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Investigation of Functional Dependency between the Characteristics of the Machining Process and Flatness Error Measured on a CMM

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Numerous studies have shown that the choice of measurement strategy (number and position of measurement points) when measuring form error on a coordinate-measuring machine (CMM) depends on the characteristics of the machining process which was used to machine the examined surface. The accuracy of form error assessment is the primary goal of verification procedures and accuracy is considered perfect only in the case of the ideal verification operator. Since the ideal verification operator in the "point-by-point" measuring mode is almost never used in practice, the aim of this study was to examine a relationship which had not been examined in earlier studies, namely how the machining process, surface roughness and a reduced number of points in the measurement strategy affect the accuracy of flatness error assessment. The research included four most common cutting processes applied to flat surfaces divided into nine different classes of roughness. In order to determine functional dependency between the observed input variables and the output, statistical regression models and neuro-fuzzy logic (artificial intelligence tool) were used. The analyses confirmed the significance of all three input parameters, with surface roughness being the most significant one. Both the statistical regression models and neuro-fuzzy models proved to be adequate, matching the experimental results. The use of these models makes it possible to determine flatness error measured on a CMM if input variables considered in the paper are known.

Keywords: Flatness, CMM, regression, ANFIS.

1. Introduction

Functional requirements of contemporary mechanical products are becoming increasingly complex. Consequently, manufacturing processes have to satisfy strict criteria concerning the permissible deviation of real geometry from the nominal (ideal) geometry. Deviations from ideal geometry on a geometric primitive can be macrogeometric (form) and microgeometric (waviness, roughness) [1]. The manufacturing process has to satisfy the specification limits of both types of deviations while maintaining maximum productivity. For instance, with flat surfaces the requirements that often have to be satisfied are those concerning form tolerance (flatness) and quality of the machined surface, i.e. roughness. Both these requirements need to be considered when choosing the machining process and its regimes, tools, material of the workpiece, etc. In the machining process, those factors that affect macrogeometry usually do not affect microgeometry of the workpiece, and vice versa. For example, form errors on the surface obtained using traditional machining processes are normally due to machine tool guide way errors, vibration, and tool flank wear [2], [3]. Roughness is mainly a function of cutting tool geometry and it depends on cutting conditions (parameters of depth, feed, and speed) [4]. This claim cannot be generalized to every machining process and type of material that is being machined. On the whole, different factors affect form error and roughness. The percentage of form deviation within the total deviation from ideal geometry is much higher than the percentage of waviness and roughness, i.e. lower frequencies with longer wavelengths are dominant in the total form deviation. The research [5] showed that with the use of Fourier transform with 30 workpieces, roughness and waviness frequency values do not exceed 15 % of the total form deviation. This research confirms the claim that profile deviation is dominant with low-order frequencies (longer wavelengths). It should be noted that dividing profile deviations into form, waviness and roughness is considered conventional and insufficient for more detailed engineering analyses of surface topography. It is recommended that surfaces should be characterized at multiple scales using multiscale analyses [6]. However, such analysis is beyond the topic of this paper.

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Additionally, verification procedures have to perform almost ideal measurements because tight tolerances do not leave much room for measurement error or measurement uncertainty although these two parameters are always present in the measurement result [7]. Different types of coordinate measuring systems (CMS) are used to measure different kinds of deviation although there are measuring instruments, too, which can measure both types of deviation, such as the micro-coordinate measuring machine (μCMM) by Bruker Alicone. The results of these measurements are sets of coordinates of points. Numerical values which quantify deviations are obtained by means of an independent software analysis. By applying the appropriate filter defined by the cut-off wavelength to a digitalized real surface, deviations are classified as form deviation, waviness, and roughness. Different types of deviation can be measured on the same machine if sampling is appropriately conducted and if the software includes appropriate filtering. However, if points are sampled on a CMM with a contact probe, the range of wavelengths belonging to roughness will be filtered by the choice of the stylus tip. Therefore, roughness is most commonly measured by the technique of contact profilometry and the stylus tip diameter is smaller than 10 μm [8]. Primary profile is obtained by the stylus tip sampling the points from real geometry in the scanning mode. Appropriate wavelength filters (λc) and mathematical formulas are used to obtain the profile and roughness parameters. Also, non-contact optical methods such as confocal laser scanning microscopy (CLSM), coherence scanning interferometry (CSI) and focus variation microscopy (FV) are increasingly being used for microtopography.

Measurement of form error on a CMM has been one of the most important topics of scientific research in the field of coordinate metrology [9], [10]. The most frequently investigated problem has been the choice of measurement strategy (number and position of points), probe type and methods of the evaluation algorithm [11]-[13]. The selected sampling strategy should be able to give the most reliable digital information about a real surface, i.e. to find any local deviation. However, this implies a large number of points, which is not economically justified, especially if measurements are taken in the "point-by-point" mode. The new generation of geometrical product specifications (GPS) proposes defining an ideal specification operator from which a verification operator is derived according to the duality principle. Namely, according to the ideal specification operator partition is performed based on the stylus tip diameter and the Nyquist criterion [14]. Measurement strategy defined this way requires a large number of points uniformly distributed across the observed geometric primitive and is almost never used in practice. However, the ideal verification operator discovers any deviation on the examined surface, and flatness assessed this way can be considered closest to the real value of flatness. In order to satisfy the criterion of accurate flatness error assessment and to drastically reduce the number of points, numerous alternative measurement strategies have been developed. Many of those are based on information about the machining process, quality of the machined surface and manufacturing signature [15], [16]. These studies used models of machining processes with the aim of employing an adequate sampling strategy in order to record any significant form deviation using a small number of points. In paper [17] a methodology was developed for the reduction of the number of points according to data obtained from a large set of points of the first workpiece. There are also studies that have looked into the relationship between roughness and choice of measurement strategy when measuring flatness on a CMM. Paper [18] examined the selection of a sufficient number of points based on the input parameter of surface roughness. The results showed that for surfaces with a lower Ra value, the sufficient number of points needed for accurate flatness assessment is smaller than for surfaces which have greater roughness. Paper [19] analyzed the relationship between flatness error and roughness of workpieces produced in different manufacturing processes. The values of flatness error were smaller with the decrease in surface roughness.

