USAGE OF THE FUZZY LOGIC TO PREDICT SURFACE QUALITY OF MACHINED PARTS DURING MILLING OPEARTION

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High level of the quality requirements of machined parts is the standard, which is not unique only for automotive industry, but in industry general. The quality of the product surface roughness is key parameter for every machined product, one of the process with the high influence to surface quality is the milling process. In this article is used fuzzy logic to predict the surface quality by milling operation. Based on milling process parameters and measured data, the surface quality will be estimated using the Fuzzy Inference System (FIS).
The result shows, that selected fuzzy model can be used to predict surface quality with the selected process parameters. Finally this study can bring cost evaluation during tool selection and machine set up parameters.

KEYWORDS

quality, fuzzy logic, surface, tool, parameter

1 INTRODUCTION

Quality management, quality of products and the rate of product delivery to the market play a significant role on current global markets and indirectly affect the degree of end clients´ satisfaction. The result parameters concerning to quality can be described in terms of a number of different result parameters like a dimensional requirements, surface characteristic requirements and any requirements regarding additional characteristics, together with possible requirements concerning functionality and performance [De Vos 2014].
One of the parameters of machined pieces used for product quality assessment is the indicator of surface quality, i.e. the roughness reached.
The technology of milling, which belongs to chip machining, is – together with turning operations – one of the most frequently used technologies. With increasing requirements towards quality there also increase the clients´ requirements towards machining of non-ferrous metals alloys, being more and more extensively used in automotive and air industry due to suitable mechanic features and low weight. Aluminium alloys are the most frequently used non-ferrous metals alloy in these branches. So as to fulfil the clients´ requirements, it is necessary to correctly choose the tool material, type of cooling and cutting conditions in machining [Michna 2014].

2 EXPERIMENT DESCRIPTION

In the first part of the experiment there was machined the etalon material while monitoring the influence of cutting conditions on final quality of surface in consideration of machine time. The FIS (FUZZY INTERFERENCE SYSTEM) was used in the second part of the experiment.
For this experiment there was chosen the aluminium alloy designed for mechanical working with high strength but low resistance to corrosion, marked according to ČSN as 42 4203 in hardened conditions. Marking according to EN AW is 2024 and chemical marking is AlCu4Mg1 (dural). The dural alloys are used in cases when low specific weight is needed together with preservation of sufficient strength, e.g. in air industry. But the corrosion resistance deteriorates [Faltus 2005]. The construction applicability in loaded conditions is approximately up to 150 °C. The chemical composition of given material is specified in table 1 and it is only approximate. The values in the table are considered to be the maximal allowed ones, unless a range is considered.

Chemical Composition					
Si	Fe	Cu	Mn	Mg	Zn
0.50	0.50	3.80÷4.90	0.30÷0.90	1.20÷1.80	0.30

Table 1. Chemical composition of machined material

2.1 *Cutting Tool and Machine*

There was selected the face-milling shank-type cutter of sintered metal (carbide) without coating. The milling cutter has four cutting edges and it is a monolith. The manufacturer recommends it for milling of non-ferrous metals alloys. The samples were machined on five-axial portal centre MCV 1210.

Figure 1. Five-axial machining portal centre MCV 1210

2.2 *Selection of Cutting Conditions and Measuring of Roughness*

Due to the fact that the tool manufacturer does not specify recommended cutting conditions for the given milling cutter, there were selected 4 values of cutting speed and feeds per tooth were selected within the range allowing simulation of the most frequently selected values of the item. After cleaning and drying from the process liquid there was performed the surface roughness measuring. There were measured the profile parameters in 2D using the touch method, so called R-parameters, in concrete terms the values of Ra (average arithmetic variation of measured profile) and Ry (maximal profile height). The average arithmetic variation of measured profile is the arithmetic average of absolute values of Z (x) coordinates within the range of the basic length. The generally reached values of Ra for milling are contained in table 2. [Sperka 2009]

	Roughing	Finishing cuts	Finishing
Ra value [um]	6.3-25	1.6-6.3	0.8-1.6
Accuracy grade	10-13	7-13	7-8

Table 2. Reached values of Ra parameter and accuracy grades of IT for the technology of milling.

2.3 *Surface assessment in case of milling under different cutting conditions*

The surface roughness measuring was performed in three points of the machined surface – due to higher precision of measuring and so as to decrease possible measuring errors. Consequently, there was calculated the arithmetic average of the Ra value. The resulting values of surface roughness for individual cutting speeds and feeds are specified in tab.3.

