Process Variability Reduction by Using the Design of Experiment—A Case Study

Jan Machac* and Frantisek Steiner

Department of Technologies and Measurement
University of West Bohemia
Pilsen, 30614, Czech Republic

ABSTRACT

Low process variability and capability index might be some of customer's requirements. Therefore it is necessary to fulfil these requirements and guarantee them in the future. Since state-of-art companies that want to keep up with competitors have to consider all actions which might prevent losses or customer's dissatisfaction. This paper deals with possibilities how to decrease the process variability and satisfy customers. For process variability decrease, statistical experiments were carried out. The paper contains a case study devoted to the usage of design of experiment (DOE) in the production process. The case study reveals ways of dealing with real production problems and offers an effective treatment.

1. INTRODUCTION

Generally, all manufacturing and measurement processes exhibit variation. The aim of all process and quality engineers is to decrease this variation. Since, most customers demand a low variability presented by the capability index. It is not always easy to find out the factor causing the process variability therefore statistical experiments are necessary to be carried out. One of essential methods for this purpose is the design of experiment (DOE). Design of experiment is very useful method for identification of critical factors associated with processes and determination of optimal settings of these process factors due to process capability and performance enhancement. In other words, design of experiment is a systematic approach that is carried out to identify the input controllable variables in a process and analyze their effects and interactions in the process output. Design of experiment is commonly used to discover which set of process variables influences the output, and what level of these variables should be kept to optimize the process performance. The aim of this study is to show how design of experiment can be successfully used in production praxis and also prove how critical factors may affect the output and how to use them in order to decrease the process variability.

2. PROCESS VARIABILITY

When monitoring any process factors, certain variability of these factors is always observed. By the size of this variability, the standard deviation σ is expressed, respectively its estimate s_x. The process variability treatment is the first presumption for the effective process control and satisfaction of customer's needs. Before analyzing and consequent variability decreasing, it is necessary to understand how and what variability can be. The monitored parameters will always vary, but when the process is stable the measured values make a diagram which can be understood as a distribution of the monitored sign. If only random influences affect the process, it is the normal distribution. The aim is to stabilize the process and decrease its variability. Causes can be common or assignable. Common causes are a spectrum of unidentified causes where each cause contributes just slightly, but their sum is a measurable character of a process. The process is usually stable and predictable. Assignable causes are concerned when a real process change revealed by a control chart occurs. The cause must be identified, removed and must not ever happen [1].

*Correspondingauthor: Tel.: (00420) 777-694912; E-mail: jmachac@ket.zcu.cz

The observed process variability consists of the variability among samples and variability of the measurement system. Analysis of reproducibility and repeatability (Gage R&R) enables to distinguish between these types of variability. Measurement system consists of following parts: Measuring devices, Methods and procedures, Operational definitions and Men. The measurement system variability should not be higher than ten percent. If higher, a complete check of the measurement system is required. When the measurement system variability is lower than ten percent, it is necessary to check all samples coming into the production process. Division of the process variability is seen in Figure 1.

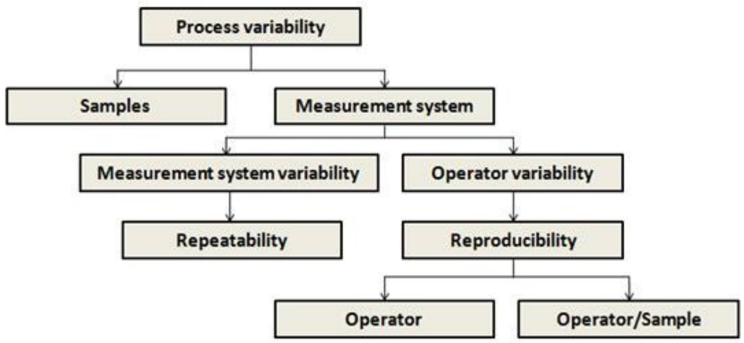

Figure 1. Process variability division.

