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NEURO–FUZZY SYSTEMS MODELLING OF HARD STEEL SURFACE ROUGHNESS PARAMETERS

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Abstract: The objective of this study is to examine the influence of machining parameters on surface finish during turning of hard steel. A new approach in modelling surface roughness which uses design of experiments is described in this paper. Used were as well adaptive–neuro–fuzzy–inference system (ANFIS) model. The values of surface roughness predicted by different models were then compared. The results showed that the proposed systems can significantly increase the accuracy of the product profile when compared to the conventional approaches. The results indicate that the design of experiments with central composition plan modelling technique and ANFIS can be effectively used for the prediction of the surface roughness for hard steel.
Keywords: turning, hard steel, ANFIS modeling, surface roughness

INTRODUCTION

Increasingly, research in manufacturing processes and systems is evaluating processes to improve their efficiency, productivity and quality. The quality of finished products is defined by how closely the finished product adheres to certain specifications, including dimensions and surface quality. Surface quality is defined and identified by the combination of surface finish, surface texture, and surface roughness. Surface roughness (Ra, Rmax) is the commonest index for determining surface quality [1, 2].

Manufacturing processes do not allow achieving the theoretical surface roughness due to defects appearing on machined surfaces and mainly generated by deficiencies and imbalances in the process. Due to these aspects, measuring procedures are necessary; as it permits one to establish the real state of surfaces to manufacture parts with higher accuracy. To know the surface quality, it is necessary to employ theoretical models making it feasible to do predictions in function of response parameters [3, 4, 5].

A lot of analytically methods were also developed and used for predicting surface roughness. An empirical model for prediction of surface roughness in finish turning [6]. Nonlinear regression analysis, with logarithmic data transformation is applied in developing the empirical model. Metal cutting experiments and statistical tests demonstrate that the model developed in this research produces smaller errors and has a satisfactory result. The mathematical models for modeling and analyzing the vibration and surface roughness in the precision turning with a diamond cutting tool [7].

Recently, some initial investigations in applying the basic artificial intelligence approach to model of machining processes, have appeared in the literature, concludes that the modeling of surface quality in machining processes has mainly used Artificial Neural Networks and fuzzy set theory [8, 9]. Average mean roughness, Ra using neural network (NN) was predicted in [10]. Surface roughness and surface finish have been considered in [12, 13, 14]. Research of the influence of machining parameters combination to obtain a good surface finish in turning and to predict the surface roughness values using fuzzy modeling is presented in [15]. Also, may notice that the neural network used in the study, where the enabling resolution of the problem that is difficult to define and mathematically model. This can be seen in the work where the neural network was based on the face milling machining processes, where is aimed to produce the relationship of cutting force versus instantaneous angle φ [16]. Use of coolants and lubricants in hard machining were presented in [17].

In this study, cutting speed, feed and depth of cut as machining conditions were selected. An adaptive neuro fuzzy inference system (ANFIS) were developed for modeling these cutting parameters.

EXPERIMENTAL PROCEDURE AND MATERIAL

Terms of the experimental study:

» The experimental machine tool was a universal lathe – Prvomajska DK480, Figure 1.

Figure 1. Turning machine

» Tool: For the study was used interchangeable plates of hard metal CNMA 120404 ABC 25/F producer ATRON from Germany. Used was insert holder for external processing PCLNR 25 25 M16.

The markings of the cutting tips according to DIN 4983 more closely define the geometry, as follows: the shape of the plate C → rhomb; the rake angle N → = 0°, C → = 7; tolerance class M; Type of tile → with opening A, W and G; length of cutting blade → 12.7 mm (12); cutting edge thickness → 4.76 mm (04); radius of tool tip → 0.4 mm (04). All tiles have a rake angle (γ=–6°).

The processing regime included the following elements:

- cutting speed v, (m /min),
- feed f, (mm /rev),
- cutting depth, a (mm).

Variation of the experiment input factor (cutting regime) was performed in 5 levels of values. The mean value between the two adjacent levels was the geometric mean of these values. Selected levels of factors are shown in Table 1.

Table 1. Experimental input factor levels

Factor Levels		Cutting speed v (m/min)	Cutting speed v (m/s)	Feed f (mm/rev)	Dept of cut a (mm)
Highest	+1.41	1.143	0.285	0.286	0.593
High	+1	1.143	0.285	0.067	0.796
Middle	0	4.571	0.033	1.667	0.197
Small	–1	0.286	0.593	0.067	0.796
Smallest	–1.41	1.143	0.285	0.077	0.782

Before the experimental performance, preparation of the workpiece was carried out. The workpiece is thermally treated steel Č3840 (90MnCrV8) whose working hardness was 55 HRC, circular cross–section Ø34 mm and length 500 mm. To make it easier to perform, and for more credible measurement results, the workpiece tends to the chuck head at one end, and relies on the other end to the spike. It is necessary to remove a certain layer of material in order to avoid throwing–ovality and the results were more reliable. The length of the workpiece bar of 500 mm, it was divided into 24 fields with a length of 10 mm on which the longitudinal cutting, without the presence of cooling and lubricating agents was provided. Each field on workpiece was planned for one experimental point measurement.