Cutting speed vc [m/min]	Feed per tooth fz [mm]				
	0.03	0.06	0.09	0.12	0.15
100	1.65	2.52	3.11	4.47	4.50
200	1.53	2.21	2.12	2.39	2.35
300	1.49	2.14	3.12	3.29	3.51
400	1.96	3.01	4.44	4.32	4.6

Table 3. Average values of Ra [um] for selected cutting conditions

Based on values contained in table 3, the maximal surface roughness value was reached at the maximal selected cutting speed v_c = 400m/min in combination with maximal value of feed per tooth f_z=0,15 mm. The lowest values of feed per tooth is reached in case of setting the feed per tooth value to f_z = 0,03.

3 RELATION TO FIS (FUZZY INFERENCE SYSTEM)

The measured and assessed data show some error. There appears vagueness and fuzzy sets are one of the possibilities of describing the vagueness.

4 UTILIZATION OF FIS (FUZZY INFERENCE SYSTEM)

A Fuzzy Inference System (FIS) is based on the terms *fuzzy set* and *fuzzy relation* which were introduced by Lotfi A. Zadeh in 1965 following the [Zadeh 1965]. The fuzzy set is one of the possible generalizations of the term set. The fuzzy set is a pair (U, μ_A) where U is universe and μ_A: U → ⟨0,1⟩ is a function describing that U elements belong to A fuzzy set. The membership is marked with $\mu_A(x)$. The fuzzy set is the generalization of a "typical" set because the following formula applies for a "typical" set A membership

$$\mu_A\text{: U} \rightarrow \{0, 1\} \text{ and } x \in \text{A} \Leftrightarrow \mu_A(x) = 1 \text{ and } x \notin \text{A} \Leftrightarrow \mu_A(x) = 0. \quad (1)$$

Let U_i, i = 1, 2, ..., n, be universal sets. Then **fuzzy relation** R on U = $U_1 \times U_2 \times .. \times U_n$ (where $U_1 \times U_2 \times .. \times U_n$ is a cartesian product of sets) is a fuzzy set R on a universal set U.

Nowadays one of the most widely used applications is a *Fuzzy Inference System* – FIS (once used as a term "fuzzy regulator"). The FIS is considered to be a fuzzy relation which gives resultant values when put together with input values. There are several types of the FIS. In this paper we applied the type P: $u = R(e)$ where an output quantity value depends only on the magnitude of an input quantity.

Let $\boldsymbol{E_i}$ = (E_i, $\boldsymbol{T}(E_i)$, E_i, G, M), i = 1, ..., n be input language variables, and $\boldsymbol{U}$ = (U, $\boldsymbol{T}(U)$, U, G, M) be an output language variable. E_i, U are the names of variables, $\boldsymbol{T}(E_i)$, $\boldsymbol{T}(U)$ is a set of language values, E_i, U are relevant universes, G is grammar, M represents the meaning of language values. The FIS is considered to be:

$$\mathfrak{R} = \mathfrak{R}_1 \text{ otherwise } \mathfrak{R}_2 \text{ otherwise, ... , otherwise } \mathfrak{R}_p, \quad (2)$$

where $\mathfrak{R}_k$, k = 1, ..., p is as follows:

$$\mathfrak{R}_k \equiv \textbf{if } E_1 \textbf{ is } X_{E1,k} \textbf{ and } E_2 \textbf{ is } X_{E2,k} \textbf{ and ..... and } E_n \textbf{ is } X_{En,k}\textbf{,}$$
$$\textbf{then } U \textbf{ is } Y_{U,k} \quad (3)$$

$X_{Ei,k} \in \boldsymbol{T}(Ei)$, $Y_{U,k} \in \boldsymbol{T}(U)$ for each i = 1, ..., n, for each k = 1, ..., p.

The meaning of the statements $\mathfrak{R}$ is expressed by M($\mathfrak{R}$) = $\boldsymbol{R}$, and M($\mathfrak{R}$) is a fuzzy relation above $\text{E}_1 \times \text{E}_2 \times ... \times \text{E}_n \times \text{U}$ which is defined as follows:

$$\boldsymbol{R} = \text{M}(\mathfrak{R}) = \bigcup_{k=1}^{p} \text{M}(\mathfrak{R}_k). \quad (4)$$

Regarding other rules $\boldsymbol{R}$ is considered as unification, and M($\mathfrak{R}_k$) is defined M($\mathfrak{R}_k$) = $A_{E1,k} \times A_{E2,k} \times ... \times A_{En,k} \times A_{U,k}$, where $A_{Ei,k}$ = M($X_{Ei,k}$) which is a fuzzy set above the universe E_i, i = 1, ..., n and $A_{U,k}$ = M($Y_{U,k}$) is a fuzzy set over the universe U, k = 1, ..., p. M($\mathfrak{R}_k$) is a fuzzy relation over the universe $\text{E}_1 \times \text{E}_2 \times ... \times \text{E}n \times \text{U}$.