3. DESIGN OF EXPERIMENT

It is an output or outputs that we check and observe in order to improve a process or customer's satisfaction and it is important to determine the factors which have the significant influence on the output. In order to obtain required value of the output, it is necessary to find out the setup of the significant factors and identify their possible interactions. The aim of experiments is to detect how to set the input factors to guarantee a low variability of the value of the required output and minimize the influence of uncontrollable factors. In general usage, design of experiments (DOE) or experimental design is the design of any information-gathering exercises where variation is present, whether under the full control of the experimenter or not. However, in statistics, these terms are usually used for controlled experiments. Formal planned experimentation is often used in evaluating physical objects, chemical formulations, structures, components, and materials. Other types of study, and their design, are discussed in the articles on opinion polls and statistical surveys (which are types of observational study), natural experiments and quasi-experiments (for example, quasi-experimental design) [2]. It is not always easy to make up a clear and acceptable problem description. It is absolutely necessary to develop all thoughts and ideas concerning the problem and goal of the experiment. When planning the experiment, the help of all interested workers (process engineers, quality engineers, managers and also operators) is usually required. The factors changing during the process should be chosen. For the factor selection, a combination of practical skills and theoretical knowledge is recommended. For designing the experiment, it is needed to use statistical software as Minitab or Statistica. Design of experiments is thus a discipline that has very broad application across all the natural and social sciences and engineering [3,4].

4. CASE STUDY

In this study, the subject for the process variability improvement is a production of fuel valves for the automotive industry. The valve is based on its simplicity. A company operating in the automotive industry, specializing in the development and manufacture of valves for fuel tanks was dealing with a difficulty. During the serial production process of high voluminous filter, high scrap rate, high process variability occurred and capability indexes were not satisfying as well. The customer requests the flow through the filter to be 140 liters per a minute (l/min) with the standard deviation of ± 10 liters / min which is the quantity monitored by a testing machine.

First of all, it was necessary to find out how the current process looked like in time. For this display, around 100 accidentally measured values were taken and the control chart was made for them in Minitab, as seen in Figure 2. Here, it is possible to see that some values are out of required tolerance boundaries. Thus, the process is statistically uncontrollable. It is also necessary to determine whether it is normal data or not. For this test, the normality test in Minitab was used. In Figure 3, the normality test of the process is seen. P-value is higher than 0.05 so it is possible to say with probability of 95 percent that this is the normal distribution.

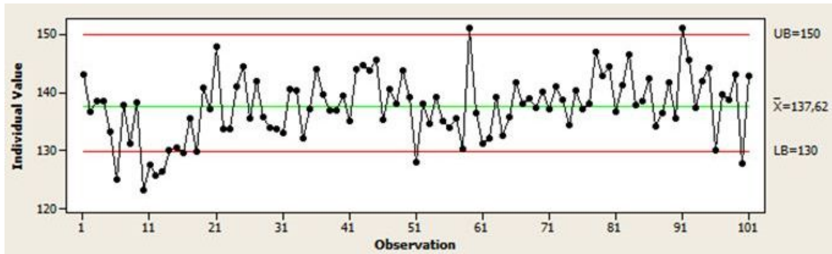

Figure 2. Control chart of the production process.

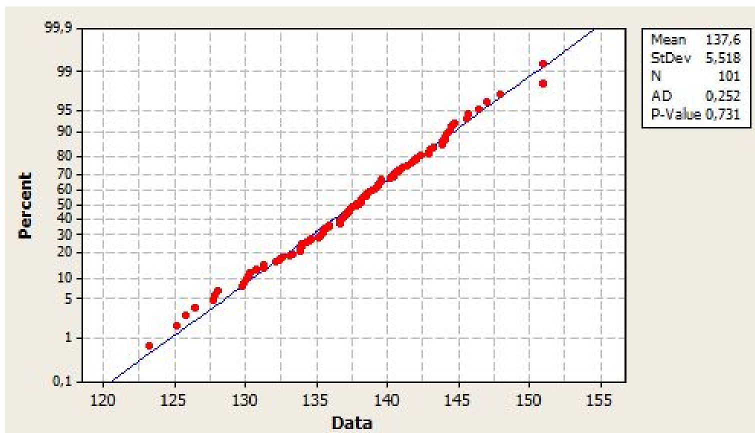

Figure 3. Normality test.

It was feasible to carry out the capability analysis of the process for the normal distribution and determine present values of C_p (Process Capability) and C_{pk} (Process Capability Index). In Figure 4, it is seen that the indices are not sufficient ($C_p = 0.69$ and $C_{pk} = 0.53$) and it is needful to initiate counter-measures in order to reduce the high process variability and increase the capability indices. The goal was set to approach the approximate value of C_p and C_{pk} indices to be 1,33 as it is required in automotive industry [5].

