Chapter 3

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THE PRODUCTION PROCESS CAPABILITY STUDY IN THE AUTOMOTIVE INDUSTRY

Abstract: This study focuses on the evaluation of process capability in the production of bumper according to regulation defined by ISO 9001:2015 Quality Management Systems. Requirements and ISO/TS 16949:2009 Technical Specification.Therefore, statistical process control is analysed on the basis of normality and stability of the process, and process capability indices C_p and C_{pk} are calculated. The values obtained for indices are C_p = 1.084 and C_{pk} = 0.972. Therefore, we can consider the process as incapable and it is necessary to find significant causes which influence the process. After aplication of corrective action were calculated the process capability indices C_p and C_{pk} again and obtained values C_p = 4.034 and C_{pk} = 3.820 show that the process is influenced by random causes only and is capable.

Keywords: C_p and C_{pk} indices, control charts; bumper process production; statistical control; quality

3.1. Introduction

The manufacturing organization is situated in Western Slovakia and deals with the manufacturing of plastic components for automotive. It was discovered by observations that qualitative errors arise in the manufacturing process.

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Therefore, it was necessary to implement the statistical control into the manufacturing process, and the chosen product was the Seat Toledo bumper, which can be seen in Figure 1.

Fig. 1 Seat Toledo front bumper

Source: Kukuľová, M. 2014

Based on the results of final inspection and frequent customer‘s complaints, it was discovered that errors in the manufacturing process are caused in the injection process. The most frequent errors discovered by Pareto analysis were: material creeping, bad weight, bubbles and demoulding. Therefore, it is required to assure the quality of the manufacturing process within each production phase. The monitoring and evaluation of manufacturing process capability presents one of the methods for ensuring and improving processes in the manufacturing organization. It includes the monitoring of stability and normality based on values obtained from the manufacturing process and the calculation of manufacturing process capability indices C_p and C_{pk} (ANDRÁSSYOVÁ et al., 2011).

By determining the process capability, we can isolate the estimated process capability (before starting the production) and permanent process capability. The C_p index shows the process variability, and the C_{pk} index shows the position of the process in a tolerance zone (FERANCOVÁ M. 2013).

In mass production the early detection of defects and taking an appropriate corrective action is nessesary. Before taking any corrective action, the defects need to be diagnosed correctly. The proper classification and identification of a particular defect is fundamental for

determination of the cause and appropriate corrective action in order to prevent defect recurrence (SÜTŐOVÁ A. 2013).

The objective of this paper is to monitor the injection process capability in the production of Seat Toledo front bumper. The process will be checked by the evaluation of control charts for average and range *R* (STN ISO 8258:1995 Shewhart control charts). If conditions for the evaluation of control charts and for the achievement of injection process capability are not met, the monitored process shall be subjected to a detailed study immediately, and corrective and preventive measures shall be proposed. If the C_p and C_{pk} indices are higher than 1.33, we can consider the process as capable (HRUBEC J. 2009).

3.2. Methodology

A bumper weight of 2670–2750 g was measured on the bumpers. This weight is considered as the level of safety and requirements of the customer.

Data collecting

Histogram

A histogram provides a graphical picture of process output. Collecting raw measurements is meaningless unless the data can be organized in a way that aids discovery and analysis. To construct the histogram each of the data are assigned to 1 of 11 class intervals. Through pattern recognition, histograms can provide valuable clues leading to improvement opportunities. Figure 2 illustrates eight different histogram shapes (AIKENS C.H. 2011).

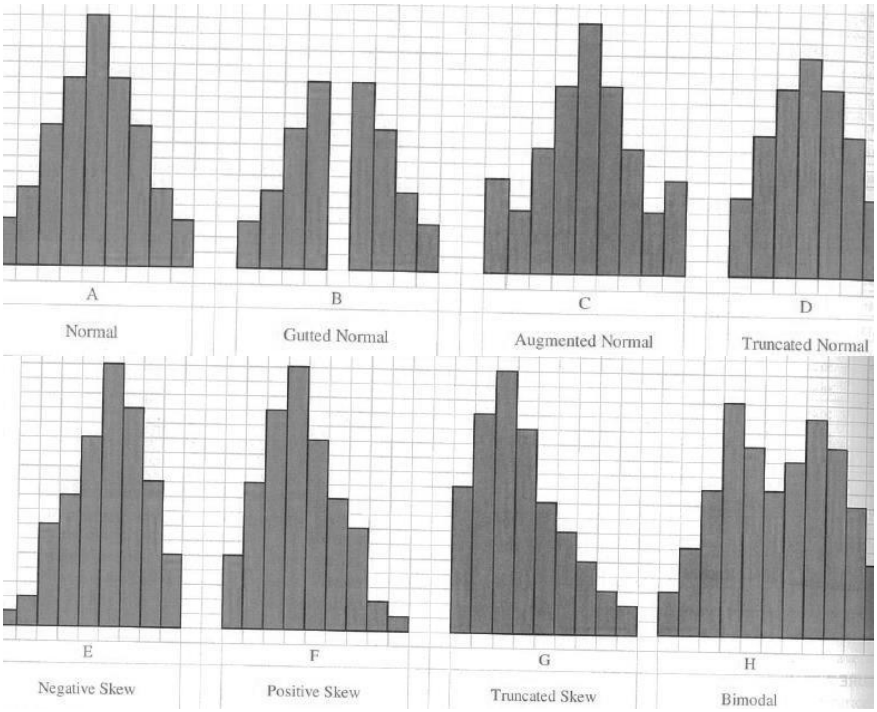

Fig. 3.2 Histogram shapes

Source: Aikens C.H., 2011

Pattern A represents a symmetrical „bell-shaped" curve that is usually referred to as a normal distribution. This is the shape of the output from many industrial processes, if they are stable and the only sources of variation present are the random fluctuations that are inherent in the system. In a normal distribution, the mean and median are equal – 50% of the output lies to the left of the average (or mean) and 50% to the right.

