AN APPROACH TO THE CAPABILITY ANALYSIS OF A MULTI-SPINDLE MACHINING CENTRE

Valter Uran[1 *] – Duško Pavletić[2] – Sandro Doboviček[2]

[1] Cimos Automotive Industry, C. Marežganskega upora 2, Kopar, Slovenia
[2] Faculty of Engineering, University of Rijeka, Vukovarska 58, 51000 Rijeka, Croatia

ARTICLE INFO

***Article history*:**
Received: 26.08.16.
Received in revised form: 03.01.17.
Accepted: 22.02.17.

Keywords:
Capability analysis
Multi spindle machining centre
Statistical process control

Abstract:

In many industries, there is a growing need to produce products with strict tolerances of individual product characteristics. Increasing productivity and profitability are also sought, demanding the production of more products per unit time, and at a lower cost with the available production equipment and with minimal investment. A strong competition creates the need to improve production efficiency. One way of addressing the challenge of precise parts manufacturing is by analysing the capabilities of the production equipment. Assessing process capability using statistical modelling plays a key role in the business decision-making process in quality management. This paper presents a statistically based approach to capability analysis of a multi-spindle machining centre.

1 Introduction

In modern industry, especially the automotive industry, there is a constant need for higher precision, environmental friendly production, a shorter cycle time, and lower production costs. The capability analysis is a proven concept that has been widely adopted to facilitate achieving high precision of manufactured products [1, 2]. It is a TQM tool described as a strategic management technique that plays a vital role in company operations management, aids in product design, setting acceptance norms, and process and operator selections in operations management [3]. Juran created a stronger link between process variability and customer specification [4]. If all the parts are processed with properties near target values and within the defined tolerances, the result will be a 100 % usable product, thus saving time and money [5]. By designing and setting up a robust production system with a sufficiently reliable process, quality controls to confirm that the product characteristics are within tolerance levels can be performed at less frequent intervals. Furthermore, capability analysis of manufacturing equipment visualizes the process ability to manufacture products to the required quality.

The capability analysis provides information on the machine's ability to produce a product with the desired characteristics. It is usually performed within a short time frame, primarily to exclude environmental and long period impacts on product characteristics, such as changes in temperature or tool wear [5]. It is primarily used during the pre-acceptance or acceptance of a new machine, or following a major overhaul. Therefore, the corresponding capability index is an indicator of the machine's ability to produce the product characteristics in accordance with the given requirements.

Chen et al. noted that the capability index can be viewed as an effective and excellent means of

* Corresponding author. E-mail address: valter.uran@cimos.eu

measuring product quality and performance [6]. Many engineering designers and shop floor controllers use capability indices as communication indicators to evaluate and improve the manufacturing process.

2 Approach to machine capability analysis

Machining accuracy depends on four characteristics: thermal effects, geometry and kinematics of the machine, static stiffness, and dynamic stiffness. Mostly, all mechanical characteristics are under the influence of a large number of variables that cause overall variability, since they change randomly, periodically, and systematically [5, 7]. Even when the influence of every known factor in the process is eliminated, or maximally reduced, the result will continue to change during the time interval [8, 9].
Methods of quality control and statistical forecasting, as a tool for machine capability analysis, play a key role in the decision-making process in quality management [10]. By monitoring variations in the production process, it is possible to predict the tendency of the process and to take preventive action necessary to maintain the required quality level of the process, and therefore the quality of products. Many factors influence the process and its outputs. Prediction and management of these impacts is a must in every production process aiming for high product quality [11]. The capability analysis can certainly serve as a good tool in achieving that goal.

2.1 Multi-spindle machining centre

The machining centre analysed in this paper is defined as a system of several physical modules interconnected by the workpiece: the machine modules, clamping device, cutting tools, and cutting process. Each module consists of several systems or components, and each of these modules has an interface to other modules through which they interact. The selected machining centre is a multi-spindle centre that enables production of two or more products in one cycle. In addition to the selected machine, examples of this production concept can be seen in multiple spindle lathes, multi-cavity tools for injection moulding, etc.; i.e. in any process in which multiple products are produced simultaneously.
In this configuration, there are factors (variables) specific to each spindle, and other factors that affect the process as a whole. The parts of each spindle will contain a variation (variation within a spindle) that will be different from the other spindles (variation between spindles). Processes with the multiple spindles represent a challenge in terms of quality assurance and, particularly, capability measurement. It is necessary to recognize and understand these variables and to ensure proper implementation of the machine capability analysis.

2.2 The capability analysis for normally and non-normally distributed data

Process control implies the monitoring of process parameters in relation to their mean or nominal value. Deviations from the nominal value can be positive or negative, indicating that the process is under control when the measured value is within the control limits. The deviations could be successfully predicted by the methods of Statistical Process Control (SPC). Process capability, which is one of the SPC tools, is estimated by the process capability index. The capability analysis is based on the following assumptions:

- the process under consideration is stable and with no significant causes of variation,
- process data distribution is normal or can be approximated by a normal distribution,
- reliable process capability estimation can be made only on the basis of the monitoring process by applying the appropriate control charts and after bringing the process to a state of statistical control.

Numerous statisticians and quality engineers such as Chen et al. [6], Kane [12], Chan et al. [13], Choi and Owen [14], Boyles [15], Pearn et al. [16], Kotz and Johnson [17], Spring [18], Palmer and Tsui [19] - have examined process capability indices to propose more effective methods of evaluating process potential and performance. In respect to the period of time in which the sample for capability analysis is taken, the estimation of process capability may be classified as either short-term process capability or long-term process capability.
Among several capability indices, the simplest is C_p, which gives information about the relationship between the sample distribution width and the given tolerances. The second index, C_{pk}, takes into account distribution position within the tolerance range. Wooluru et al. conducted the process capability analysis for a boring operation by understanding the concepts and methodologies and by making critical assumptions [20]. The C_{pk} usually represents short-term capability while long-term capability is denoted by P_{pk} [21, 22]. Larsson [5] and also Pristavka and Bujna [10] noted that the machine capability analysis is performed for a short period of time and is

described with the indicators C_m and C_{mk}. In this case, it is recommended that the analysis be conducted on a sample of at least 30 products. To calculate machine capability indicators, the following formulas are used:

$$C_m = \frac{T_g - T_d}{6s}, \quad (1)$$

$$C_{mk} = min\left|\frac{T_g - \bar{x}}{3s}, \frac{\bar{x} - T_d}{3s}\right|, \quad (2)$$

where, T_g and T_d represent the upper and lower specification limits respectively, $\bar{x}$ represents the mean and s represents the standard deviation of the observed data set. In the automotive industry, it is generally a rule that a capable machine is a machine with a C_{mk} greater than 1.67. Processes with a C_{mk} value between 1.33 and 1.67 are only conditionally acceptable [10, 23, 24].