When entering into the FIS, any fuzzy set will be above E_i (a_{Ei}). Then the magnitude of an actuating quantity a_U is determined by the formula $a_U = (a_{E1} \times a_{E2} \times ... \times a_{En})°\boldsymbol{R}$. A_U consists of the fuzzy relation ($a_{E1} \times a_{E2} \times ... \times a_{En}$) above the universe $\text{E}_1 \times \text{E}_2 \times ... \times \text{E}_n$, and the relation $\boldsymbol{R}$ defined above the universe $\text{E}_1 \times ... \times \text{E}_n \times$ U. The fuzzy set above the universe U is the result of this composition.

In many cases the fuzzy set is not required to be an output from the FIS, but a specific value $u_0 \in U$, i.e. we want to carry out *defuzzification*. The centroid method is the most widely used defuzzification method. The FIS specified this way is called *Mamdani* FIS [Mamdani 1977], [Cordon 2004].

If we do not know how the process works (i.e. FIS rules cannot be set), but the sufficient amount of input and output data is available, we can use the modification of Mamdani-FIS Sugeno (Takani-Sugeno FIS) [Sugeno 1985]. This FIS is described by suitable parameters during tuning performed on well-known data. Sugeno FIS input language values are similar to Mamdani-type FIS, but the output quantity value is expressed by a different formula:

$$\mathfrak{R}_k \equiv \textbf{if } E_1 \textbf{ is } X_{E1,k} \textbf{ and } E_2 \textbf{ is } X_{E2,k} \textbf{ and ..... and } E_n \textbf{ is } X_{En,k}\textbf{,}$$
$$\textbf{then } U \textbf{ is } F_k. \quad (5)$$

where F_k describes the value in the universe U for k-th rule.

Let us take into account the input denoted by $(x_1, \ldots, x_n) \in \mathbf{R}^n$. Then

$$F_k(x_1, \ldots x_n) = \alpha_k,$$

$$F_k(x_1, \ldots x_n) = \alpha_k + \beta_{1,k}\, x_1 + \beta_{2,k}\, x_2 + \ldots + \beta_{n,k}\, x_n. \qquad (6)$$

The rules are put in the following equation:

$$\mathfrak{R}_k \equiv \textbf{if } x_1 \textbf{ is } X_{E1,k} \textbf{ and } x_2 \textbf{ is } X_{E2,k} \textbf{ and } \ldots\ldots \textbf{ and } x_n \textbf{ is } X_{En,k}, \textbf{ then } u_k = f_k(x_1, \ldots x_n). \qquad (7)$$

This means that if the input $(x_1, \ldots, x_n)$ belongs to the area specified by the language values $X_{E1,k}$ up to $X_{En,k}$, then the output is found by the function f_k. The weighted value u_k of the input z_k is determined the same way as the FIS of Mamdani-type using the level of conformance between the inputs $(x_1, \ldots, x_n)$ and the fuzzy sets $A_{E1,k}$ up to $A_{En,k}$. When applying the rules $\mathfrak{R}_1$ up to $\mathfrak{R}_p$ we get for the input $(x_1, \ldots, x_n)$ the values u_1, up to u_p, and using weighted values w_1 up to w_p and a weighted average we obtain a resultant output value u. [Yager 1994]

5 USE FIS ON MEASURED DATA

When searching for FIS, we used the following measured data (Figure 2.).

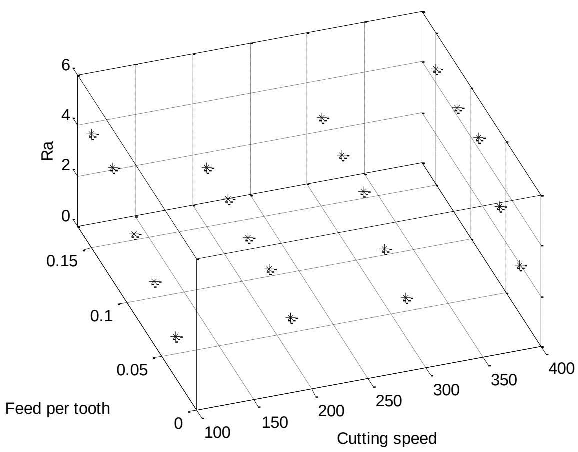

Figure 2. Measured data

To find Takagi-Sugeno FIS, we chose two basic methods:

Dividing the data area into smaller parts and selecting a suitable description using fuzzy sets. For the trapezoidal shape of the fuzzy set (FIS_1), we have the following dependence (Figure 3.).