In pattern B, the distribution looks as i fit may have originated as a normal distribution, but the middle of the distribution (the highest-quality product) has been carved out. This gutted norma lis typical of cases where a supplier can sell product that is of the highest quality – produced near the target with small variation – at a higher price than

product of a lower grade. Even though all output may fall within the allowed specification range and the average is on target and the variance can be substantially greater than if the original distribution were intact .

The augmented normal, shown as pattern C, could result from an inspector reclassifying output that is just below or above the specification limits. Hence, there is a „lumping“ effect at the first and last class intervals where the specification cutoffs occur.

Pattern D is a truncated normal. A pattern such as this could occur if a process is centered on target, its spread is wider than the tolerance limits, and the unacceptable output has not been reported in the data. A distribution can also truncate if a natural barrier, such as zero (when no negative values are possible), is encountered.

Pattern E and F represent distributions that have a skew – that is, they lack the symmetry of the normal distribution. In a negatively skewed distribution more than 50% of the distribution and the median are to the left of the mean.

Pattern G could have two possible interpretations. One scenario is that defective product was sorted from the good, because the process was incorrectly targeted. Alternatively, if negative numbers are not posiible (e.g., weights), truncation at a measurement equal to zero can produce this pattern.

Pattern H could be the resulting picture when several normal processes are overlaid , called bimodal; for example, if samples represent the output from several machines, each having a different process average (AIKENS C.H. 2011).

Graphs and charts

Run Chart - is the simplest time-ordered chart. Individual measurements are plotted in the order in which they occur, and although unnecessary, it is a good idea to connect the points for ease in interpretation. One way to check for a change in average is to count the number of „runs“.

A run is defined as a buildup of consecutive points on the same side of the average (or centerline). A run length of seven or more points provides statistical evidence that the average has changed. An alternative to the number of runs is a test for trends. Six consecutive points either increasing or decreasing with no reversal in direction provides evidence that the average is trending (AIKENS C.H. 2011). The run chart can be seen in Figure 3.3.

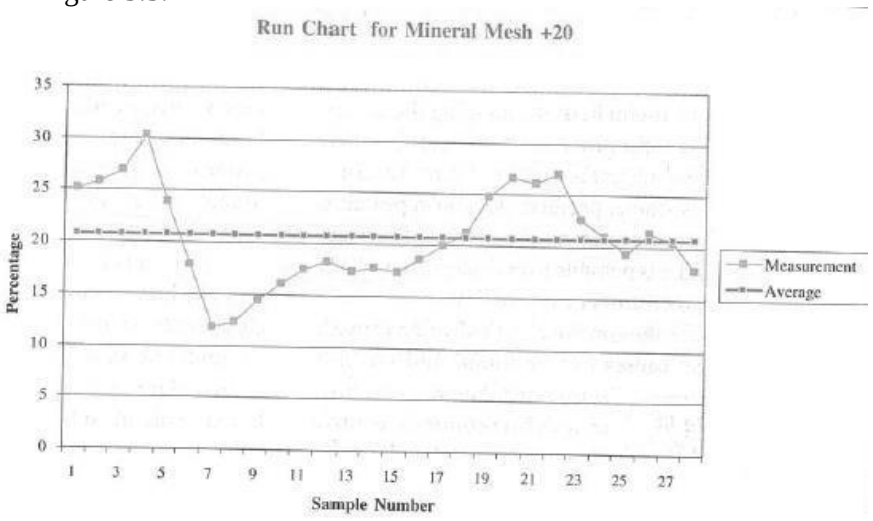

Fig. 3.3. Run chart

Source: Aikens C.H. 2011

Control chart – is a run chart with control limits. These limits represent the maximum and minimum allowable values for any individual plotted point. Any point that exceeds these limits provides statistical evidence that the process average has changed and that the chart´s centerline is no longer a reliable approximation. The maximum value is called the upper control limit and the minimum value the lower control limit. The range of permissible values that lie between the two limits represents expected variability that is due to random causes (JANKAJOVÁ E. 2015).

Random variability is present in all samples and is aptly called common cause variability. If certain sources of variability are present in some samples, but not others, one would expect the variability to exceed the bounds imposed by the control limits – such sporadic fluctuations are called special cause variability. The purpose of a control chart is to expose the presence of special cause variation. This can be done by detecting nonrandom patterns or observing any plotted points outside the control limits. There is a fundamental difference between a run chart and a control chart. The points plotted on run charts typically represent individual measurements (e.g. machine downtime, percentage yields, or scrap). Control charts can also be constructed to analyze individual measurements; however, the points normally represent a statistic (e.g., the mean, range, or standard deviation) that is computed from a sample of several measurements taken at random from the process (KOTUS M. 2015).

A control chart can be useful in understanding the underlying behavior of a process. If the process is in control (i.e., there is no statistical evidence to suggest any nonrandom patterns), we say that the process is stable, predictable, and repeatable. This means that the process output can be predicted forward and backward in time, and i tis possible to evaluate how well the process is doing relative to customer expectations. If a process is unstable, the control chart will often provide hints as to where special causes can be found and possibly eliminated (AIKENS C.H. 2011). Figure 3.4 illustrates some common control chart patterns.