Doboviček et al. noted that data collected from the process can be normally or non-normally distributed [11]. In the case of normally distributed data, the calculation of capability indices is quite straightforward. When the process data are non-normally distributed, it is necessary to transform the data or to calculate capability indices using best fit distribution (Poisson, Weibull, Binomial, Gamma Exponential, …) as a base. Initially, it is important to stress that there is no generally accepted calculation of a non-normal distribution index. Still, the most commonly used method is based on analogy with the normal distribution calculation. In that method, 99.73 % of the interval, which corresponds to 6σ normal distribution, is compared to a tolerance interval of the observed characteristics. After determining that the selected distribution model provides the best process output value, the interval containing 99.73 % of the population is defined and contains the dispersion as in cases with a normal distribution [25]. The boundaries of this interval are the 0.135 percentile and 99.865 percentile of the distribution. This interval represents the probability of 99.73 % of total population. Calculation of machine capability index, C_{mk}, in that case is [22]:

$$C_{mk} = min\left|\frac{T_g - \tilde{x}}{x_{0.99865} - \tilde{x}}, \frac{\tilde{x} - T_d}{\tilde{x} - x_{0.00135}}\right|, \quad (3)$$

where, x_p represents boundary percentiles and $\tilde{x}$ represents the 50th percentile of the observed characteristics, i.e. the median. An alternative approach to calculating the capability index for the process that shows output parameters in a non-normal distribution is transformation of the data set to a normal distribution, and then calculating the capability by the formula for the normal distribution.

2.3 Capability analysis procedure

The machine capability analysis is a formal procedure for assessing the ability of the machine to meet the given requirements [10, 26, 27, 28, 29].

After selecting the functional dimension for the analysis to perform and verify the accuracy of the measuring equipment, the following steps are taken: assessment of process stability, assessment of whether the process is “under control”, calculation of capability indices, comparison of obtained index values with target values, deciding whether to alter machine parameters, reporting analysis results and proposing improvements, Fig. 1 [9].

In order to have valid process data for the analysis, it is necessary to ensure a capable measurement system. The measurement system analysis indicates whether the measuring system has a satisfactory resolution, and whether it is stable and able to control the product. The measurement used in the analysis was performed on the Hexagon 3D coordinate measuring machine (CMM). The measurement capability analysis showed that the total variation of the measuring system was 7 %. Total variation of the measuring system of less than 10 % is considered capable. The next step was to examine whether the process exhibited only inherent variation, i.e. whether it is under control. This is performed by using the appropriate control chart, in this case the $\bar{x}R$ control chart.

3 Basic process characteristics

3.1 Characteristics of tested workpiece

The capability analysis was performed on an aluminium engine part (workpiece) produced on a multi-spindle machining centre. The selected engine part is a high-pressure pump support, as shown on Fig. 2. The analysis examined a sample of 30 + 30 workpieces. On each workpiece, twelve functional dimensions, marked D1 to D12, Table 1, were measured. The obtained results were statistically analysed using the Minitab software.

The capability analysis is one of the deciding factors in the selection and purchase of production equipment. The selected equipment has to provide evidence that it is capable of producing products of the required quality.

The machine or equipment is accepted when each defined product functional dimension is in accordance with the required capability index value. If the capability index value does not meet a required value, corrective actions must be taken.

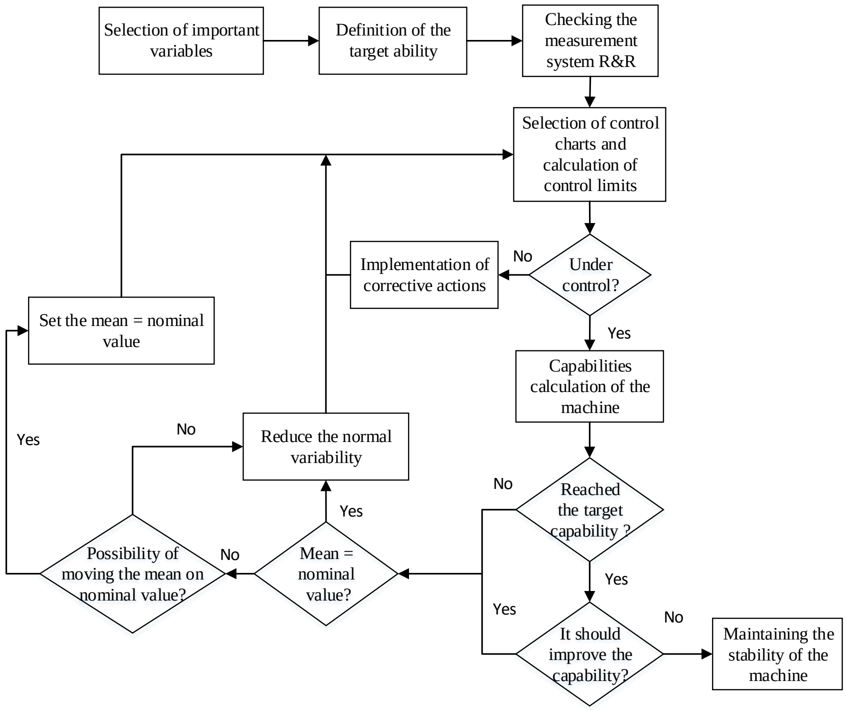

Figure 1. Machine capability analysis flowchart [9].

