Prediction of 3D Surface Roughness Using Regression Analysis and Fuzzy Logic, and their Comparative Analysis

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***Abstract* – Nowadays, more and more new quality standards are developed for manufactured components. One of these quality standards is the surface roughness, especially the 3D surface roughness.**

In manufacturing of parts, the manufacturer must strictly follow the assigned surface roughness values. It makes manufacturing complicated and requires additional control to be imposed on the components. For this reason, it is necessary to develop a technique or methodology that facilitates the control of the surface roughness in production and provides possibility to control the surface roughness according to the technological parameters.

***Keywords* – surface, roughness, prediction, regression, fuzzy logic**

I. Introduction

Nowadays, grinding, which is a relatively expensive machining option, is replaced by fine turning (rotating workpieces) or fine milling (rotating tool). During fine machining process, particular importance is given to the surface roughness of the machined workpiece and to the technological parameters, which are set on the cutting machine providing the necessary surface roughness. In practice, to find the necessary technological parameters for a desired surface roughness, it is necessary to conduct experimental machining, which increases costs and consumes valuable time. To address this shortcoming, new 3D surface roughness prediction models are developed using different techniques. This chapter analyses already existing solutions to predict surface roughness.

The aim of this study is to develop empirical models.

II. Analysis of prior research

The first studies of the surface roughness and its technological assurance in milling were carried out using purely geometric correlations – geometry of the cutter and its movement along the workpiece to be machined. For example, theoretical surface roughness in milling can be described by the following equation [10]:

$$Ra = \frac{f_t^2}{32(R \pm f_t n_t / \pi)}, \quad (1)$$

where Ra – mean average of surface roughness profile;

n_t – number of teeth in the milling cutter;

R – radius of the milling cutter;

f_t – feed per revolution of the milling cutter („+” in case of up milling and „–” in case of down milling).

In addition, there is a well-known typical equation describing the surface roughness profile (Ra, R_{zt}) according to the technological parameters (f, R) [1]:

$$Rz = \frac{f_z^2}{8R} \quad (2)$$

where f_z – feed per tooth of the milling cutter (mm).

In the given equations such factors as system vibrations and built-up formation are not taken into account, so that only geometric relationships between the workpiece and the cutting tool are taken into account. In practice, the typical known relationships between surface profile roughness and technological parameters have been developed, which include different factors of influence like build-up edge formation, change of heat flow in the cutting area, tool wear, vibration, wear of a cutter, etc. [15].

Additionally to the geometrical relationships, surface roughness prediction is studied using mathematical statistics. One of such methods of mathematical statistics is regression analysis. Objective of the regression analysis is to reveal the relationships between several variables. In this case, prediction of surface profile roughness (dependent variable) is made according to the technological parameters (related independent variables). In the work of Kadirgama et. al. [6] the study of profile roughness prediction in milling of Aluminium (AA6061-T6) has been performed. Experimental machining was performed in the range of chosen parameters, which are shown in Table I.

TABLE I

Data of Kadirgama experiment in milling AA6061-T6 [6]

Parameters	1	2	3
Cutting speed (m/min) x_1	100	140	180
Feed (mm/rev.) x_2	0,1	0,15	0,2
Axial depth of cut (mm) x_3	0,1	0,15	0,2
Radial depth of cut (mm) x_4	2	3,5	5

Turning is one of the most common metal processing operations. Lathes can occupy about 50% of the entire machine park [9]. One of the simplest ways to calculate the potential surface profile roughness depending on the technological parameters is the use of geometric patterns, resulting from interaction of the tool with the workpiece. In the turning maximal surface profile roughness R_{max} can be determined using the following equation [3]:

$$R_{max} = \frac{f^2}{8r}, \tag{3}$$

where R_{max} – maximal surface profile roughness;
f – feed;
r – radius of the cutter tip.

A sketch of machining process (turning), when the radius of the cutter tip r and feed f are taken into account for obtaining surface profile roughness, is shown in Figure 1.

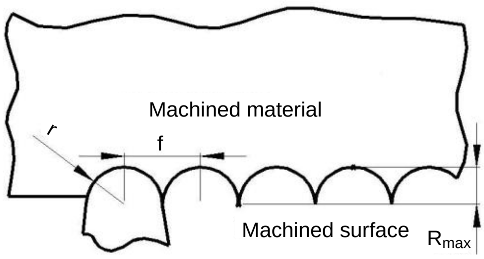

Fig. 1. Sketch for machining a surface, taking into account the radius of the cutter tip r

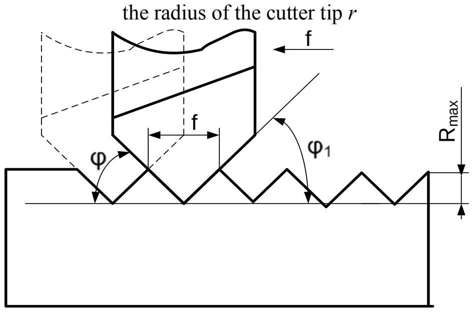

Fig. 2. Sketch for machining a surface, not taking into account the radius of the cutter tip r

In Figure 2 a sketch of the machining process (turning) is shown, when for a given surface profile roughness cutting edge angles (φ; φ_1) are taken into consideration, ignoring the radius of the cutter tip r. In this case, the maximal surface profile roughness Ra_{max} is expressed by the following equation [8]:

$$R_{max} = \frac{f}{4(ctg\varphi + ctg\varphi_1)}, \tag{4}$$

where φ – major cutting edge angle;
φ_1 – minor cutting edge angle.