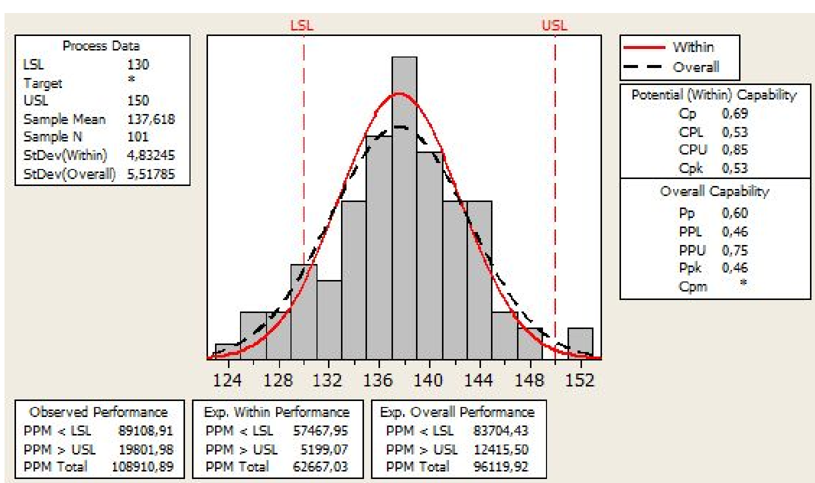

Figure 4. Capability analysis.

4.1. GAGE R&R

Then,it was necessary to determine what causes the variability. Whether product individual parts or the measurement system. Human factor was not taken into consideration due to a large number of operators working there with the same constant scrap rate. When having a wrong testing machine setting, all scrap parts might just be pseudo-scrap. Therefore, Gage R & R study was conducted to verify the measurement system. In order to verify the measurement of the test machine, the selected sample is measured for twenty five times in a row and recorded. Consequent evaluation was made in Minitab. From the results in Figure5,it shows that the measurement system is fine as it only brings the variability to the process of 3.77% (allowed value is 10%). It was considered that the process variability was affected by components of the product. Thus, design of experiment was required to be carried out in order to find out the components causing scrap. Then, selection of proper components and their parameters (called factors all together) which are the input for design of experiment needed to be performed.

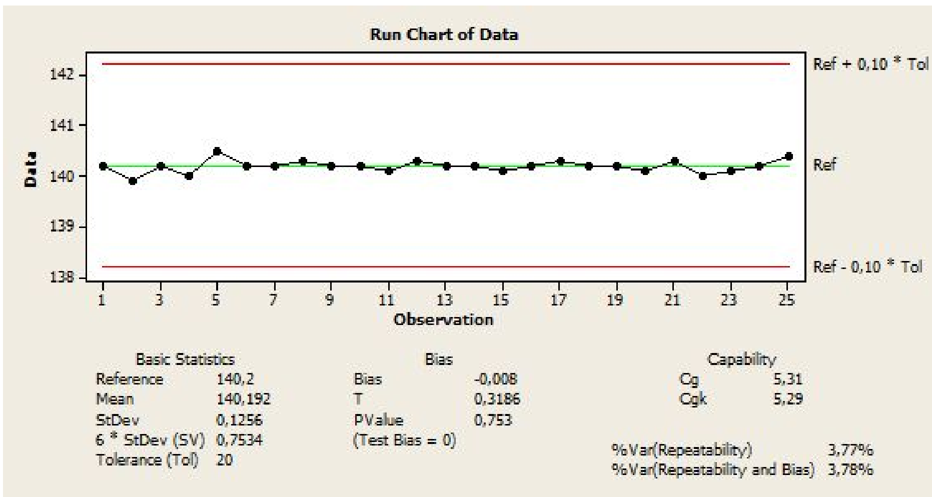

Figure 5. Gage R&R study.

4.2. DESIGN OF EXPERIMENT - PROPOSAL

Selection of proper input factors affecting the output is not always an easy procedure. Random selection is not the optimal way of design of experiment preparation. There are methods that are able to ease the selection. One of those methods is called Analytic Hierarchy Process. The method is based on the process where it is necessary to accomplish three steps. First, state the objective, it is to select right factors in this case. Then, criteria (components in this case) must be defined (spring, pin and float). Finally, picking of alternatives is required (force, height, weight, concentricity and diameter). From this information, a hierarchical tree can be arranged as shown in Figure 6.