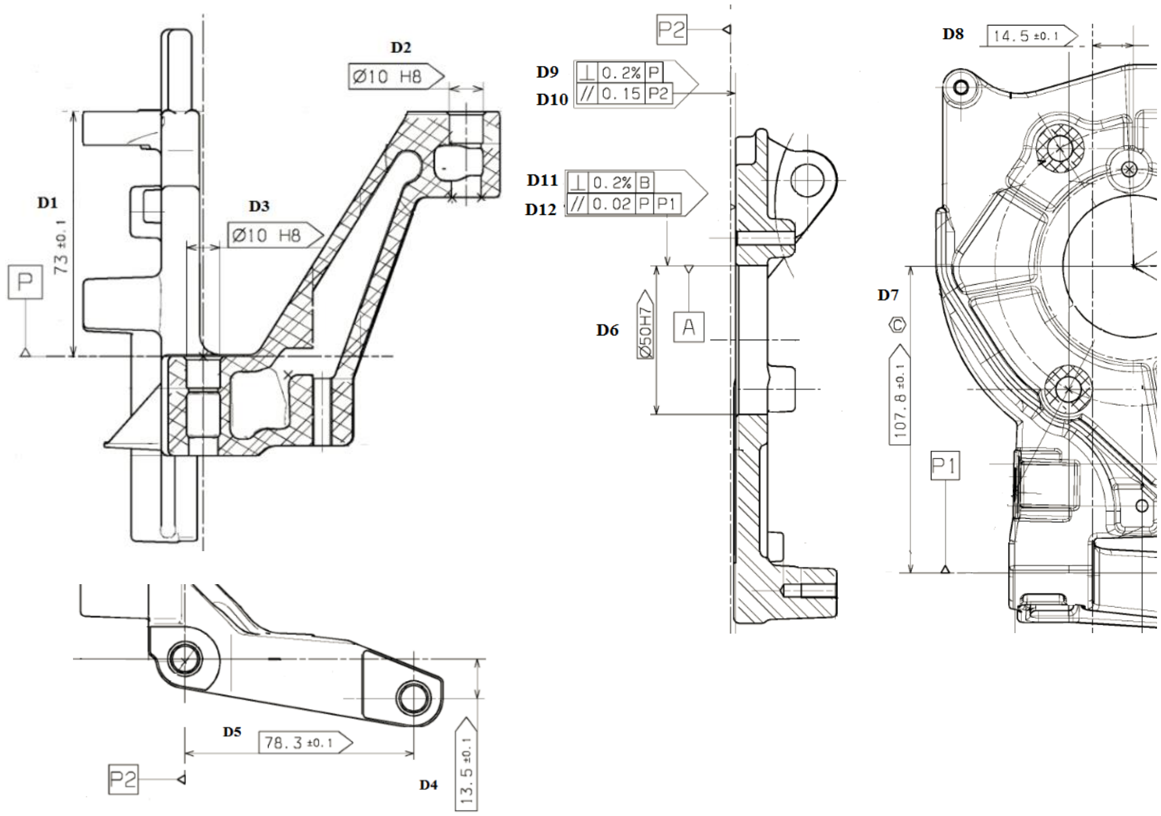

Figure 2. The defined dimensions and tolerances of support for high pressure pump.

Table 1. Critical dimensions of support for high pressure pump sample

No.	Characteristic	Tolerances [mm]
D1	The distance between the two surfaces for fixing on the engine block	73±0.1
D2, D3	Diameter of two holes for fixing on the engine block	2 x Ø10H8 (+0.022/0)
D4	Spacing two holes Ø10H8 - x axis	13.5±0.1
D5	Spacing two holes Ø10H8 - y axis	78.3±0.1
D6	Bore diameter for receiving and centering the high pressure pump	Ø50H7 (+0.025/0)
D7	The distance between the central hole Ø10H8 and Ø50H7 - x axis	107.8±0.1
D8	The distance between the central hole Ø10H8 and Ø50H7 - y axis	14.5±0.1
D9	Perpendicularity contact surface of the pumps on base P	⊥ 0.2% P
D10	Parallelism contact surface of the pumps on base P2	// 0.15 P2
D11	Perpendicularity centering surface of the pumps on base B	⊥ 0.2% B
D12	Parallelism centering surface of the pumps on base P, P1	// 0.02 P P1

3.2 Features of selected machining system

For the capability analysis, the Elha FM3+X multi spindle machining centre was selected, Fig. 3. The selected machining centre has the following characteristics:

- double spindle machine with two tools engaged simultaneously (expandable to four engaged spindles) and with two workpieces in the clamping device, Fig. 4,
- the machining concept is defined by moving the clamping device with the pieces while the spindle is fixed,
- spacing between spindles is 240 mm, the spindle is powered by electric motors,
- the machine is suitable for cast product processing that requires up to 14 operations (different tools),
- suitable for handling products with dimensions to 200x180x80 mm,
- technical characteristics: clamping device path x-y-z 400x1000x500 mm, device speed 40 m/min, acceleration 6 m/s^2, spindle speed max. 20,000 min^{-1} (for the product in question, from 9,000 – 12,000 min^{-1}), spindle torque 200 Nm, used control Sinumerik 840D.

All stages of processing are performed in the single clamping of the clamping device. The raw material is cast aluminium produced through the process of pressure casting from a two-cavity casting tool. Support and clamping are performed in three points.

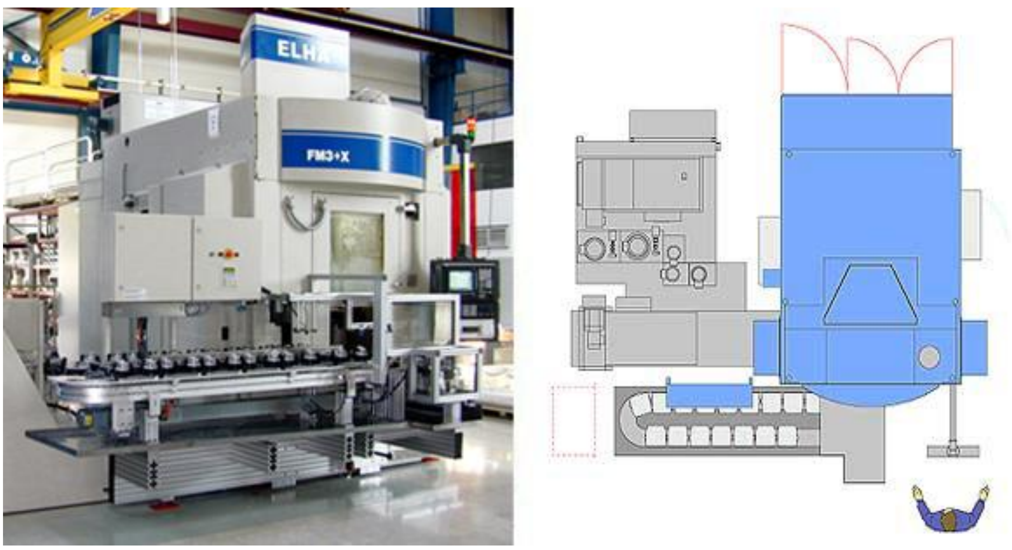

Figure 3. Picture and draft of Elha FM3 + X machine.