On the whole, it can be concluded that the choice of measurement strategy on a CMM is highly determined by the quality of the machined surface and type of the machining process. Roughness values of the machined surface can be identical when different machining operations are used, which does not imply that flatness error will be identical. It is also necessary to determine a sufficient number of points for finding the exact flatness value depending on the machining process and the quality of the machined surface. The exact flatness value is assessed using the ideal verification operator based on the ideal specification operator.

The aim of this paper is to investigate the dependency between the type of the machining process for obtaining flat surfaces, roughness of the machined surface and the number of points for measuring flatness on a coordinate-measuring machine (CMM) on the one hand (independent variables), and the value of flatness error (dependent variable) measured on the coordinate-measuring machine on the other. To achieve this goal, neuro-fuzzy logic (artificial intelligence tool) and methods for statistical data processing were used. The practical significance of this research is the construction of models that predict flatness error for machining processes of flat surfaces. The models contain information on the quality of the machined surface and the number of sampled points on the CMM. Based on these models, the dependency between micro- and macrogeometry for a specific machining procedure will be determined, as well as the effect of the number of points used in CMM measurement on flatness error.

2. MATERIALS AND METHODS

In order to analyze the effect of surface roughness, machining process and the number of points in the measurement strategy on flatness error measured on a CMM, Rugotest was used (Fig.1.). It is assumed that roughness values of this workpiece are uniform across the whole surface for a given quality and type of the machining process. It can be seen that it consists of eighteen different surfaces which were machined using the four most frequent machining operations for flat surfaces. Three surfaces were machined by side milling, five by face milling, six by grinding, and four by lapping. The size of the sampled surface was 20x10 mm. Also, the flat surfaces were grouped according to the quality of the machined surface from *N*10 to *N*2. It can be seen that certain qualities can be obtained with different operations, such as, for example, grinding and lapping or grinding and face milling. Each "*N*" corresponds to a certain Ra value expressed in µm ("*N*" is mentioned because it is on Rugotest)) [20]. The plates are mechanically joined to the bottom flat plate. This enables measurement of the eighteen plates with one fixation of the workpiece, thus excluding certain CMM uncertainty factors because measurements are taken under the same experimental conditions.

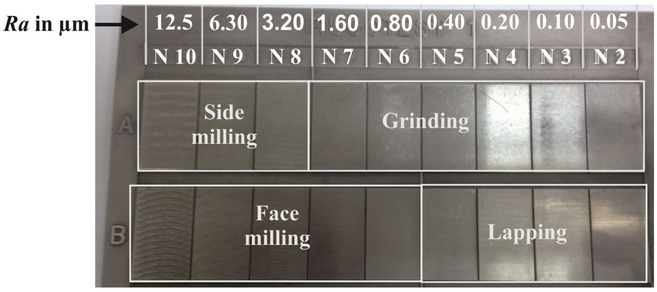

Fig.1. Rugotest used in the experiment.

The flat surfaces were measured on the Carl Zeiss Contura g2 RDS coordinate-measuring machine (MPE_E=1.9+*L*/330 µm, *L* expressed in mm) in the discrete sampling mode. To ensure CMM repeatability (the sampling system), each plate was measured five times using the identical measurement strategy and the mean value was taken as flatness error. The number of points and their position on the examined surface have a strong effect on the assessment of flatness error measured on a CMM [21], particularly if the least squares method is used for the assessment of flatness error. In order to examine the influence of the number of points on flatness error, each plate was measured with five randomly chosen samples, i.e., 10, 20, 40 and 60 points and one measurement strategy was derived from the ideal specification operator (1508). For defining the ideal specification operator, it is necessary to define information concerning the passband boundaries (upper and lower cut-off wavelength), filter and associative criterion to be used. The lower cut-off wavelength value is 2.5 mm, whereas the upper cut-off wavelength is infinite according to the definition of form deviation. Thus, the stylus tip has to be smaller than 1.5 mm, and according to the ISO/TS 12780-2 sampling density and the Nyquist criterion, grid strategy needs to be adopted where the distance between neighboring points must be smaller than 0.357 mm. Accordingly, the ideal specification operator has a total of 1508 points. The application of filtering to the sampled points is negligible in the discrete sampling mode of the CMM.