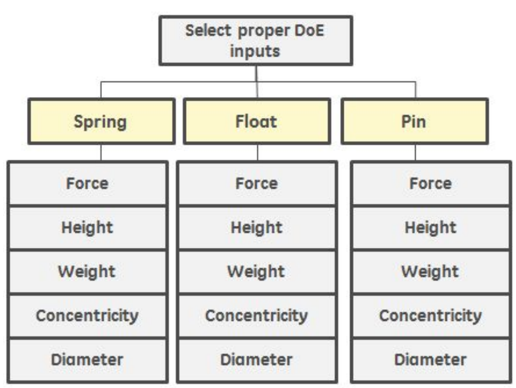

Figure 6. Hierarchical Tree.

In the next step, using judgments to determine the ranking of criteria was carried out. This step needs to be performed by designers or product specialist. The Delphi method might be also used. Further, the relative importance of one criterion over another was expressed by using pairwise comparisons according to the rate line as shown below.

1 equal - 2 moderate - 3 strong - 4 very strong - 5 extreme

According to [6], eigenvector solution is the best approach. The procedure is shown in Figure 7. The first step was the matrix squaring. The row sums are then calculated and normalized. The normalization was carried out by dividing the row sum by the row of totals (i.e. 10,5 divided by 36,75 equals 0,29). The result is the eigenvector. According to this, the most important criterion seems to be the spring.

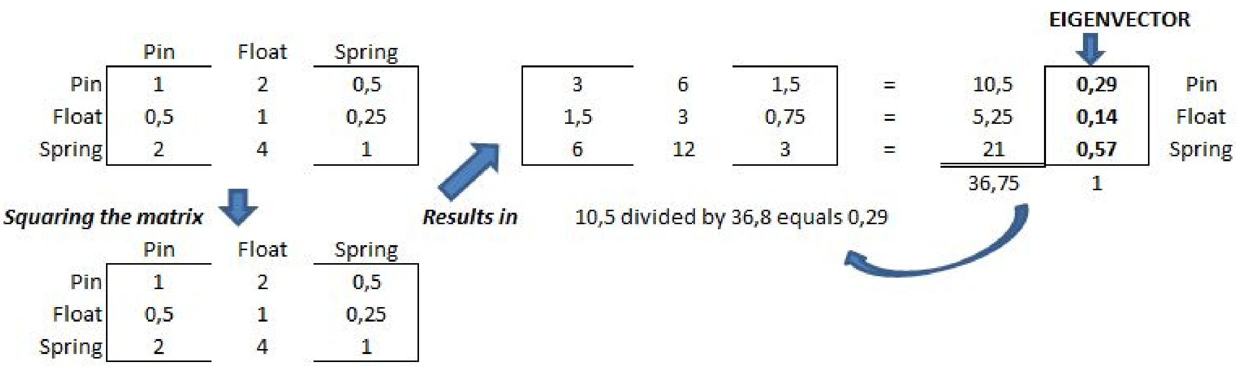

Figure 7. Eigenvector procedure for criterions.

The same procedure as was performed for criterions (components) must be done for alternatives as shown in Figure 8. The most important alternatives for all criterions are marked in Figure 9.

SPRING

	Force	Height	Weight	Concent.	Diameter									EIGENVECTOR	
Force	1	2	4	3	4	Squaring	4,99	8,82	26	14	22	=	75,81	**0,41**	Force
Height	0,5	1	2	2	3		2,91	4,99	16	8	13	=	44,9	**0,24**	Height
Weight	0,25	0,5	1	0,5	0,5		1,04	1,04	4,99	3	4,5	=	15,45	**0,08**	Weight
Concentricity	0,33	0,5	2	1	2		1,91	1,91	10,32	4,99	7,82	=	28,36	**0,15**	Concentricity
Diameter	0,25	0,33	2	0,5	1		1,33	1,33	6,66	3,41	4,99	=	18,8	**0,1**	Diameter
													183,325	1	