This relationship works only when large feeds f and/or large cutting depths d are used.

Similar mathematical statistics methods are used for prediction of surface roughness in turning. For example, in the publication of Nalbanta [11] the study is performed on how profile roughness parameter Ra changes according to the changes of the radius of the cutting tip r, feed f and depth of cut d. Conducting experimental machining and using regression the following first order regression model is obtained [11]:

$$Ra = 0{,}998 + 0{,}376d + 0{,}033f - 4{,}86r \tag{5}$$

III. 3D Surface Roughness

Advantage of using 3D parameters instead of 2D roughness parameters is a possibility to describe the processed surface roughness more accurately, because in the real life environment every component is working in three dimensions (3D). As a result, it is possible to develop more precise mathematical models, which define surface roughness according to the technological parameters.

Surface profile roughness parameters are determined by ISO standard ISO 4287:1997. Standardization of 3D surface roughness parameters is still in the development stage, but it already has an official standard number ISO 25178 [4, 5, 12]. Some parts of the standard are already officially approved, but some parts are still pending. The development of the standard points to the fact that the industry has accepted the changes in the field of surface measurement, and 3D surface roughness parameters can be considered as wholesome parameters describing surface texture. Within the standard ISO 25178 the basics of surface texture are reworked by basing them on the fact that the world around us is three dimensional [2]. 3D surface roughness parameters define a surface texture with sufficient precision to determine the nature and performance of the measured surface [5]. An extract from the table of 3D surface roughness parameters written in the standard ISO 25178 is shown in Table II.

For example, mean arithmetical deviation from plane Sa is defined by the following equation:

$$Sa = \sqrt{\frac{1}{A}\iint_A Z(x,y)dxdy}. \tag{6}$$

TABLE II

Frequently used 3D surface roughness parameters according to the standard ISO 25178

No.	Symbol and name of the parameter
1.	*Sa* – Mean arithmetical deviation from the mean plane (μm).
2.	*Sq* –Root mean square deviation from the mean plane (μm). Calculates effective value of surface amplitude.
4.	*Sp* – maximum peak height (μm). Height between the mean plane and the highest peak.

3D surface roughness parameter Sa is used as it is one of the most extensively used surface roughness parameters, similar to a 2D surface roughness parameter Ra, which is one of the most frequently used surface roughness characterizing parameters in mechanical engineering.

In 3D surface roughness measurements *Taylor Hobson Form Talysurf Intra 50* form measurement device was used. This device has atouch probe or needle which is in contact with the measured surface during measurement. The data acquired during surface roughness measurement are processed in the *TalySurf Intra* computer software showing the data of the measured surface. A graphical representation of the machined (turning) part is shown in Fig. 3. A graphical representation of the surface before and after form removal is shown in Fig. 4. Form removal must be done to eliminate waviness and other geometrical irregularities from 3D surface. One of the advantages of the system is that each measurement data file stores information about the surface in digital form. Therefore, it is possible to retrieve any information needed at any time, due to the fact that each program file includes original or raw data of the measured surface.

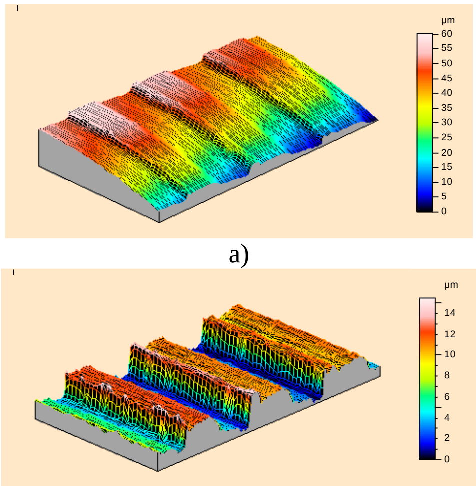

Fig. 3. 3D surface roughness representation of the measured sample in axonometric view:
a) sample before form removal; b) sample after form removal

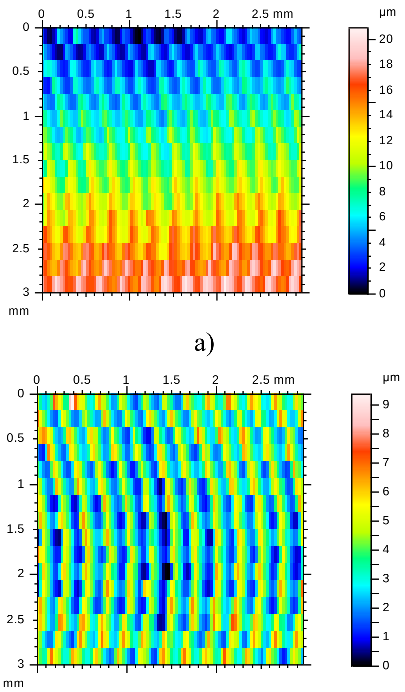

Fig. 4. Graphical representation of surface roughness of the measured sample:
a) sample before form removal; b) after form removal