2.1. Flatness error assessment

Flatness error was assessed using the non-commercial software for obtaining flatness error according to the minimum zone (MZ) criterion - One Point Plane Bundle Method (OPPBM). The minimum zone OPPBM algorithm was written in MATLAB. The software solution is presented in Fig.2. and the program starts running by importing coordinates of points (*x, y, z*) from the CMM in .txt format. Studies [22], [23] have shown that the OPPBM is a very reliable method when accuracy is concerned (compared to commercial CMM software) and also very fast. It can be seen in Fig.2. that this software also provides flatness error based on the least squares (LS) method and equations of planes, which hardly any commercial software does.

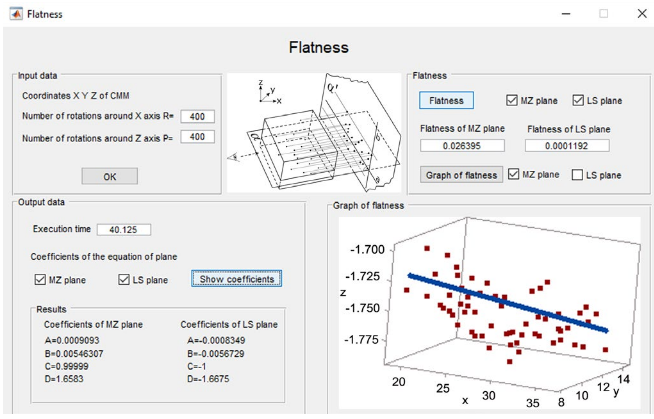

Fig.2. Flatness error assessment using the MZ method in non-commercial software.

2.2. Statistical analysis

Multiple regression analysis was used in order to examine the effect of the type of the machining process, surface roughness and the number of points in the measurement strategy, as independent input variables, on flatness error measured on a CMM, as a dependent output variable. This statistical analysis can determine the relationship between the variables by constructing an adequate model. It can also determine the effect of the input values and their interactions on the observed output [24]. Recently, a paper has been published where regression analysis was used for investigating the connection between the number of points in the measurement strategy and flatness error measured on a CMM [25]. The equation of the multiple linear regression model can be represented as (1):

$$Y=\beta_0+\beta_1 x_1+\beta_2 x_2+\varepsilon \quad (1)$$

where *Y* represents the dependent output variable (flatness error), x_1 and x_2 represent influencing factors (surface roughness and number of points in measurement strategy), β_0, β_1, β_2 represent regression coefficients and ε represents random error. Since the type of the machining process is the categorical factor, the number of the regression models obtained will be the same as the number of different types of machining, which is four in our case. The adequacy of the presented model obtained using (1) is tested via the coefficient of determination R^2 (*R-sq* in Minitab). In order to test the significance of particular input variables, analysis of variance (ANOVA) was performed with the significance threshold of α = 0.05. For adequate ANOVA analysis, it is necessary to check the normality of the output variable using specific tests such as the Anderson-Darling test, with the significance threshold of $\alpha = 0.05$. In our case, the normality check showed the value of $p = 0.061$. Since this value is greater than the set significance threshold, measurement data belong to normal distribution.

2.3. Adaptive neuro-fuzzy inference system (ANFIS)

The fuzzy set theory proposed by Zadeh [26] is based on sets where boundaries are not precisely defined. A fuzzy set is characterized by a form of membership function in which the truth values of the variables can be any real number between 0 and 1 inclusive. Construction of a complex fuzzy system requires significant time to find the valid membership function and rules to obtain a reliable solution. The main problem with fuzzy logic is determining membership functions and fuzzy rules which cannot be directly derived from the complex system. By combining neural network with fuzzy logic it is possible to avoid the complexity of defining functions and rules. In this case, a neural network is used to adjust the membership functions of the fuzzy system [27]. An adaptive neuro-fuzzy inference system integrates the advantages of fuzzy logic and neural networks. It is one of the hybrid systems, known as 'neuro fuzzy networks' [28].

ANFIS is based on a Takagi–Sugeno-type fuzzy inference system [29]. The structure of the ANFIS consists of five different adaptive layers, with nodes and connections as depicted in Fig.3.

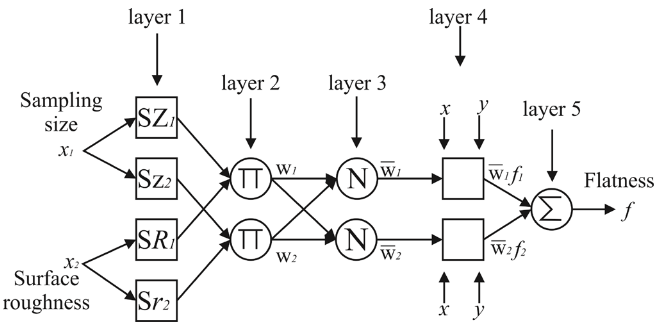

Fig.3. The first order Sugeno fuzzy reasoning.