PIN

	Force	Height	Weight	Concent.	Diameter									EIGENVECTOR	
Force	1	0,25	0,5	0,2	0,33	Squaring	4,99	1,685	3,99	0,79	1,35	=	12,8	**0,06**	Force
Height	4	1	4	0,5	0,5		20	4,99	14	2,85	4,64	=	46,49	**0,22**	Height
Weight	2	0,25	1	0,2	0,33		6,99	2,06	4,99	1,09	1,845	=	16,975	**0,08**	Weight
Concentricity	5	2	5	1	2		34	10,5	26,5	5	8,3	=	84,3	**0,39**	Concentricity
Diameter	3	2	3	0,5	1		22,5	6,5	18	3,2	4,98	=	55,18	**0,26**	Diameter
													215,75	1	

FLOAT

	Force	Height	Weight	Concent.	Diameter									EIGENVECTOR	
Force	1	2	4	3	4	Squaring	1,36	2,64	5,86	4,135	5,84	=	19,83	**0,05**	Force
Height	0,5	1	2	2	3		3,87	7,58	16,33	11,915	16,67	=	56,36	**0,15**	Height
Weight	0,25	0,5	1	0,5	0,5		7,91	15,16	35	24,5	35,5	=	118,07	**0,32**	Weight
Concentricity	0,33	0,5	2	1	2		5,58	10,92	23,5	17,5	24,75	=	82,25	**0,22**	Concentricity
Diameter	0,25	0,33	2	0,5	1		6,04	11,58	26,5	18,75	27,25	=	90,12	**0,25**	Diameter
													366,625	1	

Figure 8. Eigenvector procedure for alternatives.

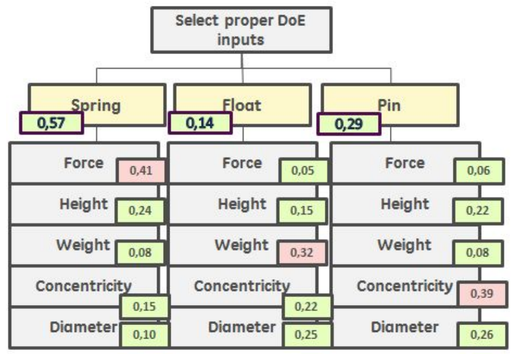

Figure 9. The most important alternativesmarked in red.

Criterions and alternatives that could affect the flow through the valve were selected from Figure 9. For each criterion (component), the most probable alternative (parameter) was selected. It was the weight of the float inside the valve and its weight range, labeled in the Design of Experiment as float weight. Next chosen factor was the spring force holding the float inside the valve. The spring is also moving in a certain tolerance field, labeled as Spring for the Design of Experiment. The last factor possibly influencing the flow is the concentricity of the float pin, in Design of Experiment identified as Concentricity.

Consequently, the Design of Experiment model for three critical factors that may affect the flow through the valve was created. For each factor, it was necessary to find parts in their upper and lower limits of the tolerance field. The upper boundary is marked as 1in the DoE model, the lower limit as -1. For each possible combination, there were performed four repetitions in a random order. Then, there were produced thirty two products and the same number of measurements carried out exactly according to the specified model, as shown in Figure 10.

	StdOrder	RunOrder	CenterPt	Blocks	Float weight	Spring	Concentricity	Flow
1	19	1	1	1	-1	1	-1	128,4
2	3	2	1	1	-1	1	-1	123,7
3	7	3	1	1	-1	1	1	124,5
4	18	4	1	1	1	-1	-1	141,7
5	23	5	1	1	-1	1	1	126,2
6	16	6	1	1	1	1	1	126,4
7	20	7	1	1	1	1	-1	126,7
8	10	8	1	1	1	-1	-1	144,7
9	30	9	1	1	1	-1	1	139,3
10	31	10	1	1	-1	1	1	125,2
11	12	11	1	1	1	1	-1	130,1
12	5	12	1	1	-1	-1	1	145,9
13	6	13	1	1	1	-1	1	141,7
14	17	14	1	1	-1	-1	-1	148,0
15	22	15	1	1	1	-1	1	143,3
16	2	16	1	1	1	-1	-1	140,8
17	1	17	1	1	-1	-1	-1	145,2
18	8	18	1	1	1	1	1	130,0
19	21	19	1	1	-1	-1	1	140,1
20	11	20	1	1	-1	1	-1	131,6
21	29	21	1	1	-1	-1	1	145,5
22	24	22	1	1	1	1	1	123,6
23	9	23	1	1	-1	-1	-1	143,2
24	28	24	1	1	1	1	-1	127,7
25	4	25	1	1	1	1	-1	127,5
26	32	26	1	1	1	1	1	130,9
27	15	27	1	1	-1	1	1	127,4
28	13	28	1	1	-1	-1	1	140,1
29	27	29	1	1	-1	1	-1	127,7
30	25	30	1	1	-1	-1	-1	136,8
31	26	31	1	1	1	-1	-1	139,9
32	14	32	1	1	1	-1	1	142,7