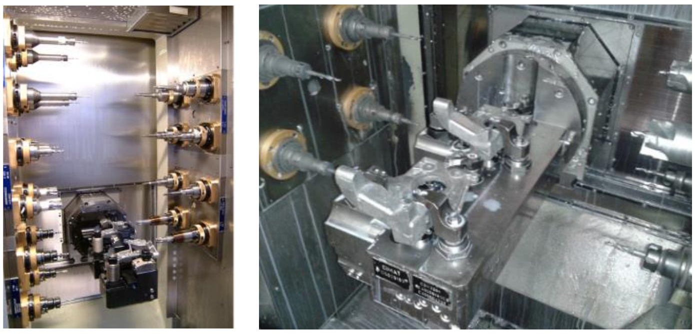

Figure 4. The working space of the machine and the position of the workpiece in the machine.

4 The capability analysis of the multi-spindle machining centre for the selected product

The capability analysis of the Elha FM3+X multi-spindle machining centre was performed for the selected product, a high-pressure pump support. In order to obtain a representative sample, products were taken randomly from the production process, without sorting. The parts produced in both nests of the double-nest casting tool were equally represented in the sample. Machining was performed under optimal production conditions, and the workpieces were taken from the process in the order they were produced and were then numbered. All workpieces were measured on a dedicated CMM.

As stated above, capability analysis is supported by Minitab statistical software. The software is used for checking the “under control” state of the observed process/data, testing the normality of the data hypothesis and process capability calculation. The result of the analysis for one of selected critical dimensions of the product, i.e. spacing between two holes Ø10H8 on the *x* axis, as denoted by D4, is shown on Fig. 5.

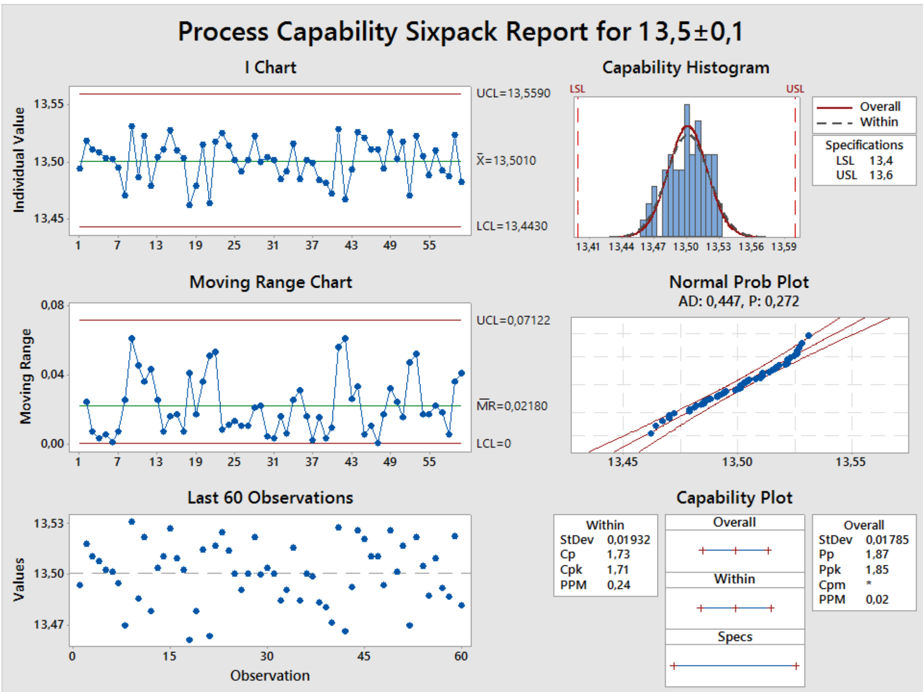

Figure 5. Report on the machine capabilities for the selected dimension (D4).

The performed capability analyses take into account the fact that data were collected in a short time period, hence in this case, there is no long-time variation. Therefore, the values of C_{pk} and P_{pk} are expected to be the same. However, a difference was found between those two values (C_{pk} = 1.71 and P_{pk} = 1.85),

due likely to the calculation procedure, i.e. C_{pk} is calculated by estimating the standard deviation using the deviation range value (moving range equation), rather than the standard deviation. Meanwhile, P_{pk} is calculated by the total standard deviation (overall).
The results of the machine capability analysis performed for all observed dimensions are shown in Table 2. The C_{mk} values, for most of the observed dimensions, were higher than the default value of 1.67. Two functional dimensions, D1 (distance 73±0.1) and D10 (parallelism, a maximum of 0.15 to the base P2), did not meet the threshold value of C_{mk}=1.67. The described procedure is commonly used approach to capability analysis. This process assumes that all the collected data are normally distributed and the corresponding relationships are used in the capability calculation. By checking the normality assumption of all collected data sets (D1 to D12), it can be seen that some of collected data are not normally distributed, hence the calculated capability index values are incorrect.

Table 2. Results of the capability analysis for the observed dimensions

No.	Tolerances (mm)	Calculation C_{mk} for sample
D1	73±0,1	0.97
D2, D3	2 x Ø10H8 (+0.022/0)	1.68; 1.95
D4	13.5±0.1	1.71
D5	78.3±0.1	1.86
D6	Ø50H7 (+0.025/0)	1.73
D7	107.8±0.1	1.84
D8	14.5±0.1	1.82
D9	⊥ 0. 2% P	3.70
D10	// 0. 15 P2	0.29
D11	⊥ 0. 2% B	2.94
D12	// 0. 02 P P1	1.72

In general, boundary dimensions, such as parallelism (D10) and perpendicularity (D9), are not normally distributed and a different approach is required for the capability analysis. Furthermore, the analysis of the capability index value for dimension D1 (distance 73±0.1), which is normally distributed, Fig. 6, shows an unsatisfactory low value of C_{mk}=0.97, Fig. 7. To find sources of high data variability, which may have resulted in the low capability index value, the data set for dimension D1 was divided into two sets, one for each casting tool nest.

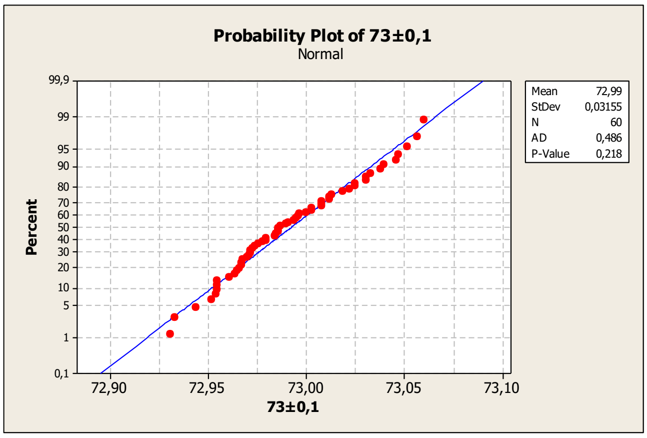

Figure 6. The normality of distribution.