IV. Design of Experiments

The aim of the experiment is to find relationships between surface roughness *Ra* of the machined surface and technological parameters used to machine the surface (cutting speed *v* (m/min); feed *f* (mm/rev. or mm/tooth); depth of cut *d* (mm)). Initially a surface of the workpiece is machined by the end mill and at defined technological parameters. After the machining of the workpiece its surface is measured and surface roughness *Sa* values are acquired following the empirical determination of surface roughness parameters according to the technological parameters, which in the end give 3D surface roughness prediction model. Figure 5 illustrates the methodology of acquiring the results.

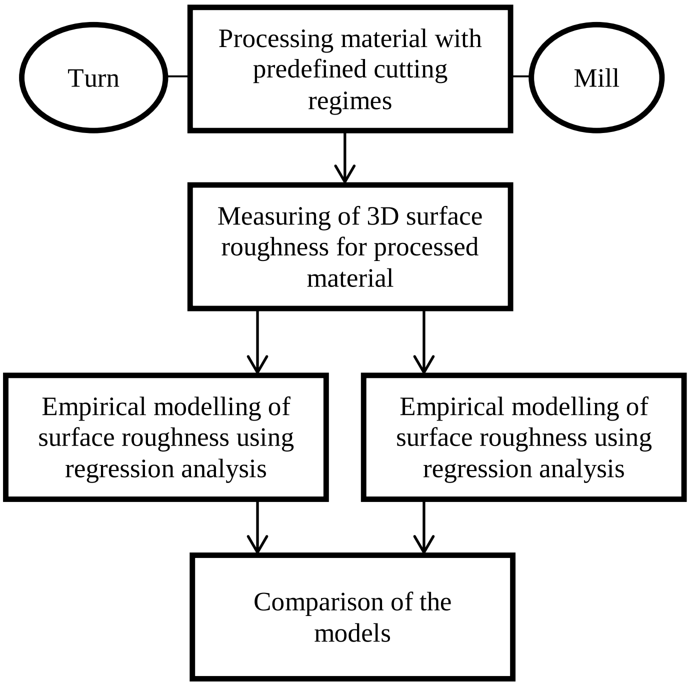

Fig. 5 Methodology of the experiments

V. Design of Prediction Model in Milling Using Regression Analysis

In the experiment a stainless steel plate (stainless steel EN 1.4301 – X5CrNi18-10) is machined. Machining is done with the four-tooth carbide end mill with the diameter of 10 mm.

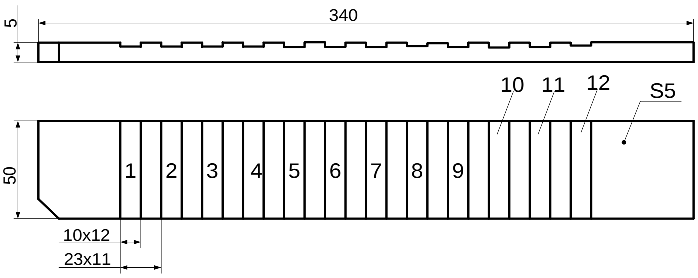

Fig. 6. Sketch of the workpiece with marked milling grooves

TABLE III

DATA SHEET OF EXPERIMENT FOR MILLING X5CRNI18-10

No	*f* (mm/rev.)	*d* (mm)	*v* (m/min)	Sa_{measur} (µm)	Sa_{calc} (µm)
1.	0,25	1,5	190	1,370	1,325
2.	0,25	0,5	190	0,631	0,879
3.	0,1	0,5	190	0,388	0,419
4.	0,1	1,5	190	0,988	0,825
5.	0,1	1,5	120	0,635	0,767
6.	0,25	1,5	120	1,370	1,267
7.	0,25	0,5	120	1,090	0,821
8.	0,1	0,5	120	0,472	0,321
9.	0,21	1	210	1,020	1,036
10.	0,13	1	210	0,871	0,770
11.	0,21	1	100	0,805	0,882
12.	0,13	1	100	0,407	0,616