For the case of determining the flatness of one of the four types of machining, the universal principle of modelling with the ANFIS system was used. For example, the first-order Sugeno fuzzy reasoning system with two inputs x_1 (sample size) and x_2 (surface roughness), one output f (flatness) is shown in Fig.3. and consists of four fuzzy sets SZ1, SZ2, SR1, SR2 and two IF -THEN rules:

$$\begin{aligned}&\text{Rule 1 :IF } x_1 \text{ is } A_1 \text{ and } x_2 \text{ is } B_1 \text{ THEN } f_1=p_1 \cdot x_1+q_1 \cdot x_2+r_1\\&\text{Rule 2 :IF } x_1 \text{ is } A_2 \text{ and } x_2 \text{ is } B_2 \text{ THEN } f_2=p_2 \cdot x_1+q_2 \cdot x_2+r_2.\end{aligned} \quad (2)$$

The layers of the first order Sugeno fuzzy reasoning system are:

1. Layer 1 is the fuzzification layer which uses membership functions in order to obtain fuzzy value from inputs. Each node in this layer implies inputs, such as sampling size and surface roughness, and it forwards external signals to layer 2. The degrees of membership from layer 1 are shown with μ_A and μ_B, as given in equation (3):

$$\begin{aligned}&O_i^1=\mu_{Ai}(x_2) \text{ for } i=1,2\\&O_i^1=\mu_{Bi}(x_2) \text{ for } i=3,4\end{aligned} \quad \ldots\ldots\ldots\ldots (3)$$

2. Layer 2 is the rule layer. This layer computes firing strengths w_i, using membership degree values from layer 1. In other words, based on the chosen membership function, which in this case is Gaussian, the inputs from layer 1 are converted into the degree of membership function. The output from layer 2 is the product according to equation (4)

$$O_i^2=w_i=\mu_{Ai}(x_1)\mu_{Bi}(x_2),\ i=1,2\ldots \quad \ldots\ldots (4)$$

3. Layer 3 is the normalization layer. It generates normalized firing strengths for each rule through equation (5):

$$O_i^3=\bar{w}_i=\frac{w_i}{\sum_i w_i},\ i=1,2 \quad (5)$$

4. Layer 4 is known as the defuzzification layer. It generates the individual output values y from the previously defined rule base. Every node in this layer calculates the normalized firing strength of a rule. Each node of this layer is adaptive in nature and given by equation (6):

$$O_i^4=\bar{w}_i \cdot f_i=\bar{w}_i\left(p_i \cdot x_1+q_i \cdot x_2+r_i\right),\ i=1,2 \quad (6)$$

5. Layer 5 is the output layer. In this layer, known as the defuzzification layer, the output is obtained using equation (7). Parameters in this layer are referred to as consequent parameters:

$$O_i^5=f(x_1,x_2)=\sum_i \bar{w}_i \cdot f_i=\bar{w}_i \cdot f_1+\bar{w}_i \cdot f_2=\frac{\sum_i w_i \cdot f_i}{\sum_i w_i} \ldots\ldots (7)$$

The principle described above is used to adapt the rules of the fuzzy system using a five-layer neural network. In this way, a fuzzy model is obtained that can predict the flatness of a machining process as a function of sample size and surface roughness. Several studies can be found in the literature in which the flatness of the machined surface is predicted [30], [31]. Research is mainly done on the basis of modeling each machining operation [32].

However, hardly any system has been developed that includes multiple machining models to determine the flatness. For this very reason, the main contribution of this paper is a system that includes intelligent models of the four most common machining types in mechanical engineering.

3. Results and discussion

3.1. Statistical analysis

The effect of the number of points in the measurement strategy, surface roughness and cutting process on flatness error measured on a CMM is given in Fig.4. (x scale is log scale).

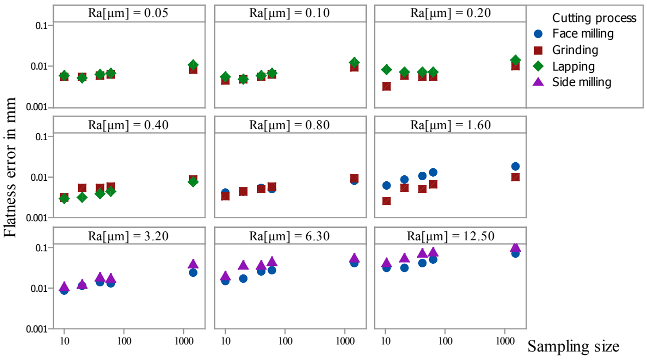

Fig.4. The effect of the number of points in the measurement strategy, surface roughness and the applied cutting process on flatness error measured on a CMM.

The figure shows the following facts:

1. With the increase in the number of points in the measurement strategy, flatness error generally increases. This increase is more conspicuous in processes with a higher *Ra* value.
2. Flatness error generally increases as the quality of the machined surface decreases.
3. With finishing, the type of the cutting process used for achieving the same surface quality had a negligible effect on flatness error, whereas with roughing (*Ra* = 6.30 and 12.50 µm), the cutting process was of great significance.
4. If flatness error is considered accurate when the number of 1508 points is used, the reduced number of points in the measurement will give flatness results that are very close to the accurate value when finishing. When roughing, however, the measurement error could be almost twice as big if, for example, the results with 60 and 1508 points are compared (with side milling *Ra* = 12.5 µm).
5. Ground surfaces have a constant flatness error (the effect of quality of the machined surface is almost negligible), whereas with lapped surfaces, the quality of the machined surface has only a slight effect. However, with milled surfaces the quality of the machined surface has a strong effect on flatness error. This can be seen in Fig.5.; *x* scale is log scale.