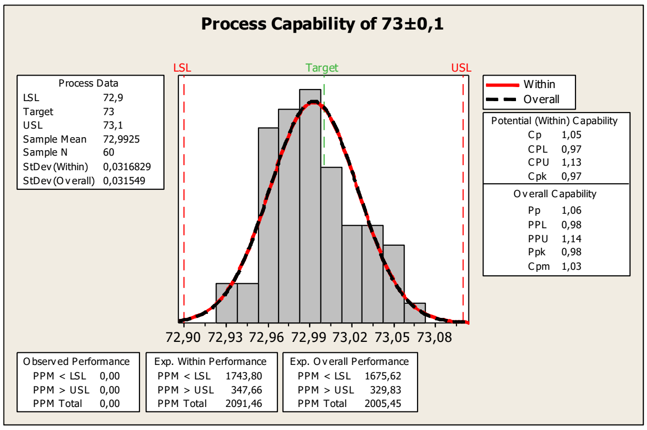

Figure 7. Distribution of dimensions 73±0.1.

The resulting capability indices, C_{mkA} = 1.03 and C_{mkB} = 0.91, were still low, Fig. 8 and 9.
The increased standard deviation that appeared on both casting tool nests, may be attributed to special causes, such as the variability of castings. The casting production is performed by a process of pressure casting in a metal (casting) tool consisting of two cavities (casting nests) and moving parts which together form the shape of the product, other tool parts for ensuring the proper functioning of the casting process (vents, cooling and heating systems, etc.).
Dimensional accuracy of casting is ensured by the precision of the casting tool parts and correctly implemented cooling and heating systems. Any variations in these parameters can result in unacceptable variation in the casting dimensions and, consequently, in unacceptable capability index values. Finding the source of variation of dimension D1 would require more extensive analysis with

known traceability of workpieces through the manufacturing process.

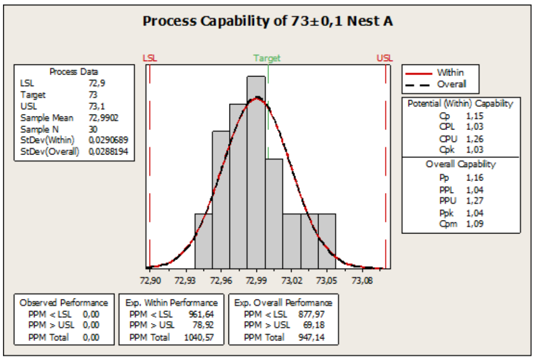

Figure 8. Distribution for nest A (Dimension D1).

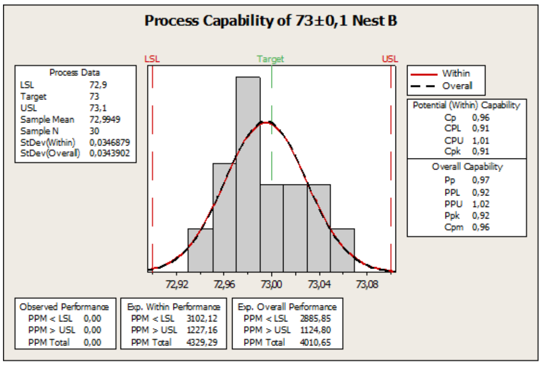

Figure 9. Distribution for nest B (Dimension D1).

By analysing dimension D9 (perpendicularity to the base P) it is found that the data are non-normally distributed. The *p*-value, probability associated with normality hypothesis testing, equal to or greater than 0.05 shows that the data are normally distributed with 95 % confidence, Fig. 10.

Goodness of Fit Test

Distribution	AD	P	LRT P
Normal	0,931	0,017	
Box-Cox Transformation	0,332	0,505	
Lognormal	0,332	0,505	
3-Parameter Lognormal	0,346	*	0,955
Exponential	7,780	<0,003	
2-Parameter Exponential	1,908	<0,010	0,000
Weibull	0,467	0,245	
3-Parameter Weibull	0,250	>0,500	0,007
Smallest Extreme Value	2,437	<0,010	
Largest Extreme Value	0,417	>0,250	
Gamma	0,325	>0,250	
3-Parameter Gamma	0,293	*	0,126
Logistic	0,823	0,019	
Loglogistic	0,455	0,216	
3-Parameter Loglogistic	0,470	*	0,722
Johnson Transformation	0,188	0,899	

Figure 10. Goodness of Fit Test for the dimension D9, "perpendicular to the base P", results from software Minitab.

In the case of the perpendicularity, it is expected that the data will not be normally distributed, which is confirmed by a normality test. Since the *p*-value for the normal distribution is less than 0.05 (p = 0.017) an approximation is required. By identification of individual distributions, it was determined that the measured data are best approximated by a non-normal 3-Parameter Weibull distribution, which is, in this case, base for the machine capability index calculation. Using the 3-Parameter Weibull distribution as the base distribution for the capability index calculation for dimension D9, the value of C_{mk} = 3.70 was obtained, and it can be concluded that the quality requirements for dimension D9 were met and no further analysis is required, Fig. 11.

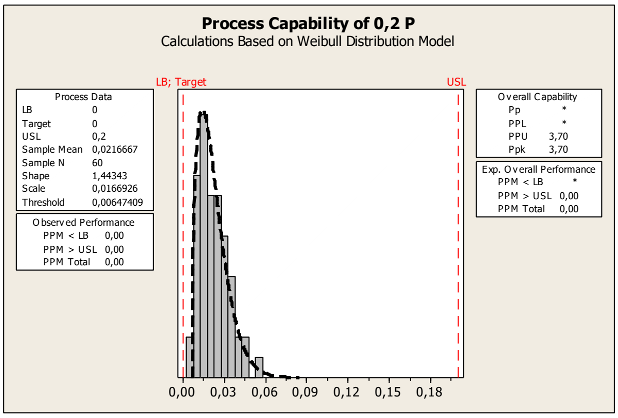

Figure 11. Approximation of non-normal distribution of the dimension "perpendicular to the base P maximum 0.2".