After machining of the material, measurements of 3D surface roughness are conducted and *Sa* values are retrieved. The data of Table III are entered into the program *MiniTab* and following the established regression analysis methodology, the following mathematical model or equation of the milling process is acquired:

$$Sa = -0{,}403 + 3{,}33 f + 0{,}446 d + 0{,}00140 v \quad (7)$$

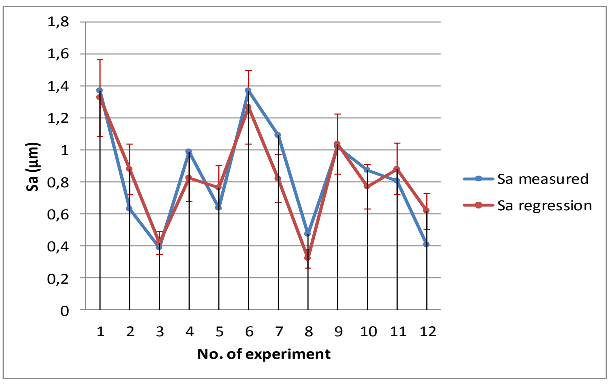

Fig. 7. Measured and calculated 3D surface roughness values in milling X5CrNi18-10

After regression analysis it is very important to ascertain the reliability of the regression analysis model. Results are shown in Figure 7, showing the values of the calculated and measured *Sa* and its prediction error 19% (18.84%).

VI. DESIGN OF PREDICTION MODEL IN TURNING USING REGRESSION ANALYSIS

Similarly to the developed prediction methodology in milling using regression analysis, a methodology for turning was also developed. To confirm the accuracy and usefulness of the methodology experiments were performed.

For machining at different cutting modes a calibrated rod material (11SMnPb30) was used. At the same time, considering the range of materials a table of technological regimes was created (Table IV). The following technological parameters were used: v – cutting speed ($130 \leq v \leq 200$ m/min.); f – feed ($0{,}1 \leq f \leq 0{,}4$ mm/rev.); d – depth of cut ($0{,}5 \leq d \leq 1{,}5$ mm).

TABLE IV

DATA SHEET OF EXPERIMENT FOR TURNING 11SMNPB30

No.	*v* (m/min)	*f* (mm/rev.)	*d* (mm)	*Sa* (µm)	Sa_{apr_1}
1.	130	0,1	0,5	0,36	0,54
2.	130	0,1	1,5	0,92	0,73
3.	130	0,4	1,5	3,68	3,57
4.	130	0,4	0,5	3,36	3,38
5.	170	0,1	0,5	0,61	0,63
6.	170	0,1	1,5	0,65	0,83
7.	170	0,4	0,5	3,53	3,47
8.	170	0,4	1,5	3,66	3,67
9.	200	0,1	0,5	0,90	0,70
10.	200	0,1	1,5	0,92	0,90
11.	200	0,4	0,5	3,54	3,54
12.	200	0,4	1,5	3,64	3,74

Carrying out the steps of the methodology and taking into account the data of Table IV, the following regression model or equation is obtained:

$$Sa_1 = -0{,}806 + 0{,}00234 v + 9{,}47 f + 0{,}195 d \quad (8)$$

Analysis of the data showed that prediction error of the first order equation is 11% (11.21%).

Stainless steel (X8CrNi18 – 9) was chosen as the second machined material and the following technological parameters were chosen: v – cutting speed ($70 \leq v \leq 90$ m/min); f – feed ($0{,}05 \leq f \leq 0{,}1$ mm/rev.); d – depth of cut ($0{,}5 \leq d \leq 1{,}5$mm).

TABLE V

DATA SHEET OF EXPERIMENT FOR TURNING X8CRNI18 – 9

No.	*v* m/min	*f* mm/rev.	*d* mm	*Sa* µm	Sa_{cal}
1	**2**	**3**	**4**	**5**	**6**
1	80	0,05	0,5	0,78	0,710
2	80	0,05	1,5	0,82	0,792

3	80	0,10	1,5	0,92	0,903
4	80	0,10	0,5	0,87	0,821
5	90	0,05	0,5	0,81	0,901
6	90	0,05	1,5	0,90	0,983
7	90	0,10	0,5	0,95	1,012
8	90	0,10	1,5	1,04	1,094
9	100	0,05	0,5	1,14	1,092
10	100	0,05	1,5	1,22	1,174
11	100	0,10	0,5	1,21	1,203
12	100	0,10	1,5	1,35	1,285

In this experiment the following regression model or equation is obtained:

$$Sa_{cal}=-0{,}970+0{,}0191v+2{,}23f+0{,}0817\,d \quad (9)$$

Analysis of the data showed that prediction error of the first order equation is 5% (5.43%).

VII. Fuzzy Logic

In 1965 professor of electronics and computer science L.A. Zadeh from Berkley University published his work „Fuzzy Sets“, where he described math of uncertain sets and fuzzy logic [14]. From this work the logic of uncertainty got its name – fuzzy logic. Fuzzy logic is considered a complement to traditional logic giving a possibility to process partly true values – between „completely true“ and „completely false“. This theory proposes the use of membership functions, which operate in the range of 0 (false) to 1 (true).

Fuzzy logic is the logic, which is developed to display the knowledge and processes of human thinking. Fuzzy logic is widely used in artificial intelligence and expert systems. Unlike the binary logic which uses values „false“ and „true“, fuzzy logic operates with logical variables which can adopt to a number of different values, such as “correct”, ”incorrect”, ”not quite right”, ”more or less correct”, “quite correctly”, “false”, “not too wrong”, ”quite wrong”, ”highly inaccurate”, which makes it closer to human thinking. Some fuzzy logic solutions are implemented in the automatic gearboxes of cars, automatic washing machines and helicopters, which obey voice commands [8].