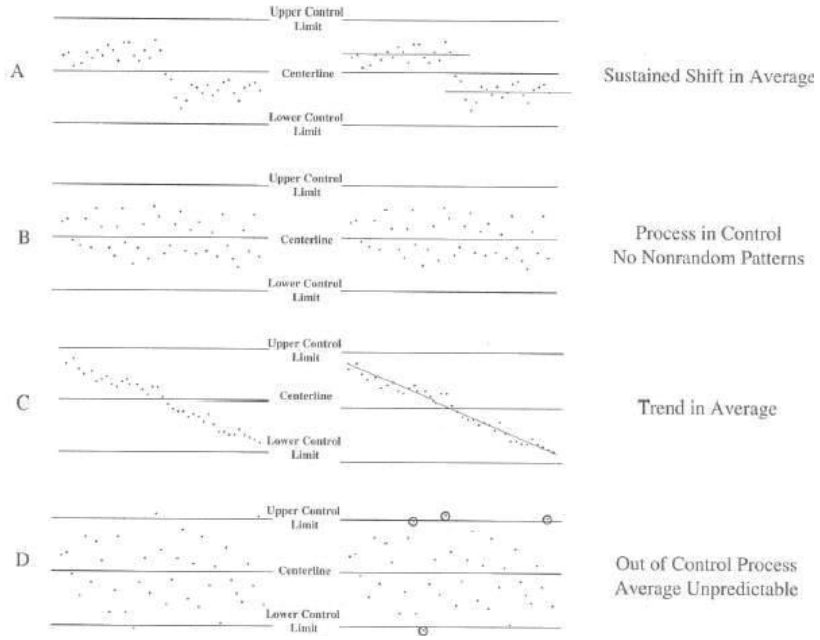

Fig. 3.4 Control charts patterns

Source: AIKENS C. H. 2011

In all cases, the x-axix represents time. In pattern B the plotted points appear to be randomly distributed about the centerline (average) and all lie within the control limits. Process B, therefore, is in a state of statistical control. The process shown in pattern A appears to have started at an average higher than the centerline and then, approximately halfway through the sampling process, experienced a sustained decrease in average. Even though none of the points exceeded either of the control limits, the pattern is nonrandom and the process is not in control.

The process depicted by pattern C is like pattern A, except the process in undergoing a continual decrease (or trend) in average. If the rend continues unabated a point will eventually fall below the lower control limit. Pattern D shows clear evidence of the presence of special causes. These nonrandom sources of variability result in a wider pattern

swing than would be expected from common cause sources alone, and consequently points fall outside both control limits (AIKENS C.H. 2011).

A control chart is the voice of the process but will provide only information it has been designed to provide. Control chart patterns are dependent on sampling strategies – that is, how the raw data are collected. This includes sample size, frequency, and specifically how individual sampling units are selected. An important consideration in determining the sampling plan is the intended purpose for the data. There are three basic reasons for collecting control chart data.

- To characterize the process output. A process in control can be used to estimate the quality characteristics of process output, including the percentage that exceeds or falls short of requirements. Such information can be invaluable in communicating with customers or justifying improvement efforts.
- To monitor process performance and intervene when necessary. A control chart can act as a tracking device and navigational aid. As a tracking devide it can validate improvements and provide early warning to an operator if the process starts losing productivity gains. As a navigation tool operators can use the control chart to indicate when they should intervene and „steer the process“ and, just as importantly, when to leave the process alone.
- To improve a process. With a properly designed sample a control chart can expose sources of variability – often converting common causes into special causes – to focus improvement efforts. More information can often be gained from charts not in control than from data that exhibit statistical stability (HRUBEC J. 2009).

($\overline{X}$,R) chart

When control charts are used to monitor variables data, a pair of charts is needed and must be read together to properly interpret data

patterns. Since either the process dispersion or mean (or both) can be out of control, charts are needed to independently evaluate the stability of each parameter. The first of the two charts to be plotted (and interpreted) deals with process dispersion and is called an R chart.

An R chart is a time-ordered plot of sample ranges that represent those sources of variability that have been captured within a sample, and is best applied in the case of small sample sizes (seven or less). The second chart in the pair is called and $\overline{X}$ (pronounced X-bar) chart and is a plot of sample averages. As we shall see, while the R chart is primarily concerned with those sources of variability captured within a sample the $\overline{X}$ chart is primarily concerned with those sources of variability that are active between samples (KORENKO M. 2015).

Statistical control

We often discussed the two broad types of variability that are captured in any sampling plan: common cause and special cause. Whenever samples are collected from a process certain sources of variability (those due to common causes) will be active. Common cause variability is the reason why individual measurements within a sample will have different observed values and can be viewed as systemically induced and short term. That is, since a sample is intended to provide a representative snapshot of how a process is behaving at any point in time, the variability captured within a sample is an estimate of the process variability that existed while the sample was being obtained. The time frame is usually relatively short and any observed fluctuations can be attributed to process design considerations. Reducing common cause variation therefore requires improving or reengineering the system. Examples of common causes are measurement error, operator inconsistencies, and within - machine capabilities (i.e., the inability of a machine to exactly replicate performance (KOTUS M. 2015).

Those variability sources that are active in some samples and not in others are due to special, or assignable, causes. As samples are collected over time, the fact that these samples can be observed to be different

(e.g., have different individual measurements, different means, different standard deviations, etc.) is due to a combination of special cause and common cause variability. Examplex of special causes are shift-to-shift differentials, machine-to-machine differences, operator-to-operator discrepancies, and any time-related factors such as materials, maintenance, and production mix. A process is said to be in a state of statistical control whe the only sources of variability active are due to common causes. This means that all sources of variality have been captured within a sample and each sample is statistically like all other samples. The absence of special causes means that there are no additional active sources that add a between-sample component. A process in control is stable, meaning that the element of time is no a factor – a sample taken at any point in time is like a sample taken at any other time. Once a process has reached this level of stability i tis said to be repeatable and predictable, and important process parameters such as mean, dispersion, and shape can be estimated with confidence (JANKAJOVÁ E. 2015).

Being in statistical control is not the same as producing quality output. Statistical control is simply the first step in process improvement. When a process is in control its parameters can be estimated with calculable risk, and its past, present, and future output can be predicted with a high level of confidence. In the absence of control, process behavior is sporadic and unpredictable. Before one can determine what steps need to be taken to improve a process i tis essential to know how the process is behaving and be able to compare actual with desired performance.

We described the control chart as a toll that can reveal the „voice of the process“, assist in understanding how processes behave, and help identify improvement opportunities. The greatest benefit comes from data that are plotted in a time – ordered sequence. Therefore it is recommended that control chart construction begin with a run chart and that a minimum of 25 to 30 points be plotted initially. These will be used to estimate the mean and standard deviation of the process and to

compute control limits. If the chart shows a state of statistical control, the mean and standard deviation can then be used to estimate process capability and quality of output (AIKENS C.H. 2011).