Measuring the surface roughness parameters with the Talysurf 6 measuring device was done. After processing by a computer on the screen, was written or printed results. The personal computer was connected to the Talysurf–6 measuring device using a serial connection COM–3. Instead of the printer, a computer was connected with a special adapter with a measuring machine Talysurf–6. The basic parts of the measuring device Talysurf–6 are shown in Figure 2.

During study measured was the values of workpiece surface roughness parameters: Ra, Rmax. The measurement results of these parameters and estimated values by three factorial models are given in Table 2.

Figure 2. Surface roughness measurement system Talysurf–6 connected with computer

Table 2. The measurement and modeled results – Input parameters

No.	Factor v [m/min]	f [mm/rev]	a [mm]	R_i measured R_a [μm]	R_{max} [μm]	R_i Model R_a [μm]	R_{max} [μm
1	90	0,05	0,10	0.51	3.2	0.47	2.81
2	160	0,05	0,10	0.53	2.8	0.50	2.76
3	90	0,20	0,10	1.17	4.8	1.26	5.10
4	160	0,20	0,10	1.2	4.8	1.32	5.01
5	90	0,05	0,50	0.75	6.2	0.63	4.20
6	160	0,05	0,50	0.85	6.1	0.66	4.13
7	90	0,20	0,50	2.01	7.6	1.66	7.63
8	160	0,20	0,50	2.1	7.6	1.74	7.49
9	120	0,10	0,22	0.93	4.5	0.91	4.57
10	120	0,10	0,22	0.77	4	0.91	4.57
11	120	0,10	0,22	0.91	4.4	0.91	4.57
12	120	0,10	0,22	0.76	4.3	0.91	4.57
13	80	0,10	0,22	0.69	3.56	0.88	4.63
14	180	0,10	0,22	0.71	4	0.94	4.51
15	120	0,045	0,22	0.43	2.4	0.52	3.24
16	120	0,25	0,22	1.91	8.01	1.73	6.78
17	120	0,10	0,07	1.06	6.6	0.74	3.43
18	120	0,10	0,70	0.98	5.5	1.11	6.11
19	80	0,10	0,22	0.65	3.93	0.88	4.63
20	180	0,10	0,22	0.7	3.5	0.94	4.51
21	120	0,045	0,22	0.39	2.5	0.52	3.24
22	120	0,25	0,22	1.82	8.3	1.73	6.78
23	120	0,10	0,07	1.04	2.8	0.74	3.43
24	120	0,10	0,70	1.38	6.2	1.11	6.11

IMPLEMENTATION OF FACTORIAL EXPERIMENTAL PLAN

In the table 3 are given results data dispersion analyses, adequacy of models and significance of parameters.

Table 3. Adequacy of models and significance of parameters

Model adequacy		R_a Fa=4,33219	R_{max} Fa=1,65230
Significance	F_{ro}	16.62	1372,91
	Fr1(v)	0.66 (*)	0,03*
	Fr2(f)	282.91	35,04
	Fr3(a)	23.35	16,03

For training the ANFIS during modeling was used "MatLab" software, which is the most powerful software for technical calculations [18].

Training and testing are the most important characteristics of ANFIS because just training and testing determine its characteristics. To create and train an ANFIS in the MATLAB is used Fuzzy Logic Toolbox. Adaptive neuro–fuzzy inference system is an architecture which is functionally equivalent to a Sugeno type fuzzy rule base [19]. An ANFIS gives the mapping relation between the input and output data by using the hybrid learning method to determine the optimal distribution of membership functions [20]. Both artificial neural network (ANN) and fuzzy logic (FL) are used in ANFIS architecture [21]. In 1993, Jang first introduced the Adaptive Neuro–Fuzzy Inference System, which was reported as a very efficient system for solving the defined equations involving the automatic elicitation of knowledge expressed only by the if–then rules.

In our case ANFIS is a five–layer neural network that simulates the working principle of a fuzzy inference system. The ANFIS model generated from the membership functions and rules were data–driven by the process data for each mechanical property. Though there are many numbers of membership functions available like triangular, trapezoidal, Gaussian, etc. Each set of process data collected from the extrusions consisted of 30 data points from which 24 and 6 were selected randomly for training and testing, respectively. The models were developed and implemented using 100 epochs. The input and output data sets contained three inputs (cutting speed, feed rate and depth of cut) and one output (surface roughness Ra or Rmax).