VIII. Design of Prediction Model in Milling Using Fuzzy Logic

One of the aims of the research is to develop methodology of 3D surface roughness prediction by using fuzzy logic. To reach this aim experiments were conducted, which resulted in fuzzy logic prediction models. The developed methodology would allow implementing the given surface roughness prediction technique in the workshops or in the work of technologists.

The functional relationship in fuzzy sets is defined as follows: $f\,(f;\ v;\ d) = Sa$, where f defines nonlinear relationship between surface roughness Sa (fuzzy output value) and feed f, cutting speed v and depth of cut d (fuzzy input values). In the beginning the input values are defined, then the given input values undergo fuzzification or defined in a language understandable to fuzzy logic. The next phase is generation of output values by means of fuzzy interface according to the fuzzy rules previously inserted into the database. Finally, the interface of defuzzification defines the output value, which in the given case is 3D surface roughness parameter *Sa*. To develop a prediction methodology based on fuzzy logic FuzzyTECH 5.54 software was used. FuzzyTECH is made to facilitate solving fuzzy logic problems.

In the beginning, data fuzzification is done or membership functions for input values are defined. It should be noted that experience and expertise of the system’s developer plays a big role in evaluation of values of membership functions. The developer of the system has to know the cutting process and its resulting effects on the surface roughness. Partly this task has been made easier by experimental data and conclusions obtained in the third chapter which can be considered as a preliminary information database. Unlike regression, development of fuzzy logic prediction model requires skilled workforce, which has full understanding about the machining processes and has the knowledge about the main factors that influence surface roughness. A technologist by himself can serve as a knowledge database or the model can be developed considering the conclusions of the previously done machining processes.

Input values of the experiment are taken from Table IV. For the feed three membership functions were chosen. Series vector of the feed is $f^T = \{M, V, L\}$ where: M = *small* (0.1 mm/rev.); V = *medium* (0.175 mm/rev.); L = *large* (0.25 mm/rev.). At the given values the degree of support (DoS) is 1 (one). For example, if degree of support for membership function is 1 (one) then *medium* value is 0.175, but 0 is at 0.1 and 0.25. the given relationship can be displayed with the following membership functions (Fig. 8):

$$A_s(f) = \begin{cases} 1, when\ f \le 0.1 \\ (0.1 - f)/0.075, when\ 0.1 < f < 0.175; \\ 0, when\ f \ge 0.175 \end{cases} \quad (10)$$

$$A_m(f) = \begin{cases} 0, when\ f \le 0.1 or \ge 0.25 \\ (f - 0.1)/0.075, when\ 0.1 < f < 0.175 \\ (0.25 - f)/0.075, when\ 0.175 < f < 0.25 \\ 1, when\ f = 0.175 \end{cases}; \quad (11)$$

(4.4)

$$A_l(f) = \begin{cases} 0, when\ f \le 0.175 \\ (f - 0.175)/0.075, when\ 0.175 < f < 0.25. \\ 1, when\ f \ge 0.25 \end{cases} \quad (12)$$

(4.5)

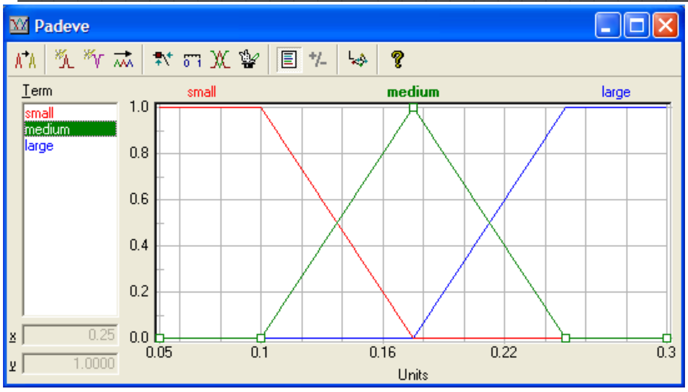

Fig. 8. Three feed *f* membership functions in milling X5CrNi18-10

Similar fuzzification procedure was done to the cutting speed *v* choosing three membership functions. Series vector of the cutting speed is vT = {M, V, L} where: M = small (120 m/min); V = medium (150 m/min); *L* = *large* (190 m/min). For the depth of cut *d* five membership functions were chosen. Series vector of depth of cut is d^T = {*LM*, *M*, *V*, *L*, *LL*} where: *LM* = *very_small* (0.5 mm); *M* = *small* (0.75 mm); *V* = *medium* (1 mm); *L* = *large* (1.25 mm); *LL* = *very_large* (1.5 mm).

