performance using advanced experimentation methods, such as Taguchi robust parameter design. Taguchi's orthogonal experimentation is frequently adopted to reduce the trials number but still obtain reasonably rich information with certain statistical level of confidence. Robust parameter design was successfully used in optimising many single-response processes, optimising both the mean and the variance of a response, making a process immune to noise sources, and ultimately improving process and/or product quality. In a modern industry, demands for short life cycles and high-quality products require efficient and objective use of experimentation. With the limited amount of data provided in an unreplicated experiment based on orthogonal array, it is very demanding to study both location and dispersion effects. The identification of the control factor effects on location (mean) and dispersion (variation) of the observed quality characteristic (response) has been proven effective in many single-response process optimisations [7], [8], [9]. The location and dispersion modelling approach gives models for measures of location and dispersion separately, in term of control factors and interactions main effects on a response. At each control factors setting, the sample mean y_i and sample variance σ_i (where n_i is number of replicates at for the ith control factors setting), are used to present the location and dispersion [7]:

$$\gamma_i = \frac{1}{n_i}\sum_j y_{ij}\,,\ \sigma_i^{\,2} = \frac{1}{n_i - 1}\sum_j (y_{ij} - \overline{y_i})^2 \tag{3}$$

The half-normal probability plot is a graphical tool that uses ordered estimated effects to help assess which factors are important. A half-normal distribution is the distribution of the $|Y|$ with Y having a normal distribution. Quantitatively, the estimated effect of a given main effect or interaction and its rank relative to other main effects and interactions is given via least squares estimation. Unimportant factors are those that have near-zero effects and important factors are those whose effects are considerably removed from zero. Hence, unimportant effects tend to have a normal distribution centred near zero while important effects tend to have a normal distribution centred at their respective true large (but unknown) effect values [9].

From the analysis presented in section 2.1 it was concluded that the process needs optimisation in order to solve the location problem (achieve the target base enamelling thickness) and improve process performance. An experiment was performed to identify the optimal setting of critical-to-quality (CTQ) control factors. The parameters adopted as control factors and their values used in the experiment (Table 1) are: enamel parameters: SW, DW, and SW DW interaction; process parameters: PS, AS, and PS AS interaction. In order to accommodate four control factors and two interactions studied at two levels, orthogonal array L16 was used to design the experimental plan [10].

Table 1. Control factors and levels used in the experiment

Control factor	Symbol	Unit	Level '-1'	Level '+1'
Specific weight	SW	gram cm^{-3}	8	11
Deposit weight	DW	gram cm^{-3}	1,68	1,70
Pouring speed	PS	turns min^{-1}	0	3
Automat speed	AS	parts min^{-1}	5	9

Half-normal plots were developed to show the significance of the effects of control factors and their interactions on the response (base enamelling thickness) location and dispersion. Half-normal plot for the response location (MEAN) is shown at Figure 3 up. From the location plot it is visible that effects of factors SW, DW, PS and interaction AS·SW·DW are significant. Then, the regression analysis for the response location (MEAN) was conducted, showing regression equation as follows:

$$MEAN = 87.8 + 6.51 \cdot SW + 5.74 \cdot DW + 3.02 \cdot SW \cdot DW \cdot AS + 2.79 \cdot PS \quad (4)$$

Table 2 shows statistical parameters for the regression equitation (4). The above significant control factors and interaction for the response location are used as predictors. Each predictor in a regression equation has a coefficient associated with it. In multiple regressions the estimated coefficient (*Coef.*) indicates the change in the mean response per unit increase in the responding predictor when all other predictors are held constant. If the *p*-value of a coefficient is less than the *α*-level (α=0.05), there is evidence of a significant relationship between the predictor and the response. Value *T* is used for comparison with the *t*-distribution to determine if a predictor is significant.

Figure 3 down shows the half-normal plot for the response dispersion, presented over *Ln Sigma*^{2}. The reason to use the natural logarithm is that it maps positive values to real (both positive and negative) values, and by taking its inverse transformation, any predicted value on the *ln* scale will be transformed back to a positive value on the original scale. Also, *ln* transformation converts a possible multiplicative relationship into an additive relationship, which is easier to model statistically [7]. The dispersion plot shows significant effects of PS, PS·AS, DW and PS·DW for the response dispersion. Statistical parameters for the dispersion regression equitation are given in Table 2. The obtained regression equation for the response dispersion (*Ln Sigma*^{2}) is:

$$LnSigma^2 = 3.22 + 0.25 \cdot PS + 0.2 \cdot PS \cdot AS + 0.19 \cdot DW + 1.6 \cdot DW \cdot PS \quad (5)$$