Now we can describe the generic control chart structure. Sample data points are randomly selected in time sequence from a process that is assumed to be normally distributed. It is also assumed that the points are independent and not autocorrelated. The chart´s centerline is equal to the average of all the data plotted (a point estimate of the distribution mean) and the spread of the distribution is estimated using all 25 or 30 samples. Upper and lower control limits are constructed equidistant from the centerline three standard deviations away. These limits represent the largest and smallest measurements that one would expect, assuming that the hypothesized distribution (i.e., normal with mean = centerline and standard deviation – one – third the distance from from centerline to control limits) is correct and does not change over time.

Once control is established, the limits and centerline on the control chart are fixed. Process sampling is continued and each sugsequent sample is plotted on the chart. As long as the chart shows no evidence of any nonrandom patterns, one can assume that the process mean and dispersion remain where they were when control was first established (KORENKO M. 2015).

Tests for statistical control

Statistical control must be achieved before a control chart can be used to effectively monitor a process. A chart in control can provide the basis for knowing when to intervene in a process (make adjustments) and as importantly, when to leave a process alone. There are several tests for nonrandomness that should be applied, depending on whether the chart is a new startup, or is ongoing.

Steps for initiating a variables control chart

The first step in constructing a control chart is to determine the sample size and frequency of sampling. There is always a trade – off between the size of an individual sample and how often the samples are

taken. A good rule of thumb for variables measurements is to think five. A sample size of 5 is ideal in most circumstances. The ideal size of 5 might be reduced to 4 or 3 if measurements are costly or difficult to obtain. If, on the other hand, a sample of 5 is insufficient to capture all sources of process variability (e.g., six spindles, seven layers, etc.), the ideal sample size should be increased. As for frequency, samples should be taken at convenient intervals, giving due consideration to process stability and whether changes occur gradually or abruptly. Once these decisions are made the following 10 steps should be followed (Aikens C.H. 2011).

Step 1 Obtain between 25 and 30 random samples from the process.

Step 2 Compute the average and either the range or standard deviation of each sample. Use these data as the basis for calculating estimates of the process mean and standard deviation.

Step 3 Plot the sample points on a chart in time sequence and connect the points using straight lines.

Step 4 Draw a centerline on the chart equal to the mean of the raw data.

Step 5 Construct upper and lower control limits on the chart equal to the mean plus and minus three standard deviations, respectively.

Step 6 If all plotted points are inside the control limits, proceed to step 7. otherwise, investigate any points that are outside. If (and only if) the out – of – control points can be easily explained, eliminate the points from the data set and return to step 2. examples of explanations that could justify removing points from the data set are transcription errors, an unusual machine problem, or a power failure.

Step 7 Count the total number of plotted points above the centerline and the total number below the centerline. Let the symbol *s* represent the smaller of the two counts and the symbol *r* represent the larger of the two counts.

Step 8 count the total number of runs. A run consists of a count of consecutive points lying on the same side of the centerline. The start of a new run occurs each time a line connecting the points crosses the

centerline. Apply the test for too few runs. If the number of runs is less than or equal to the critical value, stop. The process is not in control. Otherwise, continue.

Step 9 Count and record the length of each run (that is, the number of consecutive points making up each run). Apply the test for the length of the longest run. If the longest run is equal to or greater than the critical value, stop. The process is not in control. Otherwise, continue.

Step 10 Look for any obvious nonrandom patterns in the data. Examples are

- Hugging the centerline – all (or most) of the points are within one standard deviation of the chart´s centerline.
- Hugging the control limits – most of the points lie between two and three standard deviations of the mean, but no points (or relatively few) are actually outside the control limits.
- Stratification – when each data point is identified by machine, shift, operator, or some other criterion, these identifiers will cluster into distinct groupings, each of which appear to come from a different distribution.

Trends – although there are no points outside the control limits, and neither of the runs tests have been violated, the data appear to be following a trend over time (AIKENS C.H. 2011).

If any nonrandom patterns are observed, stop. Otherwise, the control chart can be operationalized. To operationalize the control chart, the control limits are fixed at the levels where control was observed and the chart can then be used to plot samples taken from future production. Control limits or the centerline are not altered unless there is statistical evidence that the process has changed from the initial conditions.

Note that when a rational subgroup cannot be formed (e.g. in the case of a continuous and highly homogeneous product) a sample size of 1 must be selected and an individuals chart, must be used. In this case the 10 – step process does not apply.

The analysed values of measured parameters are collected from the manufacturing process of front bumpers.

We proceeded as follows:

- Measured values were included in subgroups k = 75, with the subgroup size n = 2 (Table 1). Each 50 values were measured in one day, we measured 3 days.

The measured values are used for the calculation of:

Average value of attribute in subgroup: $\overline{X_i} = \frac{1}{n}\sum_{j=1}^{n} X_{ij}$ (3.1)

where:
i – 1, 2,..., k – sequential number of subgroup
j – 1, 2,..., n – sequential number of measured value in subgroup
k – number of subgroups,
n – subgroup size,
X_{ij} –measured value in the i-th subgroup.

Range in subgroup: $R_i = MAX(X_{ij}) - MIN(X_{ij})$ (3.2)

where: MAX(Xij) and MIN(Xij) – the maximum and minimum value measured in the i-th subgroup.

Averages X_j and ranges R_i are plotted into control charts. Points are linked by lines to visualise the groups and trends.

Average of process: $\overline{\overline{X}} = \frac{1}{k}\sum_{i=1}^{k} \overline{X_i}$ (3.3)

where: i – 1, 2,..., k– sequential number of subgroup

Average range: $\overline{R} = \frac{1}{k}\sum_{i=1}^{k} R_i$ (3.4)

where: R_i, X_i –ranges and averages in the i-th subgroups (i= 1, 2,..., k).