For the surface roughness *Sa* which fuzzy logic output value, six membership functions were chosen. Series vector of surface roughness is d^T = {*PM*, *LM*, *M*, *V*, *L*, *LL*} where *PM* = *extra_small* (0.4 µm); *LM* = *very_small* (0.6 µm); *M* = *small* (0.8 µm); *V* = *medium* (1 µm); *L* = *big* (1.2 µm); *LL* = *very_big* (1.4 µm). In Figure 9 the membership functions for surface roughness are shown.

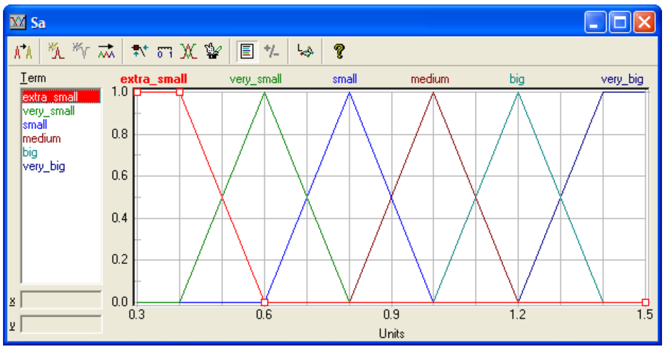

Fig. 9. Six surface roughness membership functions in milling X5CrNi18-10

After development of membership function of fuzzy logic it is necessary to create a database of fuzzy rules. The said database consists of rules which should be followed by the system and on the basis of which the output values are obtained. The given fuzzy rules dictate interaction between input and output variables, allowing appropriate control procedures for the system to work with the desired result, in this case, how cutting parameters should be changed to obtain the desired surface roughness. In Table VI a data base of fuzzy rules in form of matrix is shown, where the given fuzzy rules determine a work of the fuzzy logic system. These rules are designed according to the conclusion drawn in the machining process. For example, **if** cutting speed *v* is small and **if** depth of cut *d* is very large, and **if** feed *f* is large **then** 3D surface roughness *Sa* is very large.

TABLE VI
EXTRACT FROM A MATRIX OF FUZZY RULES

***v* →**	**small**			**medium**		
***f* →**	**small**	**medium**	**large**	**small**	**medium**	**large**
***d* ↓**						
very small	*PM*	*M*	*V*	*LM*	*M*	*M*
small	*LM*	*M*	*V*	*LM*	*M*	*M*
medium	*PM*	*LM*	*M*	*LM*	*M*	*V*
large	*LM*	*V*	*L*	*M*	*L*	*L*
very large	*LM*	*V*	*LL*	*M*	*V*	*L*

After development of membership functions and database of fuzzy rules, it can be said that the surface roughness prediction model using the tools of fuzzy logic has been developed. The next step is defuzzification of the data to verify predictability or confidence of the model.

Data defuzzification is a step in which linguistic values are transferred into numerical values. The fuzzy model with opened windows of defuzzification is shown in Figure 10. In the window named „*watch: interactive debug mode*" it is possible to change input values interactively which then are processed according to the fuzzy rules, resulting in the output value which in this case is a value of surface roughness. In window shown in Figure 10, "Sa" is shown as an output value or surface roughness value, as well as process of defuzzification where the output value is determined by the above mentioned Centre of Area method.

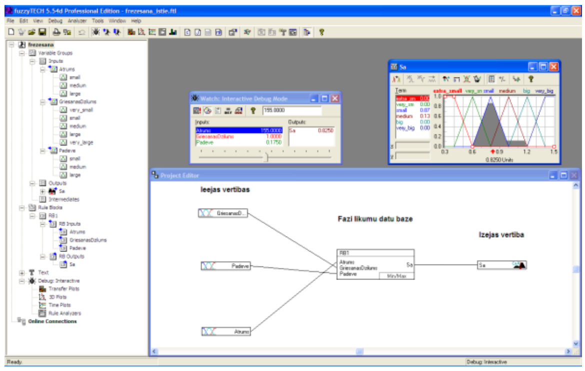

Fig. 10. Fuzzy model with defuzzification for milling X5CrNi18-10

In further analysis it is possible to retrieve graphs showing the relationship between input values (horizontal axis) and output value (vertical axis). The surface roughness *Sa* dependence on technological parameters (cutting speed *v* and feed *f*) is demonstrated in Figure 11.

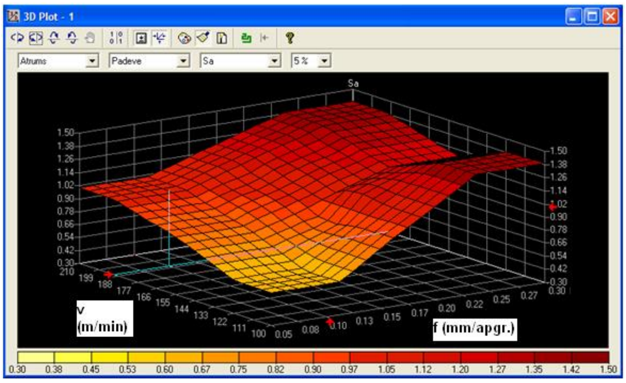

Fig. 11. 3D plot of 3D surface roughness *Sa* according to the cutting speed *v* and feed *f* in case of milling X5CrNi18-10

IX. Design of Prediction Model in Turning Using Fuzzy Logic

Similarly, as described in the previous chapter, a fuzzy logic prediction model in turning was developed. Cylindrical stainless steel (X8CrNi18 – 9) was used as a workpiece. First of all, a block diagram showing correlation between parameters was made, as shown in Figure 11.