For dimension D10 (parallelism, maximum 0.15 to the base P2), the measured data were non-normally distributed and it was found that the 2-parameter exponential distribution (p = 0.016) can be used for approximation, Fig. 12. For this characteristic, there is an evident presence of a special cause in the process, called the “double hump” effect (camel-hump). The analysis per nests, for given data set, are shown on Fig. 13 and 14. An increase in the standard deviation appeared for both nests, and each nest presented a specific pattern, characterized by a double hump. As the further analysis is necessary, the sampling of the aforementioned two dimensions, D1 (distance 73±0.1) and D10 (parallelism, maximum 0.15 to the base P2), was repeated prior to machine adjustments. Sampling was conducted by sorting casts according to the casting tool nests. First, all the castings from the nest A were analysed and measured, followed by castings from the nest B. In the repeated measurement, for the second sample of dimension D1 (distance 73±0.1), it cannot be concluded that the sample data are normally distributed, Fig. 15.

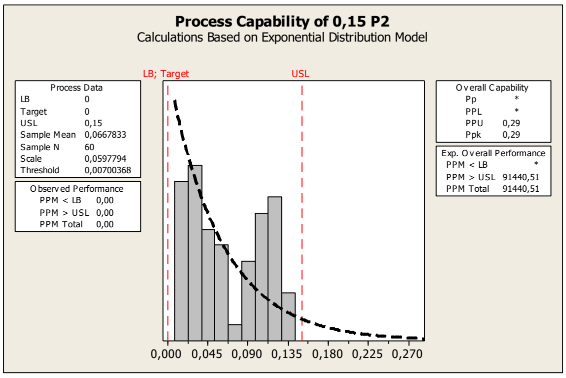

Figure 12. Analysis of the distribution of the dimension "parallelism, maximum 0.15 to the base P2".

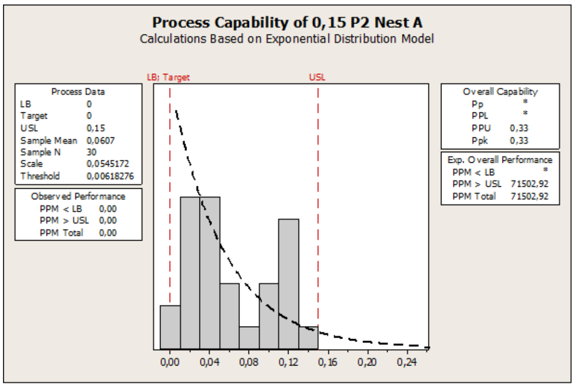

Figure 13. Distribution for nest A (Dimension D10).

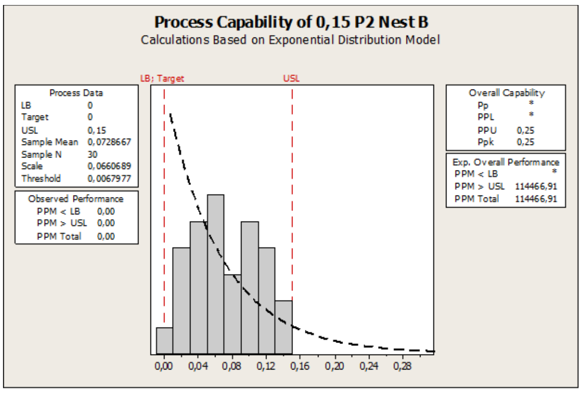

Figure 14. Distribution for nest B (Dimension D10).

Although the capability index value for dimension D1 is acceptable, from the Fig. 16 it can be seen that two groups of data can be distinguished, which is also confirmed by Multi-vary analysis, Fig. 17.

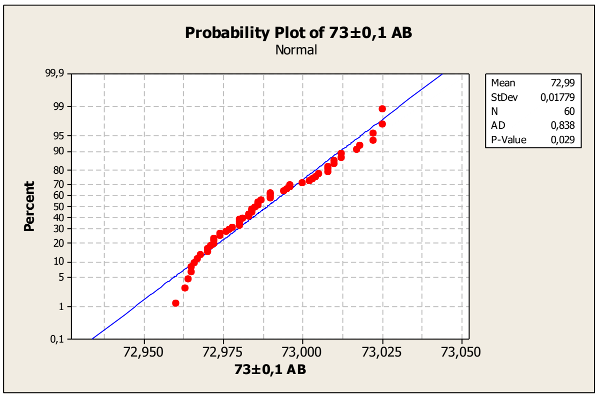

Figure 15. The probability plot of dimension D1.

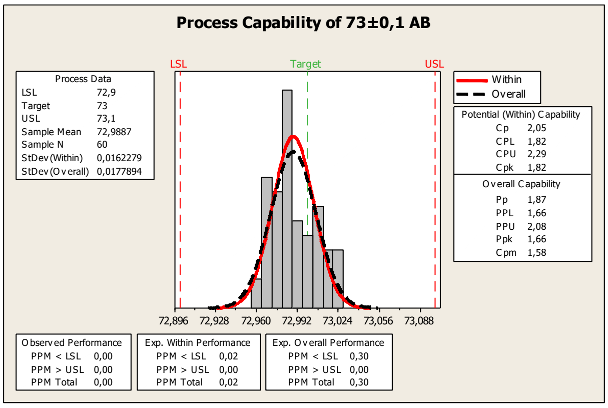

Figure 16. Distribution of dimensions D1, 73±0,1.

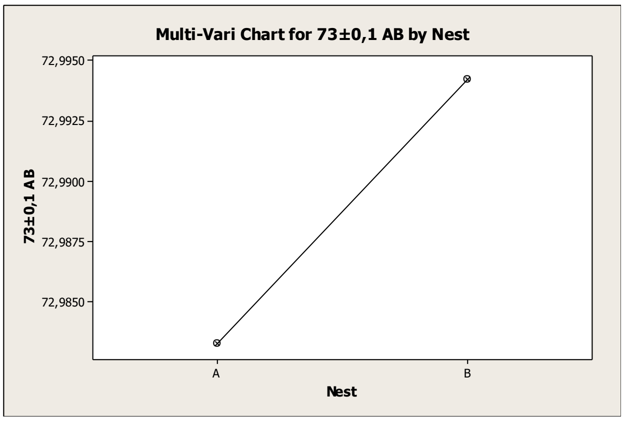

Figure 17. Difference in sample means of data obtained from two casting tool nests (A and B).

It can be concluded that the expected normal distribution of dimension D1 in the sample data is not achieved due to the existence of two subgroups of data within the samples, and the data that can be associated with the nests A and B. Still, the capability indices calculated for each nest separately show satisfactory values, Fig. 18 and 19.