Upper and lower control limits for range and average:

For range:

$UCL_R = D_4 \, x \, \overline{R}$ (3.5) $LCL_R = D_3 \, x \, \overline{R}$ (3.6)

For average:

$UCL_{\bar{X}} = \overline{\overline{X}} + A_{2x} \overline{R}$ (3.7) $LCL_{\bar{X}} = \overline{\overline{X}} - A_2 \, x \, \overline{R}$ (3.8)

where: D_4, D_3 and A_2 are the constants of control limits; they are changing depending on subgroup size from 2 to 25, the values A_2= 1.880, D_3= 0.000, D_4= 3.267 conform to the size n= 2 (STN ISO 8258:1995; PETRÍK J. 2009).

Plotting and evaluation of control charts for average $\overline{X}$ and range *R*

Calculated values are used for plotting the control charts for average and range, which are analysed and evaluated after that. The manufacturing process is statistically controlled when its variability is caused by random causes only. If the manufacturing process is affected by definable causes, it is necessary to determine the causes of negative effects and corrective measures leading to the achievement of process stability (Korenko M. 2012).

Production process capability

We can evaluate the manufacturing process capability if the following conditions are met:

- process is statistically controlled (stable),
- measured values from the process are characterised by normal distribution,
- technical and other specifications are defined by customer requirements,
- nominal value is located in the centre of tolerance range.

Values of manufacturing process capability are expressed by the capability indices Cp and Cpk. Before starting to calculate the process capability indices, process standard deviation must be estimated.

Estimation of process standard deviation: $\hat{\sigma} = \frac{\overline{R}}{d_2}$ (3.9)

where: R–average range in subgroups

d_2–constant of a central line, changing according to subgroup size from 2 to 25, the value d_2= 1.128 corresponds to n= 2 (STN ISO 8258:1995)

Process capability index Cp : $C_p = \frac{USL - LSL}{6.\hat{\sigma}} = \frac{T}{6.\hat{\sigma}}$ (3.10)

where: *USL*,*LSL*– upper and lower specification limits

T- tolerance of attribute

Corrected process capability index C_{pk}:

$$C_{PK} = \frac{USL - \overline{\overline{X}}}{3.\hat{\sigma}} \quad (3.11) \qquad C_{PK} = \frac{\overline{\overline{X}} - LSL}{3.\hat{\sigma}} \quad (3.12)$$

The resulting cutting process indices must meet the previously specified condition ($C_p \geq 1.33$ and $C_{pk} \geq 1.33$), which can be corrected by the given organization according to internal requirements (cannot be lower).

Measuring equipment capability index C_{gm}: $C_{gm} = \frac{0,2.T}{6.s_w}$ (3.13)

Corrected equipment capability index C_{gmk}:

$$C_{gmk} = \frac{\left(X_r + 0,1.T\right) - \overline{X}_a}{3.s_w} \quad (3.14) \quad \text{or} \quad C_{gmk} = \frac{\overline{X}_a - \left(X_r - 0,1.T\right)}{3.s_w} \quad (3.15)$$

where:

s_w – standard deviation,

$\overline{X}_a$ - average value,

X_r - conventional true value,

T – tolerance of attribute.

Production facility

capability index C_m: $C_m = \frac{USL - LSL}{6.\sigma_{N-1}} = \frac{T}{6.\sigma_{N-1}}$ (3.16)

where: T – tolerance of attribute,

USL, *LSL* – upper and lower tolerance limit.

Corrected production facility capability index Cmk:

$$C_{mk} = \frac{USL - \overline{X}_N}{3.\sigma_{N-1}} \quad (3.17) \qquad C_{mk} = \frac{\overline{X}_N - LSL}{3.\sigma_{N-1}} \quad (3.18)$$

Standard deviation we can calculate:

$$\sigma_{N-1} = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}\left(X_i - \overline{X}_N\right)^2} \quad (3.19)$$

where: N - total number of measured values

Average value from total measured values we can calculate:

$$\overline{X}_N = \frac{1}{N}\sum_{i=1}^{N} X_i \quad (3.20)$$

where: $i = 1, 2, \ldots N$

X_i – i-th measured value of the attribute

3.3. Results and discussion

The manufacturing process of front bumpers was statistically evaluated for individual parameters of each characteristic. Calculation was carried out by means of Microsoft Excel, using data collected from the manufacturing process with quality control. Values from the process were tested with respect to normal distribution, which was not confirmed, as can be seen in Figure 3.5 (histogram).The measured values presented in the histogram show that the process is not in statistical control. We constructed also the control charts. The values of range R_i and primarily their location within control limits were analysed on the basis of the control chart for range *R*. Based on analysed variability, the manufacturing process was not stable. The same situation is by the control chart for average *X*. In Figure 3.6 (*R* chart), we can see the values for range *R*, and the average values for measured data are shown in Figure 3.7 (*X* chart).