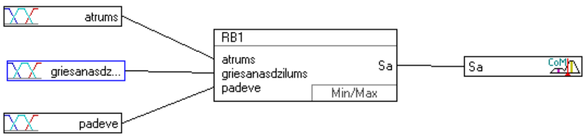

Fig. 11. Block diagram showing relationships between process parameters in turning

After the fuzzification of parameters, membership functions are made as shown in Figure 12.

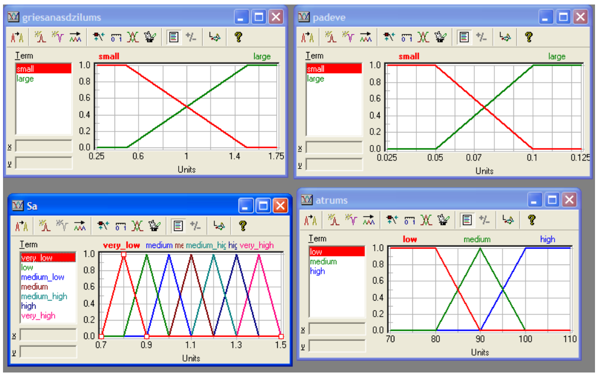

Fig. 12. Membership functions for parameters in case of turning X8CrNi18 – 9

The next step is development of fuzzy rule database followed by defuzzification of data and, finally, generation of prediction model is performed. 3D plot for surface roughness *Sa* is shown in Figure 13. Following a similar methodology a prediction model for turning stainless steel 11SMnPb30 was made.

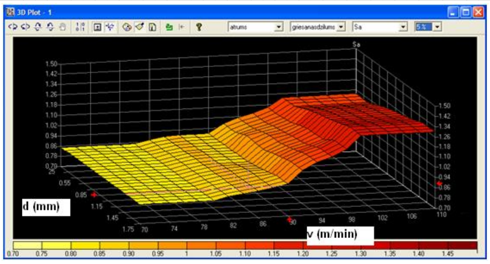

Fig. 13. 3D plot for surface roughness *Sa* according to technological parameters (*v* and *d*) in the case of turning X8CrNi18 – 9

X. Comparative Analysis

A comparative analysis was performed to compare the obtained prediction models (regression and fuzzy logic). From the results, which are summarized in Figure 14, it can be seen that 3D surface roughness prediction model obtained by fuzzy logic has a prediction error of 6%, while 3D surface roughness prediction model obtained by regression analysis has a prediction error of 19%. It can be concluded that by the use of fuzzy logic more accurate 3D surface roughness prediction models can be acquired.

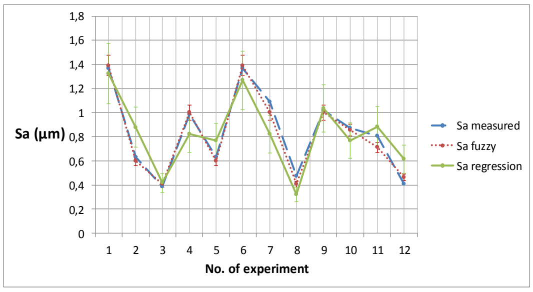

Fig. 14. Comparative graphic of 3D surface roughness parameters in milling of X5CrNi18-10

From the results, which are summarized in Figure 15, it can be concluded that 3D surface roughness prediction model obtained by the use of fuzzy logic has a prediction error of 4%, while the 3D surface roughness prediction model obtained by the regression analysis has a prediction error of 6%. It can be concluded that by the use of fuzzy logic a little more accurate 3D surface roughness prediction models can be acquired.

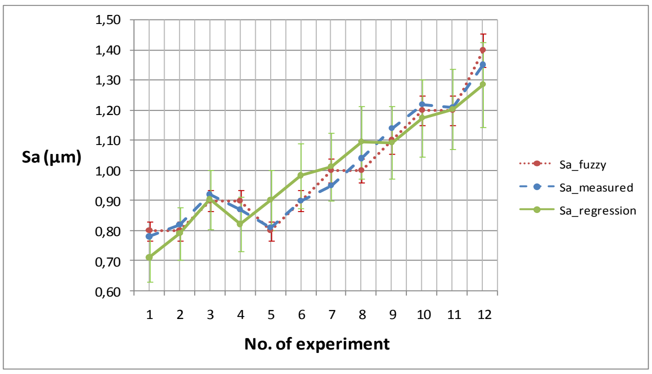

Fig. 15. Comparative graphic of 3D surface roughness parameters in turning of X8CrNi18 – 9

From the results, which are summarized in Figure 16, it can be seen that 3D surface roughness prediction model obtained by the use of fuzzy logic has a prediction error of 4%, while the 3D surface roughness prediction model obtained by the of regression analysis has a prediction error of 11%. From this experiment it can be concluded that by the use of fuzzy logic more accurate 3D surface roughness prediction models can be acquired.