Figure 10. The Design of Experiment (DoE) model.

Subsequent measurement data was recorded and completed in the model. The actual evaluation of the model was again performed in the Minitab statistical software. The evaluation consists of several optional graphs. In Figure 11, it can be seen the Pareto Chart of these factors and all sorts of combinations. The results clearly show that the most significant factor was the B factor, or spring, and its force. Results of Main Effect Plot uniquely determined the weight of the float and the concentricity of pin had no effect on the flow. Furthermore, it also shows the clear influence of the spring, and its force. Thus, as shown in Figure12, the bigger spring force, the lower the flow rate is. In order to verify this theory, it was necessary to perform several tests.

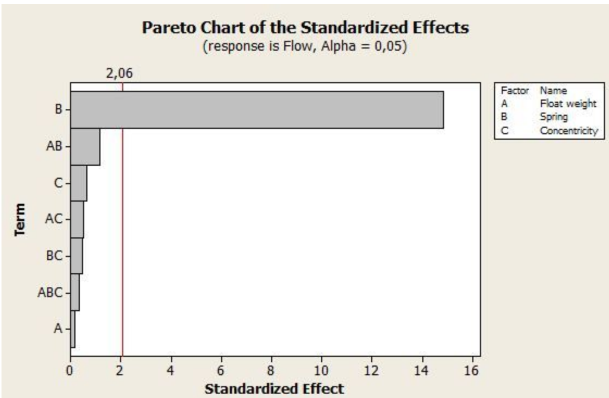

Figure 11. Pareto Chart.

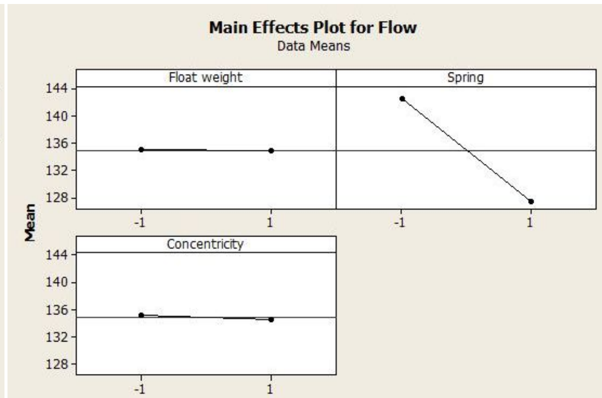

Figure 12. Main Effect Plot.

4.3. VERIFICATION

In order to verify the result of Design of Experiment, a test with adjusted springs was carried out. For the test, approximately one hundred springs with force on the upper boundary of the tolerance were selected. Further, products from selected springs were assembled and tested in the test machine. The resulting values were recorded as shown in Figure 13. Optically, the control chart looks much better than at the beginning of the process, no value coming outside of the limits. Therefore, it was not necessary to find out whether the process is capable and how indices C_p and C_{pk} look like. For this purpose, the statistical software Minitab was used again. The results of the capability test can be seen in Figure 14. C_p and C_{pk} indices were 1.41 and 1.31 which wasa great improvement compared to the original 0.69 and 0.53.The goal for C_p was successfully accomplished. The value for C_{pk} missed the goal only of 0,02 but it can be also recognized as a success. Recommendation for the company was to start negotiating with suppliers in order to receive springs that are on the upper tolerance level.