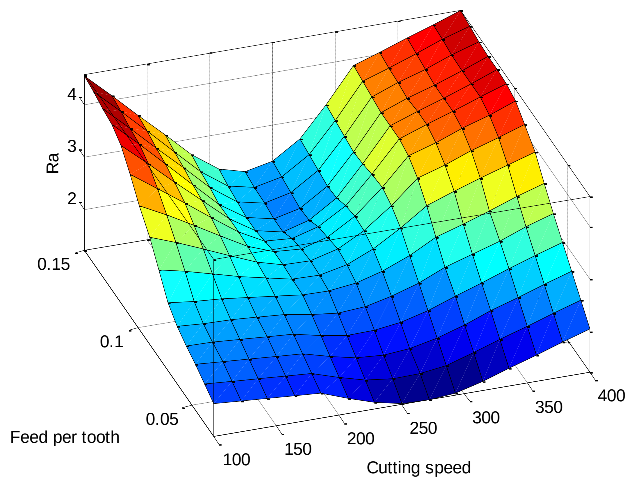

Figure 3. FIS_1 - dividing the data area into four areas, trapezoidal shape of the fuzzy set

For fuzzy sets in the form of Gaussian curves (FIS_2, FIS_3) we have the following dependence: (Figure 4,5):

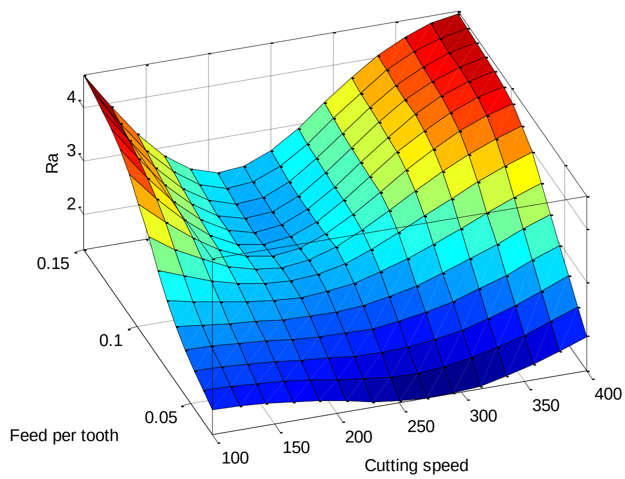

Figure 4. FIS_2 - dividing the data area into four areas, fuzzy sets in the form of Gaussian curves

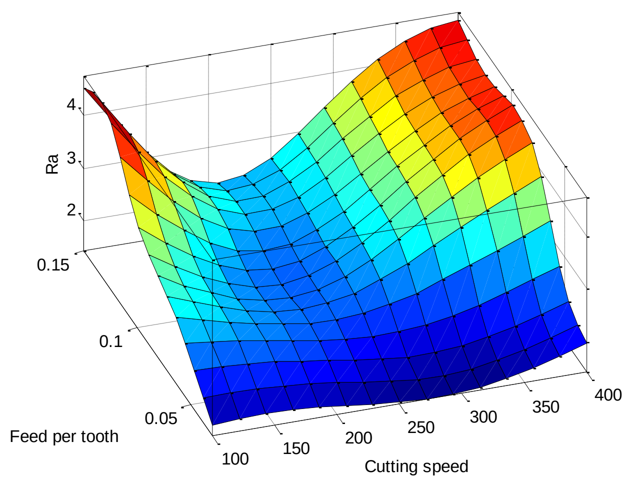

Figure 5. FIS_3 - dividing the data area into six areas, fuzzy sets in the form of Gaussian curves

Using cluster analysis (FIS_4) (Figure 6.)