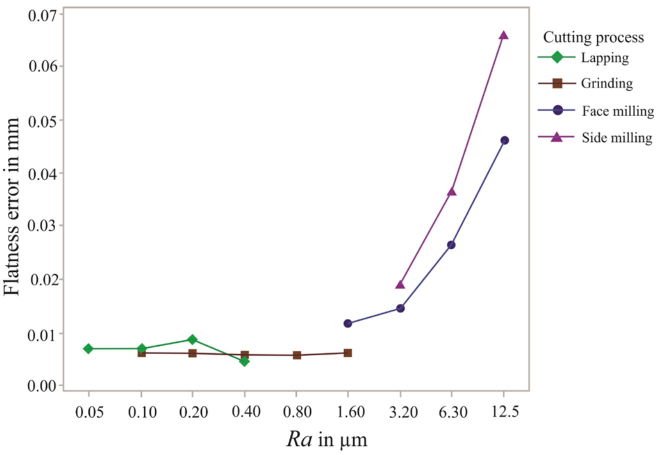

Fig.5. The effect of the cutting process and quality of the machined surface on flatness error.

Minitab 17 statistical software was used for the statistical analysis of the experimental data. Multiple linear regression was used for establishing functional dependency between the input and the output. With the type of the cutting process being categorical input and the number of points and roughness being continuous input, linear regression models for each cutting process were developed and shown in Table 1.

Table 1. Linear regression models for output depending on input.

Cutting process	Regression Equation
Face milling	Flatness = -0.00056 + 0.000008 Sampling size + 0.003858 *Ra*
Grinding	Flatness = 0.00131 + 0.000008 Sampling size + 0.003858 *Ra*
Lapping	Flatness = 0.00342 + 0.000008 Sampling size + 0.003858 Ra
Side milling	Flatness = 0.00933 + 0.000008 Sampling size + 0.003858 *Ra*

The analysis of variance (ANOVA) showed that all three input variables are statistically significant ($p < \alpha$; $\alpha = 0.05$). The most significant factor is the quality of the machined surface ($F = 227.14$), then sampling size ($F = 42.74$), and finally the cutting process ($F = 6.76$). The statistical analysis also showed a high degree of adequacy of the model (*R-sq* > 85 %).

The effect of the number of points in the measurement strategy can be described as scaling the function depending on roughness and type of the cutting process, which can be seen in Fig.6.

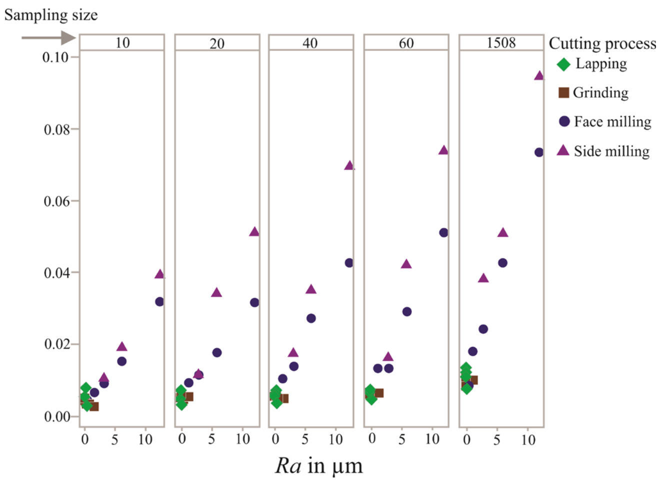

Fig.6. The effect of roughness and type of the cutting process on flatness error with different numbers of points.

Bearing in mind the significance of the number of points and observing Fig.6., it is clear that this effect is generally scaled depending on roughness and type of the cutting process. Apart from these models, another interesting thing was examining the effect of roughness on the mean value of flatness error where the effect of the cutting process and the number of points was neglected. When the mean values of flatness error depend only on roughness, the resulting function shown in Fig.7. is obtained, with x axis presented in log scale. It can be seen in Fig.7. that this resulting function is an approximation of the four functions shown in Fig.5.

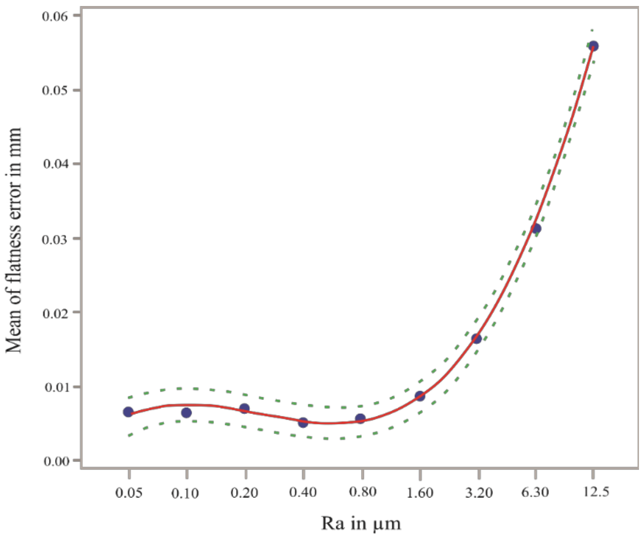

Fig.7. Resulting function.