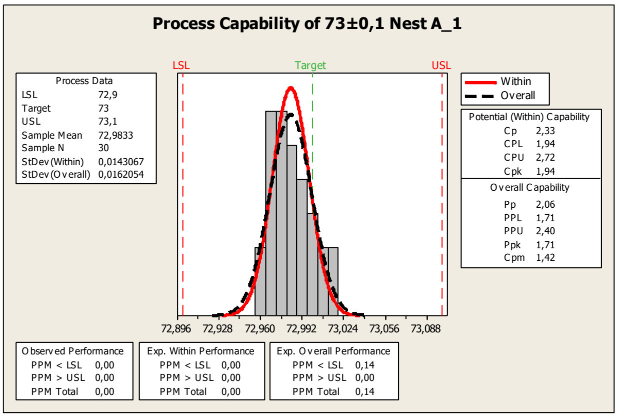

Figure 18. Process capability, dimension D1, nest A.

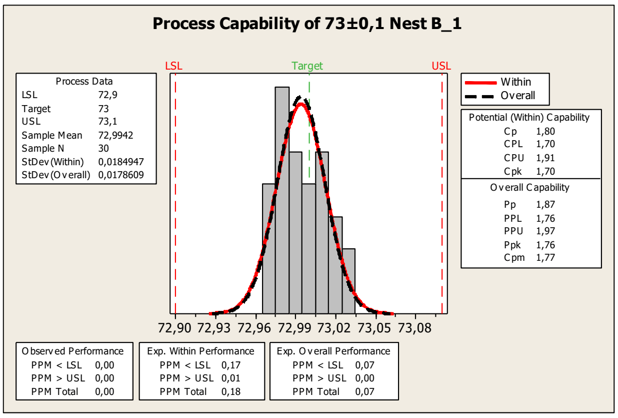

Figure 19. Process capability, dimension D1, nest B.

By analysing dimension D10 (parallelism, max 0.15 on base P2), the data were found to be non-normally distributed. The data fit test was performed and 3-Parameter Weibull distribution selected as the best fit distribution for the observed data set, Fig. 20.

The performed data fitness analysis shows that the 3-parameter Weibull distribution can be used in further process capability calculation (*p*-value = 0.482). The results are shown in Fig. 21. The overall process capability achieved value of C_{mk} = 1.79 satisfies the requirements for the confirmation of machine capability.

The process capability analysis for the data selected by casting tool nest also shows satisfactory results, although the variance of the measurement form the nest B was slightly higher than the variance for the nest A, Fig. 22 and 23.

Goodness of Fit Test

Distribution	AD	P	LRT P
Normal	0,784	0,040	
Box-Cox Transformation	0,327	0,513	
Lognormal	0,773	0,042	
3-Parameter Lognormal	0,366	*	0,032
Exponential	6,193	<0,003	
2-Parameter Exponential	3,233	<0,010	0,000
Weibull	0,347	>0,250	
3-Parameter Weibull	0,352	0,482	0,371
Smallest Extreme Value	1,808	<0,010	
Largest Extreme Value	0,364	>0,250	
Gamma	0,378	>0,250	
3-Parameter Gamma	0,350	*	0,760
Logistic	0,781	0,023	
Loglogistic	0,573	0,094	
3-Parameter Loglogistic	0,417	*	0,191
Johnson Transformation	0,285	0,617	

Figure 20. Results of fit test for dimension D10.

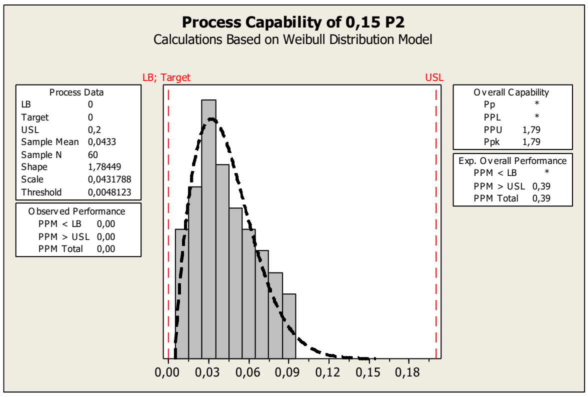

Figure 21. Process capability for dimension D10 using Weibull distribution model.

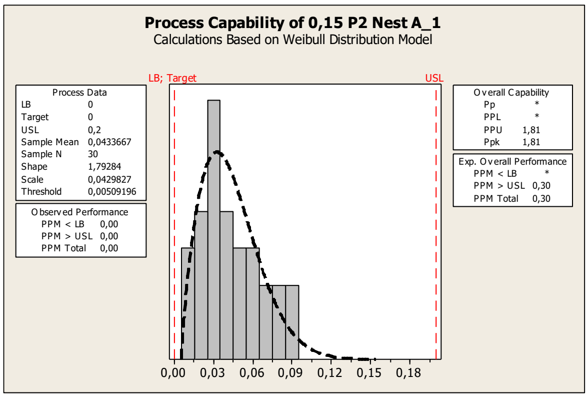

Figure 22. Process capability for dimension D10 nest A.

Table 3 shows the results of the initial capability analysis for dimensions D1 and D10, performed without data selection based on the casting tool nest, and modified capability analysis that involves data stratification and calculation based on non-normal distribution models.

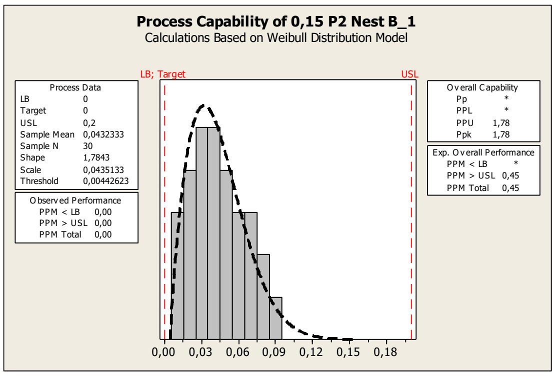

Figure 23. Process capability for dimension D10 nest B.

Table 3. Capability index for dimension D1 and D10 after first and second sampling

No.	Tolerances [mm]	Calculation C_{mk} for sample 1	Calculation C_{mk} for sample 1 for nest A i B
D1	73±0.1	0.97	1.94; 1.70
D10	// 0.15 P2	0.29	1.81; 1.78

The final conclusion is that the overall process capability of the multi spindle machining centre Elha FM3+X for the given products is acceptable (C_{mk} value greater than 1.67), therefore the machine is suitable for the use in the production process.