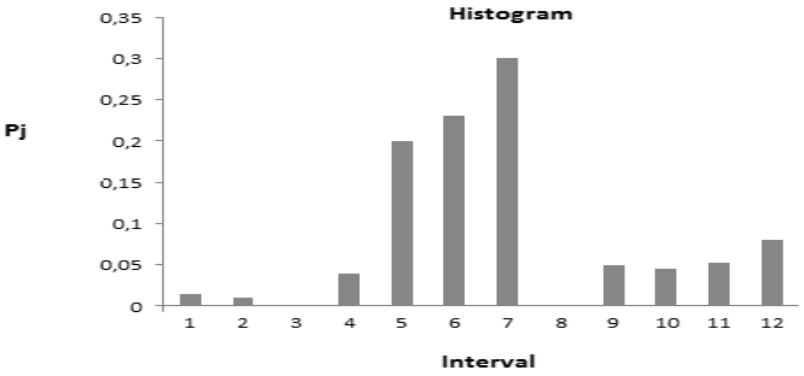

Fig. 3.5. Histogram

Source: KUKUĽOVÁ M. 2014

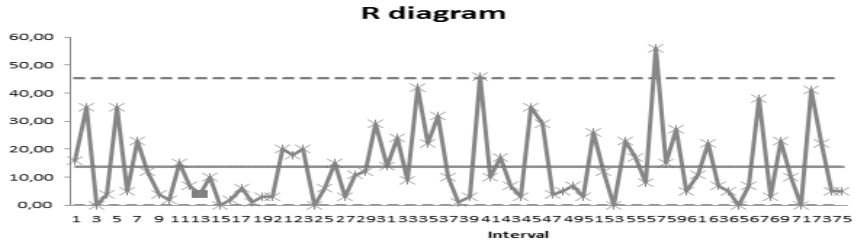

Fig. 3.6. Control chart for range R

Source: KUKUĽOVÁ M. 2014

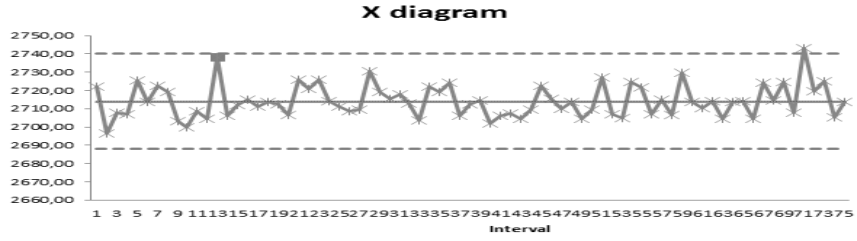

Fig. 3.7. Control chart for average X

Source: KUKUĽOVÁ M. 2014

We have obtained the following values:

$UCL_X = 2740.20$ $CL_X = 2714.11$ $LCL_X = 2688.02$

$UCL_R = 45.34$ $CL_R = 13.87$ $LCL_R = 0$

The control chart for average *X* shows the position of the manufacturing process. The manufacturing process was not statistically controlled and therefore not stable (KUKUĽOVÁ, 2014).The control chart for average *X* and for range *R* shows that the manufacturing process front bumpers is not in statistical control and some points are out of the control limits. We can also consider that the process is not influenced by random effects only. After this findings we calculated the indices C_p and C_{pk}. The calculated values are $C_p = 1.084$ and $C_{pk} = 0.972$, by which our claims were confirmed.

So as the next step we constructed the Ishikawa diagram which identified 6 areas responsible for the process instability. The areas are: environment, people, machine, material, methods, measuring equipment. As the first analysed area is the measuring equipment – digital scale. The digital scale was analysed by R&R method. There were measured 90 weights by 3 workers, each worker measured 3 times and these workers weighed 30 samples.

After calculation were obtained following values:

EV = 71.2% (repeatability)

AV = 18.0% (reproducibility)

R&R = 14.1%

According to obtained values we consider the system as conditionally convenient. But the company consider this result as convenient. So as the next step we measured 50 samples for calculating the C_{gm} and C_{gmk} indices. We measured the Seat Toledo front bumpers´s weight - the right weight of the bumper is 2710 g with the tolerance ± 40g. We have obtained the following values:

$\bar{X}_a = 2710.0163$ $s_w = 0.0397837$ $C_{gm} = 2.51$ $C_{gmk} = 2.30$

According to these values we consider the digital scale as capable, because the indices C_{gm} and C_{gmk} are higher than required minimum value 1,33. The calculated values are $C_{gm} = 2.51$ and $C_{gmk} = 2.30$.

As the second we have analyzed the production facility - injection molding machine Husky QuandLoc Tandem.

We measured the Seat Toledo front bumpers´s weight - the right weight of the bumper is 2710 g with the tolerance ± 40g. We have measured 150 values.

Calculated values are used for plotting the control charts for average and standard deviation, which are analysed and evaluated after that. The values of standard deviation were analysed on the basis of the control chart for standard deviation *s*, which can be seen in the Figure 3.8. After that we constructed the control chart for average *X*, which can be seen in the Figure 3.9.

We have obtained the following values:

$UCL_X = 2743.4413$ $LCL_X = 2686.4121$ $CL_X = 2714.9267$

$UCL_s = 11.1193$ $LCL_s = 0$ $CL_s = 9.024$

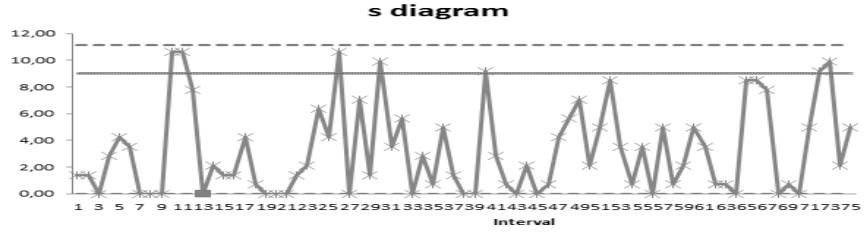

Fig. 3.8. Control chart for standard deviation s

Source: KUKUĽOVÁ M. 2014

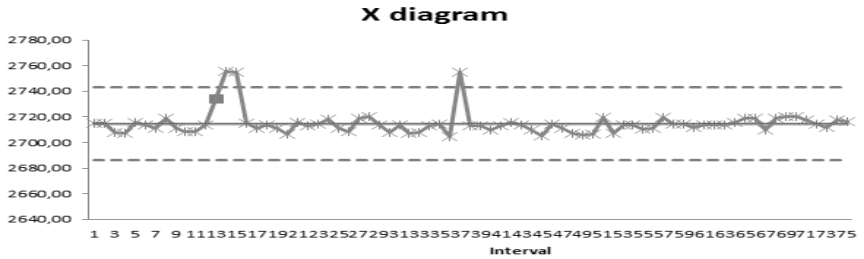

Fig. 3.9. Control chart for average X

Source: KUKUĽOVÁ M. 2014

As we can see on the control chart for average, three points are out of the upper control limit, so the manufacturing process can not be stable.

Values from the process were tested with respect to normal contribution, which was not confirmed, as can be seen in Figure 3.10 (histogram).