A cubic regression model was designed using the Box-Cox transformation method. The shape of its function is presented in (8):

$$\begin{gathered}\text{Mean of Flatness error}= \\ 0.005827+0.00798\ log10\ (Ra)+ \\ 0.02134\ log10(Ra)^2+0.01162\ log10(Ra)^3\end{gathered} \tag{8}$$

The adequacy of the model can be seen in Fig.7. where *R-sq* > 95 %. The presented model, which takes only roughness into account, almost ideally coincides with the experimental values. However, the number of points in the measurement strategy and the type of the machining process should always be considered

3.2. Analysis employing Adaptive neuro-fuzzy inference system

This concept of the neuro-fuzzy network was used to develop the ANFIS models for the prediction of flatness in various machining processes such as side milling, grinding, face milling, and lapping. Four ANFIS models were developed using two input parameters such as sampling size (SZ) and surface roughness (SR), and the output parameter of flatness (FS), by using 80 % and 20 % of training and testing data, respectively. The already existing algorithm in MATLAB was used to achieve the favorable training and test of data. The initial parameters of all ANFIS models for prediction of flatness are presented in Table 2.

The hybrid algorithm was used to generate ANFIS models. There are several shapes of membership functions, like triangular, trapezoidal, Gaussian, etc. [33]. In the presented study, the gaussmf MFs (Gaussian membership functions) displayed the smallest test error and the lesser value of mean absolute percentage error, in relation to other MFs. An example of ANFIS training is shown for side milling. Out of a total of 15 face milling data, 12 were taken for training and 3 for system testing. The training of the ANFIS model was carried out using 100 epochs. As shown in Fig.8., the obtained value of training error was $9.09 \cdot 10^{-3}$. With the previous model training, the root mean square error did not change significantly after 60 epochs. The values of ANFIS output were compared with test data (experimental values). The comparison between the predicted and the experimental data is illustrated in Fig.9. The obtained value of training RMSE error was $8.85 \cdot 10^{-3}$.

Table 2. Initial parameters for the ANFIS model.

Method of training	MFs (membership functions)	Number of MFs	Number of Epochs	Output function
Hybrid	gaussmf	2 2 2	100	Constant

In Fig.10., ANFIS structure has two inputs and one output and it consists of two membership functions and four rules. All four generated models have the same network setup parameters. In addition to the presented model for determining the flatness of face milling in a similar way, other models were obtained. In face milling, 20 experimental points were used to train the network, while 5 experimental points were used for testing. In that case, the training error was $4.35 \cdot 10^{-3}$ and the testing error was $6.35 \cdot 10^{-3}$. Out of a total of 30 experimental points, 24 were used for training and 6 for testing the network during grinding. RMSE errors were $6.37 \cdot 10^{-3}$ and $8.31 \cdot 10^{-3}$ for training and testing, respectively. Finally, for network training and determination of flatness in the lapping process, 16 data for training and 4 for testing were used. RMSE errors were $8.15 \cdot 10^{-3}$ for training and $8.55 \cdot 10^{-3}$ for network testing. By comparing the obtained errors with the current literature [34], [35], it can be concluded that the models are well generated.

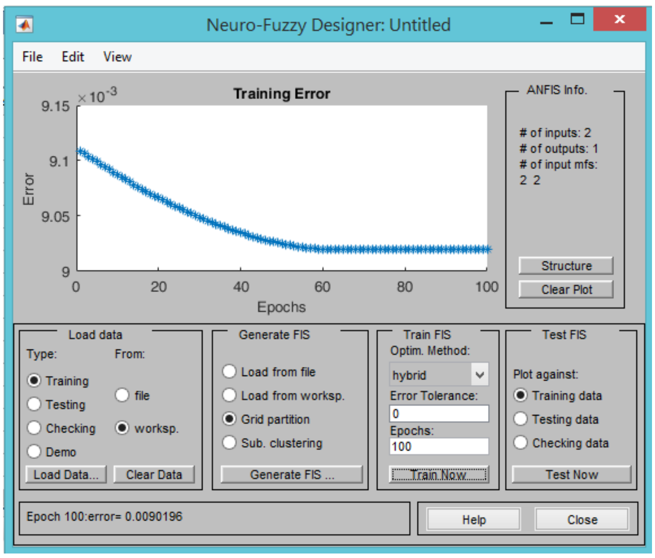

Fig.8. Comparison between the testing and FIS output data of flatness.

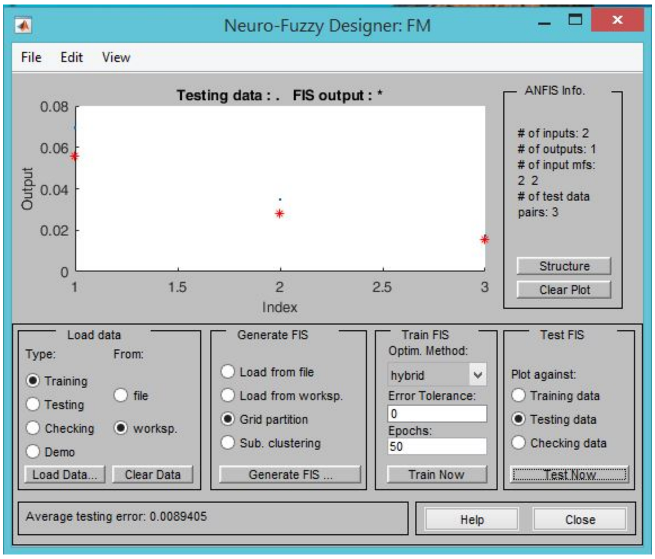

Fig.9. Comparison between the predicted and the experimental data.