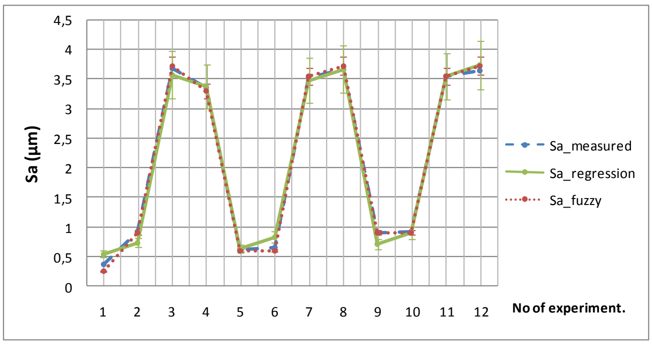

Fig. 16. Comparative graphic of 3D surface roughness parameters in turning 11SMnPb30

From the experimental results it can be concluded that the fuzzy logic prediction models are more accurate than the regression prediction models.

XI. Conclusion

Fuzzy logic can be successfully adapted to solve the tasks of 3D surface roughness technological assurance.

3D surface roughness prediction models in milling and turning are developed, giving an opportunity to the manufacturing engineers operatively set-up necessary technological parameters in order to obtain the desired 3D surface roughness.

Prediction errors are evaluated for developed fuzzy logic and regression models in milling X5CrNi18-10. Regression model prediction error is 19%, while the fuzzy logic model prediction error is 6%. It can be concluded that the developed fuzzy logic prediction model methodology offers considerably more accurate 3D surface roughness prediction model.

Regression model prediction error in turning is 6% (11SMnPb30) and 11% (X8CrNi18-9), while the fuzzy logic model prediction error is 4% (11SMnPb30) and 4% (X8CrNi18-9). Although prediction errors for both models of the experiment in turning 11SMnPb30 are similar, the trend remains – the developed fuzzy logic prediction methodology is able to provide more accurate 3D surface roughness technological assurance.

The developed methodology for obtaining fuzzy logic 3D surface roughness prediction models reduces run-in time of machining, respectively, reducing production costs and time. The developed fuzzy logic models can be used by technologist to set up the necessary technological parameters according to the desired 3D surface roughness without additional experiments.

Research is based on two types of metal processing: milling and turning, but the achieved results can be adapted to other types of metal processing, for example, grinding.

Fuzzy logic prediction models are useful for development of adaptive control system for CNC, realizing it through the FLC controller, which is operationally linked to the CNC control unit.

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Artis Kromanis, Juris Krizbergs. 3D virsmas raupjuma prognozēšana, izmantojot regresijas analīzi un faziloģiku, un to salīdzinošo analīzi.

Šis pētījums koncentrēts uz prognozēšanas metodēm, kas var būt noderīgas virsmas raupjuma prognozēšanai metāla griešanā, īpaši virpošanā un frēzēšanā. Izmantotās prognozēšanas metodes: regresijas analīze un īpaši faziloģika. Pētījumos konstatēts, ka iegūtās prognozēšanas metodes var izmantot arī citiem metāla apstrādes veidiem, piemēram, slīpēšanai. Izvēlēti 3D virsmas raupjuma parametri, kas uzskatāms par novitāti apstrādātās sagataves virsmas raksturošanā. Rezultāti pierāda, ka izveidotajai metodikai, izmantojot regresijas analīzi un faziloģiku, ir pielietojums 3D virsmas raupjuma prognozēšanai metāla griešanā. Salīdzinot ar regresijas analīzi, faziloģikas izmantošanā uzrādīti izcili rezultāti. Faziloģikas prognozēšanas modeļi ir noderīgi adaptive vadības sistēmu izveidē CNC mašīnām.

Артис Кроманис. Юрис Кризбергс. Прогнозирование 3D шероховатости поверхности с помощью регрессионного анализа и нечеткой логики, и их сравнительный анализ.

Данное исследование фокусируется на предсказания методов, которые могут быть полезны для прогнозирования шероховатости поверхности в резке металла, особенно в токарной и фрезерной обработки. Как методы прогнозирования используются регрессионный анализ и особенно нечеткая логика. Исследования показала, что полученные методы прогнозирование также могут быть использованы для других технологий обработки металла, например, при шлифовании. Параметры шероховатости поверхности были выбраны из 3D шероховатости поверхности параметров, что можно рассматривать как новизну для описания поверхности обрабатываемой заготовки. Результаты показали, что разработанная методика может быть использована для предсказания 3D шероховатость поверхности, используя регрессионного анализа и нечеткой логики, при резке металла. Использование нечеткой логики показали исключительные результаты по сравнению с регрессионного анализа. Нечеткие модели логики прогнозирования являются полезными для развития систем адаптивного управления для станков с ЧПУ.