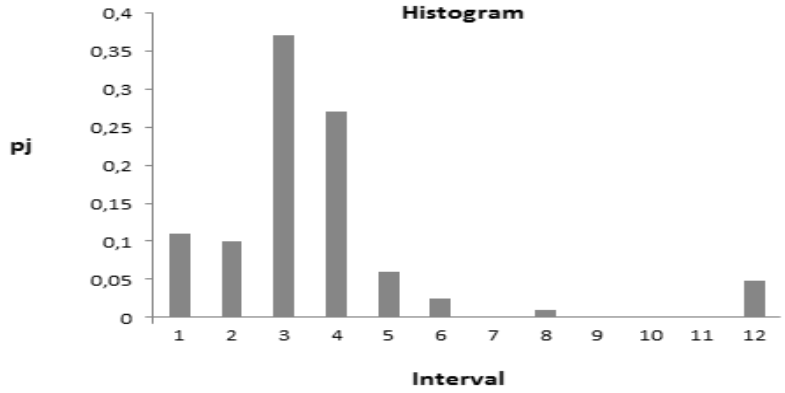

Fig. 3.10. Histogram

Source: KUKUĽOVÁ M. 2014

The measured values for production facility capability presented in the histogram show that the process in not in statistical control, some points are out of tolerance limits.

We also calculated the values for production facility capability indexes:

$C_m = 1.327$ $C_{mk} = 1.164$

The obtained values are lower than minimum required value 1.67, so we can consider the production facility as incapable. There is necessary to find the effect which influenced that the facility is incapable and take corrective actions.

The environment analysis

By the bumper production process it is necessary to take care about the cleanliness at the workplace. It is neccesary because of do not bear

the impurities to the workplace. The company is still maintaining the cleanliness, the hygiene rules are complied in each production hall. In each hall the air temperature is right setted and is still controlled. The same situation is with the air humidity. So we consider the company´s environment as satisfactory.

Material analysis

It is used one type of granulate named Stamylan P 108 MF 10 for car Seat Toledo bumper production. This type of material has the company prescribed in technical documentation and it is satisfactory. The granulate is before filling into the injection molding machine mixed with admixtures. The admixtures are also prescribed for this type of material and written in technical documentation. In the company there were never a problem with granulate substitution and also the admixtures. This fact was confirmed by production workers, but also by quality engineer. So we can exclude, that the material has an influence for bumper production with bad weight.

Workers analysis

The company workers are qualified to carry out their activities and regularly retrained. There is available the trainee documentation in the company signed by workers. By the production process there is available the technical documentation and the working procedures for each worker. So we can say that the workers have no influence for bumper production with bad weight.

The scrap costs

Now we will calculate the scrap costs in each months where were the wrong bumpers produced because of their bad weight. We can also say how much money the company lost.

There were produced 155 bumpers with wrong weight in September 2013. The costs for production of one bumper are 9 €. So the company lost in September 1 395 €. There were produced 169 bumpers with wrong weight in October, so the company lost in this month 1 521 €. The last

observed month was November. The company produced 157 bumpers with wrong weight, so they lost in this month 1 413 €.

In month September was from the total number of produced bumpers 1 063 with some defect, what represents 9 567 € in costs. In October the total number of defected bumpers is 1 006, what represents 9 054 € in costs. In month November the total number of defected bumpers is 929, what represents 8 361 € in costs.

Corrective actions - production facility

According to the production facility evaluation we consider that it was incapable – the capability indices are lower than required value. So we should find the critical point and realize the corective actions. There are only two things responsible for bumpers with wrong weight. First is improperly dried granulate and the second incorrect amount of material which is sprinkled into the dispenser.

It was found by examination that into the granules dispenser were sometimes sprinkled wrong amount and it caused that the bumpers were made with the wrong weight. Therefore, it was proposed, that the worker will control the batched amount of granules using the computer. It was found that one opening on the dispenser is blocked. The workers removed this disorder and after that we acceded to the production facility capability survey.

We measured the Seat Toledo front bumpers´s weight - the right weight of the bumper is 2710 g with the tolerance ± 40 g. We have measured 150 values.

Calculated values are used for plotting the control charts for average and standard deviation, which are analysed and evaluated after that. The values of standard deviation were analysed on the basis of the control chart for standard deviation *s*, which can be seen in the Figure 11. After that we constructed the control chart for average *X*, which can be seen in the Figure 3.12.

We have obtained the following values:

$UCL_X = 2725.1865$ $LCL_X = 2700.4135$ $CL_X = 2712.8$

$UCL_s = 11.3965$ $LCL_s = 0$ $CL_s = 4.799$

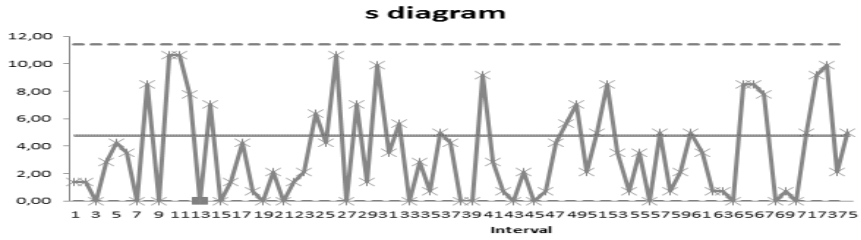

Fig. 3.11. Control chart for standard deviation

Source: KUKUĽOVÁ M. 2014

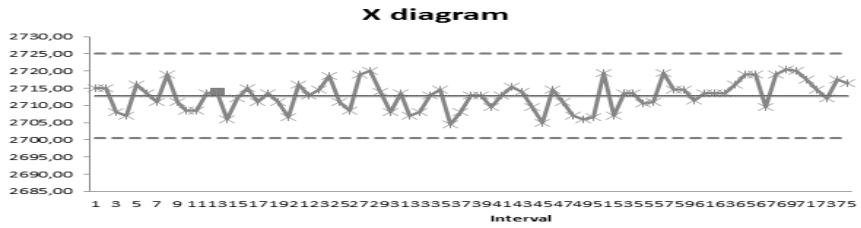

Fig. 3.12. Control chart for average

Source: KUKUĽOVÁ M. 2014

As we can see on the control charts for standard deviation and average, the manufacturing process is stable, each point is within the control limits. We can also consider that the process is influenced by random effects only.

Values from the process were tested with respect to normal contribution, which was confirmed, as can be seen in Figure 3.13 (histogram).