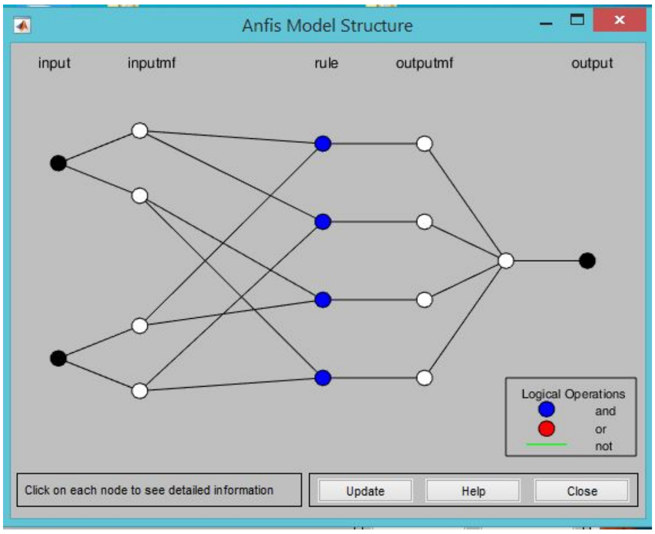

Fig.10. The ANFIS structure that has two inputs and one output.

The influence of the sampling size and surface roughness on the output response, namely flatness, was conducted based on the generated ANFIS models of various types of cutting process. Fig.11. illustrates the influence of sampling size and surface roughness on flatness in the side milling operation. It can be seen that surface roughness and sampling size of the side milling operation have a strong influence on flatness error. This is explained by the fact that the tool makes a trace on the machined surface. A larger sample size is required to estimate adequate flatness.

Fig.12. shows the influence of sampling size and surface roughness on flatness in the face milling operation. A similar effect was observed as with side milling. It clearly shows that the value of flatness decreased depending on the sampling size. For example, in rough face milling when surface roughness is 12.5 µm at 60 points, it gives an error of flatness almost twice as large as at 1508 points.

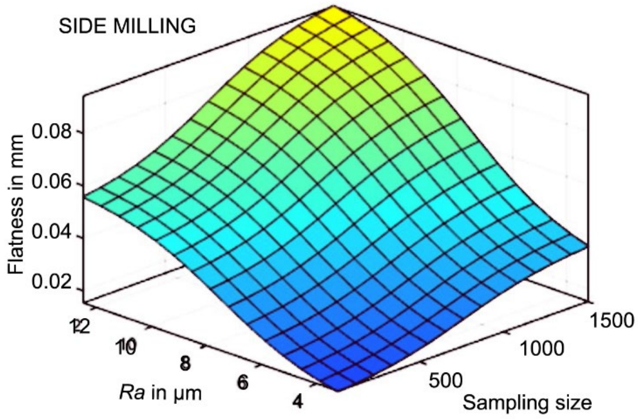

Fig.11. Influence of sampling size and surface roughness on flatness in side milling operation.

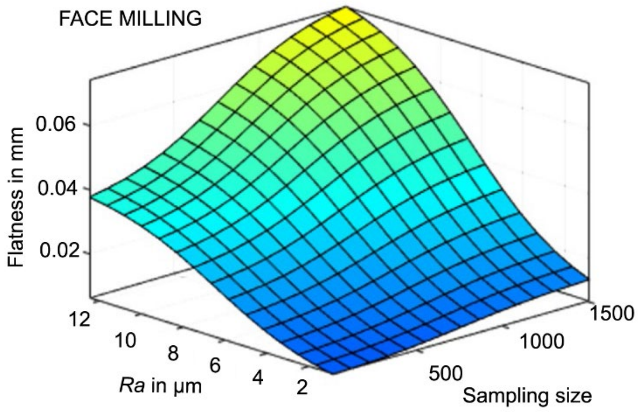

Fig.12. Influence of sampling size and surface roughness on flatness in face milling operation.

The influence of surface roughness and sampling size on flatness in the grinding operation is shown in Fig.13. Here flatness values are less dependent on surface roughness because this is the final machining. A surface machined this way does not require a large number of sampling points.

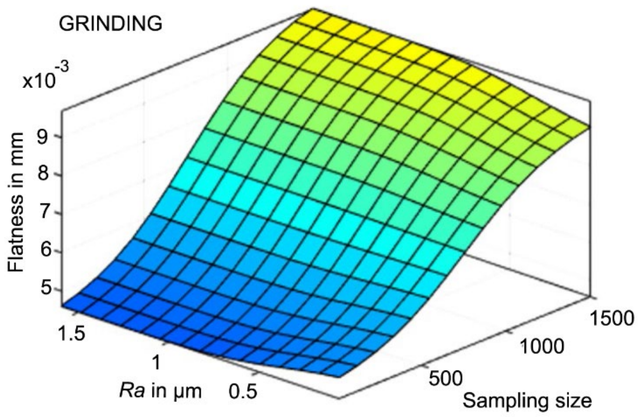

Fig.13. Influence of surface roughness and sampling size on flatness in grinding operation.