5 Conclusion

The process capability index is the important parameter in assessing the state of the quality and readiness of the production equipment in order to meet requirements. Determination of capability index represents the final test at the assessment of quality or purchase of the production equipment and at the restart of equipment after servicing or a prolonged delay. Although, basically, the analysis of the production equipment capabilities itself may be a simple procedure, in the case of sophisticated equipment, such as a multi-spindle machining center, determining of the capability can be complex procedure.

This study provides a practical example of determining the capability index of a multi-spindle machining centers used for the production of aluminum parts in the automotive industry. Due to the configuration of the multi-spindle machining centre, the variations are specific to each spindle and it is necessary to recognize, understand and ensure proper implementation of the capability analysis of the machine.

For the observed machining centre, the quality features of products (dimensions) are mainly normally distributed. Still, there are some product dimensions that cannot be modelled by normal distribution and, as such, need to be taken into account during the process capability analysis. Initially, the capability analysis is done on taken sample. Based on the obtained results, necessary corrections in the process are performed. The final analysis, on second sample, confirmed that the equipment met the criteria of acceptance with capability index of $C_{mk} = 1.67$.

In this paper, the method of determining the capability of non-normally distributed product dimensions is discussed in particular. Current practice shows that the approach to capability analysis of such dimensions is not appropriate. Often, the reason for this is the complexity of the calculation within production conditions. Therefore, this paper presents a practical and applicable scientifically based approach to determining the process capability for complex modern production equipment.

References

[1] English, J. R., Taylor, G. D.: *Process capability analysis – a robustness study*, International Journal for Production Research, Vol. 31, No. 7, pp. 1621-1635, 1993.

[2] Mahesh, B. P., Prabhuswamy, M. S.: *Process variability reduction through statistical process control for quality improvement*, 5th International Quality Conference, Center for Quality, University of Kragujevac, Srbija, 2011.

[3] Kalkutaki, G. M., Nagre, M. R.: *Improving process capability through inline measurement in automobile industry: Case Study*, International Research Journal of Engineering and Technology, Vol. 3, Issue 6, 2016.

[4] Juran, J. M.: *Quality Control Handbook*, 2nd ed., McGraw-Hill, New York, pp. 11-27, 1962.

[5] Larsson, A.: *Capability in Machining Systems*, A Licentiate Thesis, Royal Institute of Technology, Sweden, 2002.

[6] Chen, K. S., Huang, M. L., Li, R. K.: *Process capability analysis for an entire product*, International Journal for Production Research, Vol. 39, No. 17, pp. 4077-4087, 2001.

[7] Wei, H., Jian, X., Da-Yong, Z., Fe, L., Jian-Wei, L., Kun-Lin, L.: *Placement study of composite*

vibration isolation system for machinery equipment, Engineering review, Vol. 36, Issue 3, 203-210, 2016.

[8] Soković, M et. al.: *Measuring system analysis for quality assurance in a Six-Sigma process*, Strojniski vestnik-Journal of Mechanical engineering, 2005

[9] Pavletić, D., Soković, M.: *Six Sigma: A complex quality initiative*, Strojniski vestnik-Journal of Mechanical engineering, 2002

[10] Pristavka, M., Bujna, M.: *Monitoring the capability of production equipment in organization*, Acta technologica agriculturae, Vol. 2, p. 39-43, 2014.

[11] Dobovišek, S. et al.: *Logical procedure for determing the appropriate method of calculating the process capability*, Tehnički vjesnik 20, 5(2013), 739-746.

[12] Kane, V. E.: *Process capability indices*, Journal of Quality Technology, 18, pp. 41-52, 1986.

[13] Chan, L. K., Cheng, S. W., Spiring, F. A.: *A new measure of process capability* C_{pm}, Journal of Quality Technology, 20, pp. 162-175, 1988.

[14] Choi, B. C., Owen, D. B.: *Applied Multivariate Statistical Analysis*, 3rd ed., Prentice-Hall, New York, 1990.

[15] Boyles, R. A.: *The Taguchi capability index*, Journal of Quality Technology, 23, pp. 17-26, 1991.

[16] Pearn, W. L., Kotz, S., Johnson, N. L.: *Distributional and inferential properties of process capability index*, Journal of Quality Technology, 24, pp. 216-231, 1992.

[17] Kotz, S., Johnson, N. L.: *Process capability index*, Chapman and Hall, London, 1993.

[18] Spring, F. A.: *An unifying approach to process capability index*, Journal of Quality Technology, 29 (1), pp. 49-58, 1997.

[19] Palmer, K., Tsui, K. L.: *A review and interpretations of process capability indices*, Annals of Operations Research, 87, pp. 31-47, 1999.

[20] Wooluru, Y., Swamy, D. R., Nagesh, P.: The *Process Capability Analysis – A Tool for Process Performance Measures and Metrics – A Case Study* , Inetrnational Journal for Quality Research 8(3), pp. 399-416, 2014.

[21] Soković, M et. al.: *Application of Six Sigma methodology for process design quality improvement*, 13th Scientific International Conference „Achievements in Mechanical and Materials Engineering, AMME, 2005

[22] *Quality Management in the Bosch Group, 9. Machine and Process Capability*, 3. Edition, 2004.

[23] Hong W. P.: *Machine Capability Index Evaluation of Machining Center and Comparative Analysis with Machine Property*, Journal of Korean Society of Manufacturing Technology Engineers, 22:3, (2013).

[24] Kurekova, E.: *Measurement Process Capability – Trends and Approaches*, Measurement Science Review, Vol 1, No.1, 2001.

[25] Swamy, D. R., Nagesh, P., Wooluru, Y.: *Process Capability Indices for Non-Normal Distribution – A Review*, Inetrnational Conference on Operations Management and Research, Mysuru, India, 2016.

[26] Škůrková, K. L., Nemec, M., Kosnáčová, P., Marková, P.: *Using the Statistical Tools in machines's vapability evaluation – Part1*, Ceon Repozytorium Centrum Otwarte Nauki, 2013.

[27] Rajvanshi, P. K., Belokar, R. M.: *Improving the Process Capability Analysis of a Boring Operation by the Application of Statistical Techniques*, Intrnational Journal of Scientific & Engineering Research, Vol. 3, Issue 5, 2012.

[28] Bhushan, S., Saner, N.: S*tatistical Analysis of Process Capability to Reduce Cost – A Case Study At Kiran Machine Tool Jalgaon*, Global Journal for research analysis Vol. 4, Issue 9, 2015.

[29] Abdolshah, M., Yusuff, R. M., Hong, T. S., Ismail, Y. B.: *Overal Processes Capability Index for Assembly Production Lines*, Journal of Applied Sciences, Vol. 9, Issue 20, pp. 3764-3769, 2009.