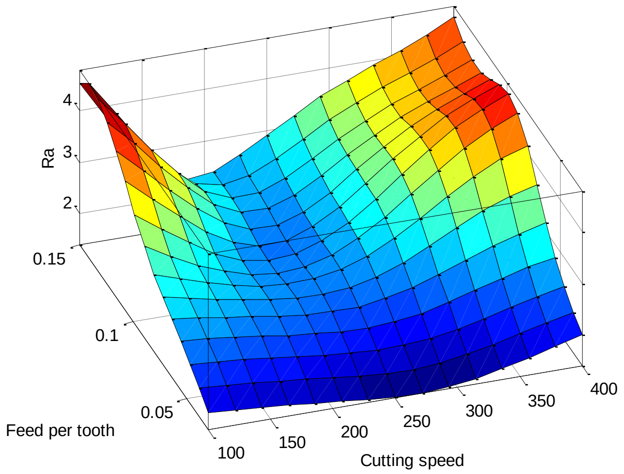

Figure 6. FIS_4 - cluster analysis, fuzzy sets in the form of Gaussian curves

Found dependencies behave very similarly. For a more detailed description of the behaviour we focus only on the FIS that was created by dividing the data area into four areas and fuzzy sets were selected Gauss curve. The dependency found - which is displayed in the form of a surface - is displayed using contours. Each contour shows the possible combination of cutting speed and feet per tooth for the selected Ra (Figure 7,8).

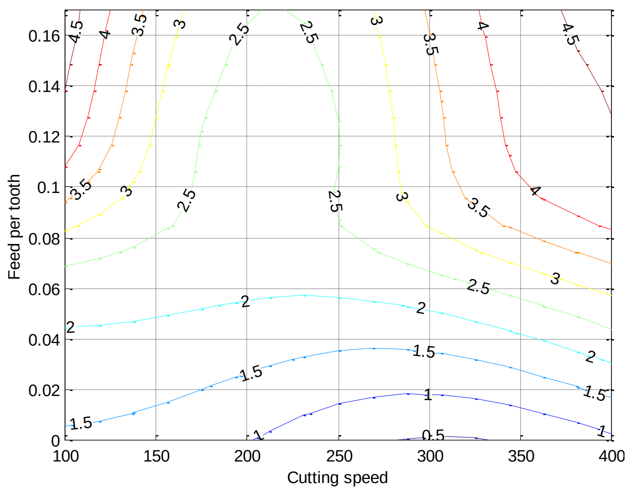

Figure 7. Contour of FSI_2 - dividing the data area into four areas, fuzzy sets in the form of Gaussian curves

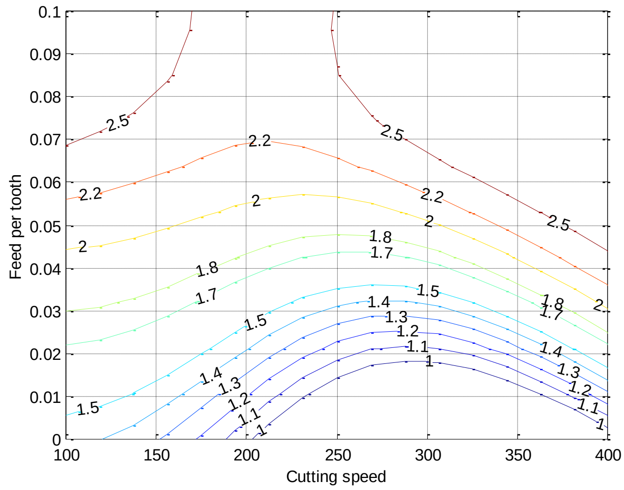

Figure 8. Contour of FSI_2 - dividing the data area into four areas, fuzzy sets in the form of Gaussian curves

6 CONCLUSIONS

Finally, it is possible to state that results of the experiment and generation of dependence using the FIS is identical in fact, so we can suppose that generated dependence corresponds with real situation. Application in practice is apparent based on figure No.7, when we can see generation of FSI contours FSI (Contour of FSI), when each contour line allows – depending on requirements towards surface quality (Ra) – selection of suitable combination of machining conditions (feed per tooth and cutting speed).

The generated dependencies are valid only for the selected material, tool and machine. If we use a similar line of machines with similar technical parameters in practice, it is possible to use generated dependencies for speeding-up and setting of optimal cutting conditions.

For more precise data prediction and consequent selection of machining / cutting conditions it would be suitable to generate dependencies on more measured values.

The above stated article provides more possibilities for use of dependencies using statistic methods and mainly the regression analysis. [Demsar 2006]

Cutting speed (m/min)	200	300	400
Feed per tooth (mm)	0.15	0.03	0.15
Measured Ra value (um)	2.35	1.49	4.6
FIS_1 calculated Ra value (um)	2.4327	1.2946	4.5832
FIS_2 calculated Ra value (um)	2.3922	1.3525	4.5624
FIS_3 calculated Ra value (um)	2.3062	1.4416	4.6015
FIS_4 calculated Ra value (um)	2.3403	1.4486	4.5825
FIS average of calculated Ra value (um)	2.36785	1.384325	4.5824

Table 4. Comparison of measured Ra and calculated Ra for selected cutting conditions

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