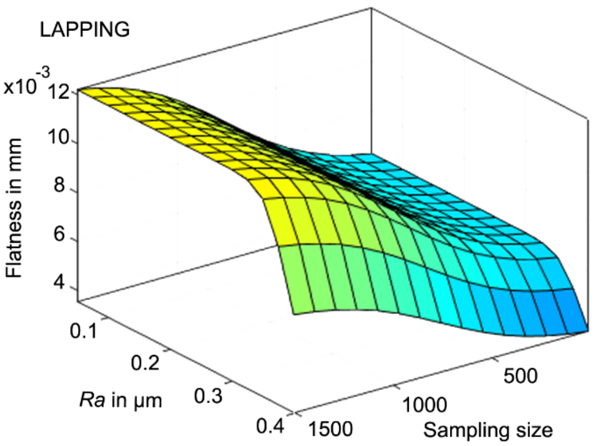

Fig.14. Influence of surface roughness and sampling size on flatness in grinding operation.

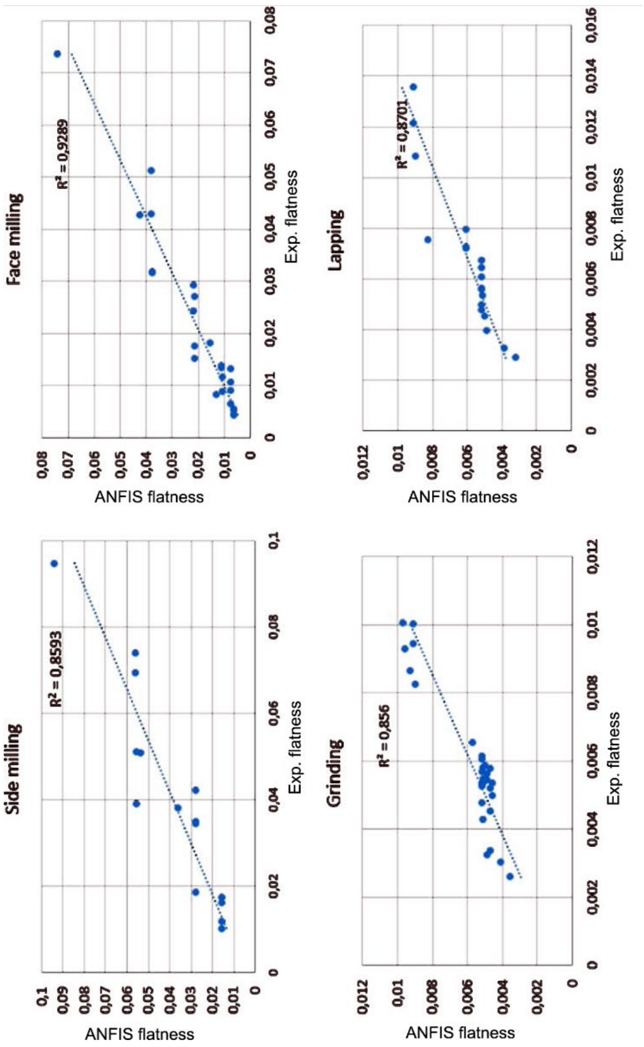

Fig.15. Comparison of experimental results and results obtained using ANFIS.

Similar influence of input parameters on the output was obtained in the lapping process. Fig.14. demonstrates the surface view for flatness of the lapping process in relation to change of sampling size and surface roughness. It shows no impact on the value of flatness for any number of samples and surface roughness from 0.1 to 0.3 μm.

Regression graphs were plotted to compare the values obtained from both the experimental and ANFIS prediction data of flatness, as shown in Fig.15. The graphs show good agreement with experimental data. The fit of values R^2 for all models was from 0.8560 to 0.9289.

It can be said that the models created using linear regression (Table 1.) and ANFIS are in close agreement and they match the experimental results. ANFIS did not include the model of the effect of only roughness on flatness as it has been shown using the cubic regression model (8), although close agreement of the cubic regression model with ANFIS would have probably been achieved.

In the final analysis, it can be concluded that if the type of the machining process, machined surface roughness and the number of points in the measurement strategy are known, the error can be successfully modeled and this has been shown using these two methods. On the basis of modeling, it can be concluded that with the finishing operation a small number of points is sufficient for accurate flatness assessment, whereas with roughing, the number of points has to approach the number of points in the ideal verification operator. However, this is not so if the selection of points is not random.

The analysis of experimental results by means of multiple regression analysis and ANFIS provided good models. However, the quality parameters of CMM, as well as the use of different machines, tools, equipment and other factors that affect the machining procedure and the measured Ra value should also be taken into account.

4. CONCLUSIONS

The aim of this study was to model (mathematically formulate) the effect of the type of the machining process, surface roughness and number of points in the sampling strategy on the assessment of flatness error on a CMM. The study was conducted on workpieces which were machined applying four most common machining processes for flat surfaces (side milling, face milling, grinding, and lapping). The experiments were performed using a surface roughness comparator. Using the statistical analysis and ANFIS, the following conclusions can be drawn:

1. All three parameters have a significant effect on the observed output and surface roughness has the strongest effect of all.
2. The adequacy of the models with both types of modeling is more than 85 %.
3. Furthermore, a cubic regression model was constructed and it modeled the experimental results using only roughness as an input variable. This points to the fact that flatness measured on a CMM can be predicted on the basis of roughness of the machined surface and the type of the machining process.
4. The general conclusion is that when flatness is assessed in roughing operations, the number of points needs to approach the number of points in the ideal verification operator, or adaptive sampling strategies need to be employed, which would require further research.

Additionally, it would be interesting to examine the effect of 3D parameters of roughness on flatness error in future investigations, or to focus on spacing parameters instead of Ra.

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