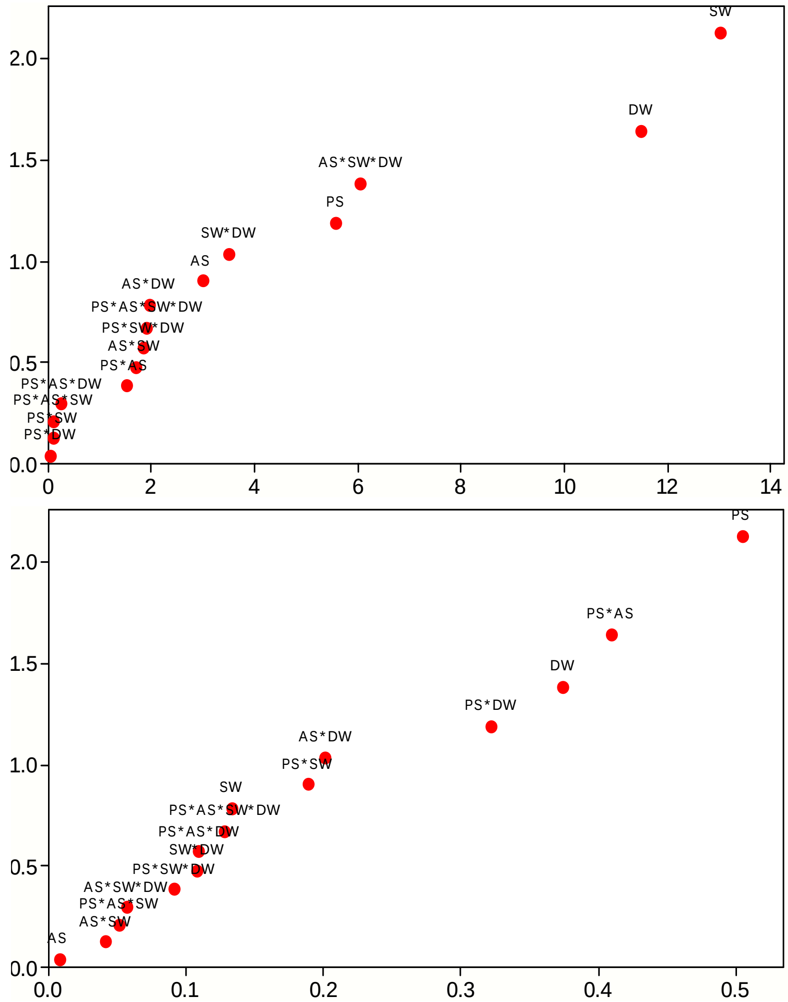

Fig. 3. Half-normal plot of location (up) and dispersion (down) effects

Since the objective of the experiment is to achieve the nominal (target) response mean value, and following the two-step procedure for Nominal-the-Best (NTB) problems [7], the first step is to select the levels of dispersion factors to minimise dispersion. From the dispersion effects relation (5), in order to minimise dispersion the following levels of dispersion factors are selected: PS level '-1', AS level '+1'. The factor SW could be used to bring the mean on the target (value 95 μm), depending on DW level. This is presented in the equitation (6), obtained from the location effects relation (4):

$$95 = 87.8 + 6.51 \cdot SW + 5.74 \cdot DW + 3.02 \cdot SW \cdot DW \cdot (+1) + 2{,}79 \cdot (-1) \qquad (6)$$

There are two possible solutions of the equitation (6): (a.) if DW is set to level '-1' then calculated SW is 16.2; (b.) if DW is set to level '+1' calculated SW value is 10.5. Since due to machine limitation it is impossible in practice to set the SW value to 16.2, the second solution is adopted resulting in the final optimal control factors setting: DW=1.70; SW=11; PS=0; AS=9.

Table 2. Statistical parameters of regression equitation for location and dispersion modelling

Location modelling				Dispersion modelling			
Predictor	Coef.	T	P	Predictor	Coef.	T	P
Constant	87.80	95.79	0.000	Constant	3.22	55.33	0.000
SW	6.51	7.10	0.000	PS	0.25	4.33	0.001
DW	5.74	6.26	0.000	PS·AS	0.20	3.51	0.005
SW·DW·AS	3.02	3.30	0.007	DW	0.19	3.20	0.008
PS	2.79	3.04	0.011	DW·PS	0.16	2.76	0.018

2.3 Discussion

Process analysis performed under the assumption of normally distributed data provided highly misleading results, showing that process performance indices are higher than capability indices, which is practically impossible. This highlights the importance of the accurate process performance calculation, providing correct data for the customer and for the process improvement. Based on the conclusions drawn from the process analysis for a non-normal distribution, the experiment was performed to optimise the process with respect to the target value for the product's characteristic mean (location) and to reduce variation (dispersion). The experimental analysis was performed using ANOVA and using location and dispersion modelling. Although both methods displayed the same optimal factors setting, the later showed significant interaction effects on mean (AS·SW·DW) and variation (PS·DW), that ANOVA did not detect [10]. Verification run was performed using optimised factors setting, confirming the experimental results. The obtained results present significant improvement in comparison to the previous performance. According to Taguchi's quality loss function, loss caused by previous performance was $L_p(Y) = K \cdot 70.06$ units [1], and loss encountered after optimisation is $L_o(Y) = K \cdot 2.99$ units. The achieved improvements are monitored in a practice and documented to ensure the sustainability. Significant reduction of a waste, COPQ and non-added-value activities rework and inspection, and improvement of process performance are expected to be sustained.

3 Concluding remarks

Important issues regarding process analysis and improvement have been highlighted in this study. The significance of the accurate estimation of process performance indices for non-normal distribution was shown. The use of the location and dispersion modelling clarified a total contribution to the process variation, and it was shown as a successful method to optimise the observed single-response process.

However, it would be difficult to apply the presented method for the multi-response process optimisation. Therefore, the authors developed the method consisted of two stages. In the first stage, a statistical factor effects approach was developed, based on Taguchi's quality loss function, principal component analysis and grey relational analysis, to uncorrelated and synthesis responses into a single measure. Since this approach could not provide the overall global optimum, in the second stage the intelligent approach was developed using neural networks (to model the process behaviour) and a genetic algorithm (GA) (to perform search in a continual space), to ensure that the actual global optimum is found [11]. The method was further improved using simulated annealing (SA) as the optimisation tool, instead of GA [12].
Implementation of six sigma presented first steps in introducing the advanced quality improvement programs in Serbian industry. While six sigma is widespread adopted as a primary quality improvement program among a variety of industries, authors stressed on the importance of a business culture changes and a theoretical underpinning, in order to bridge the gap between the theory and practice of six sigma methodology.

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