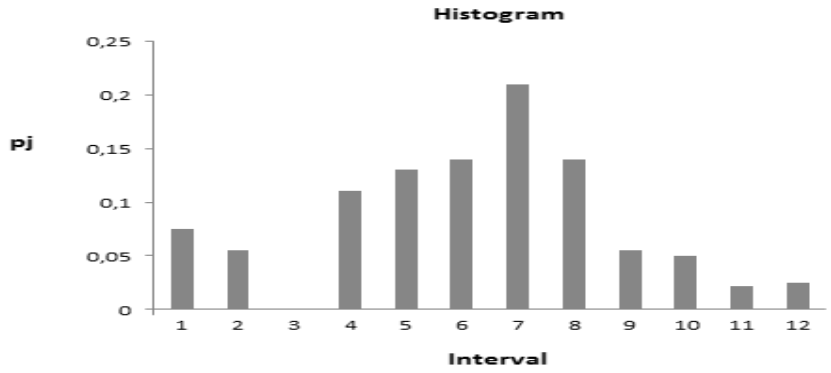

Fig. 3.13. Histogram

Source: Kukuľová M. 2014

The measured values for production facility capability presented in the histogram show that the process is in statistical control, each point is within the tolerance limits. We also calculated the values for production facility capability indexes:

$C_m = 3.049$ $C_{mk} = 2.835$

The obtained values are higher than minimum required value 1.67, so we can consider the production facility as capable. The corrective actions were successfully applied.

Corrective actions - process capability study

After the corrective actions for production facility was successfully aplied, we started with measuring values for process capability verification. We measured the Seat Toledo front bumpers´s weight - the right weight of the bumper is 2710 g with the tolerance ± 40g. There are 150 measured values needed for indices calculation.

Calculated values are used for plotting the control charts for average and range, which are analysed and evaluated after that. The values of range were analysed on the basis of the control chart for range *R*, which

can be seen in the Figure 3.14. After that we constructed the control chart for average *X*, which can be seen in the Figure 15.

We have obtained the following values:

$UCL_X = 2720.6103$ $LCL_X = 2703.6265$ $CL_X = 2712.1184$
$UCL_R = 8.3394$ $LCL_R = 0$ $CL_R = 2.9710$

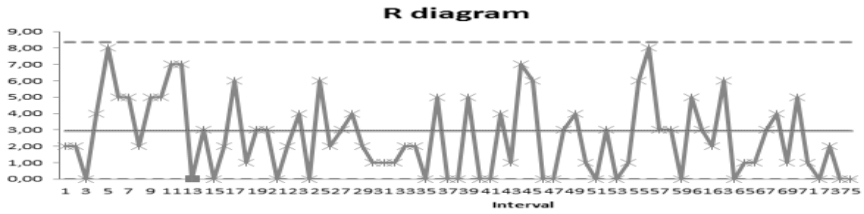

Fig. 3.14. Control chart for range

Source: KUKUĽOVÁ M. 2014

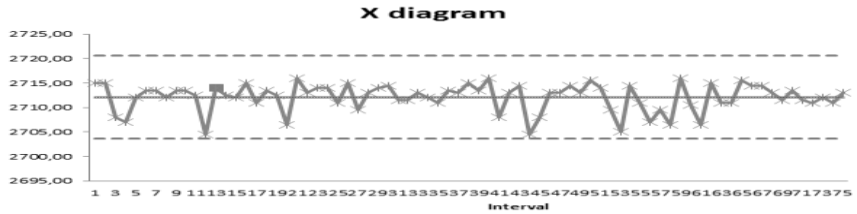

Fig. 3.15. Control chart for average

Source: KUKUĽOVÁ M. 2014

As we can see on the control charts for range and average, the manufacturing process is stable, each point is within the control limits. We can also consider that the process is influenced by random effects only.

Values from the process were tested with respect to normal contribution, which was confirmed, as can be seen in Figure 3.16 (histogram).

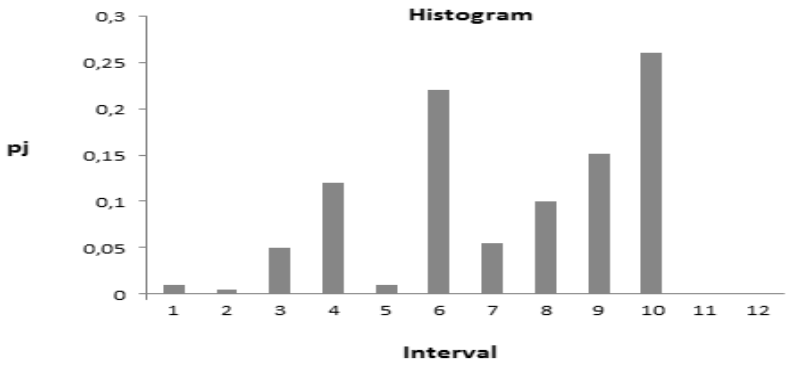

Fig. 3.16. Histogram

Source: KUKUĽOVÁ M. 2014

The measured values for process capability presented in the histogram show that the process is in statistical control, each point is within the tolerance limits. We also calculated the values for process capability indices:

$C_p = 4.034$ $C_{pk} = 3.820$

The obtained values are higher than minimum required value 1.33, so we can consider the manufacturing process as capable.

3.4. Conclusion

The methods of statistical process control and evaluation of manufacturing process capability verify an ability of the process to meet the defined requirements of product quality. Manufacturing process capability showed that the process provides products satisfying demanding quality criteria and customer requirements, but after aplying the corrective actions. There were find that into the granules dispenser were sometimes sprinkled wrong amount and it caused that the bumpers were made with the wrong weight. It was found that one opening on the dispenser is blocked. The workers removed this disorder and after that we acceded to the production facility capability survey. The indices before

corrective actiones were lower that minimum required value 1.33. But after applying the corrective actions the C_p = 4.034 and C_{pk} = 3.820 were obtained. Therefore, we can consider the process as capable and the corrective actions as successfully applied.

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