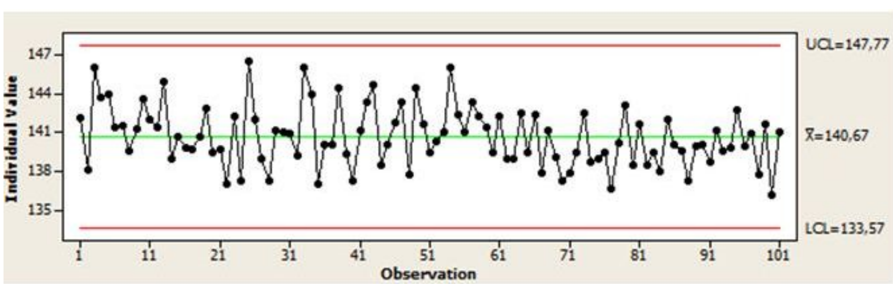

Figure 13. Control Chart of the improved process.

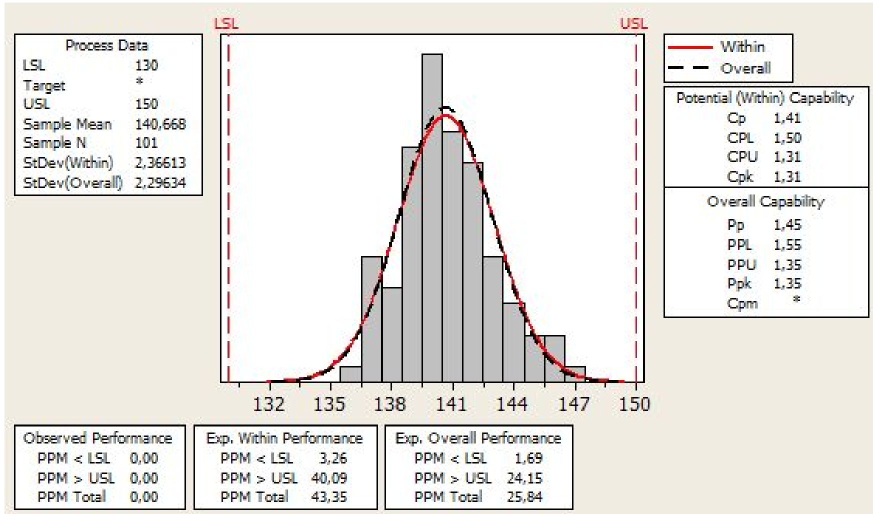

Figure 14. The capability test of the improved process.

5. SUMMARY

Decreasing the variability of production processes is the issue for many production companies. The index values of C_p and C_{pk} may be specified by the customer to a specific value. Therefore, it is necessary to monitor these values and strive for the greatest numbers. There are many techniques to achieve high C_p and C_{pk} indices. This case study describes a real case, the found solution was to improve the process by means of statistical experiments, namely by Design of Experiment with usage of Minitab. When, both indices were nearly increased by the value of 1. Such an improvement will certainly bring significant savings for the company. However, the method cannot be used in all cases and it is not always easy to make a Design of Experiment model. In this case, it was a real situation and a real example of usage of Design of Experiment methodology.

ACKNOWLEDGEMENTS

This research has been supported by the European Regional Development Fund and the Ministry of Education, Youth and Sports of the Czech Republic under the Regional Innovation Centre for Electrical Engineering (RICE), project No. CZ.1.05/2.1.00/03.0094.

REFERENCES

[1] SC&C Partner, Lean Six Sigma Workbook, SC&C Partner spol. s.r.o., 2011.

[2] O. Senvar, H. Tozan, Products and Services from R&D to Final Solutions, IMTECH, 2010.

[3] S.C. Chen and T.C. Hsia: "Promoting Customer Satisfactions by Applying Six Sigma: An Example from the Automobile Industry", Quality Management Journal, Vol.12, No.4, pp.21–33, 2005http://pqa.net/courses/data/page13.html (accessed June 15, 2013).

[4] E. Jarosova, Navrhovani experimentu a jejich analyza, CSJ, 2007.

[5] M. Douglas, Introduction to Statistical Quality Control, John Wiley & Sons, New York, 2004.

[6] T. L. Saaty: "Decision making with the analytic hierarchy process", Services Sciences Journal, Vol.1, No.1, 2008.

[7] P.C.Irwin: "Powdercoatingprocess-improvementsusing statistical and DOE methodologies", Electrical Insulation.

Conference and Electrical Manufacturing&Coil Winding Conference, USA, 1999.