EXPERIMENTAL RESULTS AND ANALYSE

Equations (1) and (2) for surface roughness parameters Ra and Rmax, modeled by design of central compositional experimental plan determined by software:

$$R_a = 2{,}8264 \cdot v^{-0.04471} \cdot f^{0.59975} \cdot a^{0.00716} \quad (1)$$

$$R_{max} = 9{,}0036 \cdot v^{-0.3717} \cdot f^{0.3739} \cdot a^{-0.6148} \quad (2)$$

As mentioned before, ANFIS modeling was used for analysis and optimization of surface roughness parameters in turning process. The obtained results of ANFIS model are given in the Table 4, side by side with the experimental results. For reduction of a model deviation, is needed to increase the number of experimental inputs trials.

Calculation of percental deviation for measured and model surface roughness parameters values was performed according next formula

$$E = \frac{\left| Ri_{exp} - Ri_m \right|}{Ri_{exp}} \cdot 100\% \quad (3)$$

where are: Riexp– experimental value, Rim– model value

Table 4. Experimental values and values of surface roughness obtained with percentage deviation

No.	Factor			R_i – experimental roughness		R_i – modeled roughness	
	v [m/s]	s [mm/rev]	a [mm]	R_a [µm]	R_{max} [µm]	R_a [µm]	R_{max} [µm]
1	81	0.1	0.22	0.7	3.93	0.99561	3.9245
2	182	0.1	0.22	0.65	3.5	0.74177	2.87921
3	121	0.045	0.22	0.39	2.5	0.42268	2.47317
4	122	0.25	0.22	1.82	8.3	1.85709	8.19655
5	123	0.1	0.07	1.04	2.8	0.97167	6.17389
6	119	0.1	0.7	1.38	6.2	0.84962	5.0787
	Average deviation %					6.20950	8.8208

Figures 3 and 4 shows the correlation between the experimental and obtained values by factorial experimental design of surface roughness parameters (Ra, Rmax). From the diagram can be seen that the points are near regression line and correlation is good.

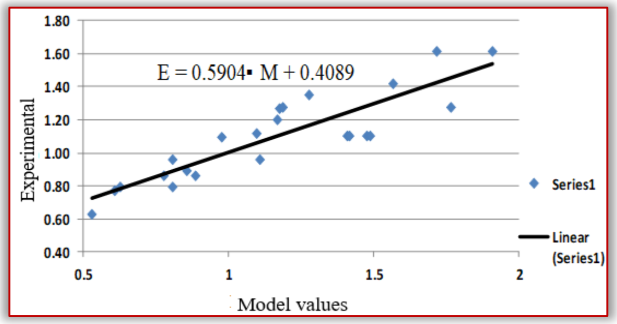

Figure 3. Correlation between experimental and obtained values of surface roughness– Ra

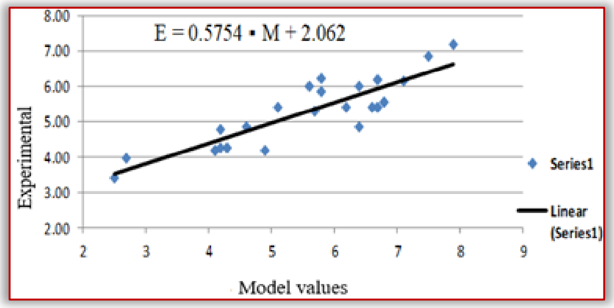

Figure4. Correlation between experimental and obtained values of surface roughness– Rmax

Deviation of experimental and model values of surface roughness is shown on Fig 5. Deviation of 6 testing numbers of ANFIS is on Fig 6.

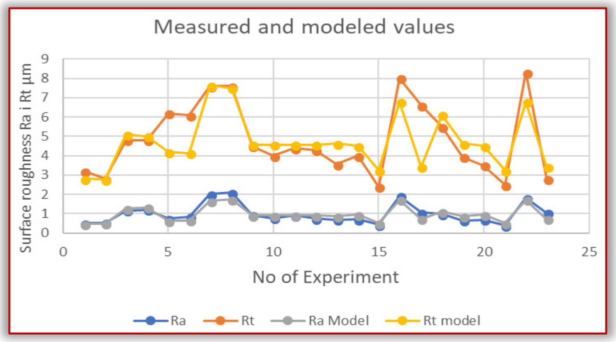

Figure 5. Deviation of experimental and model values of surface roughness

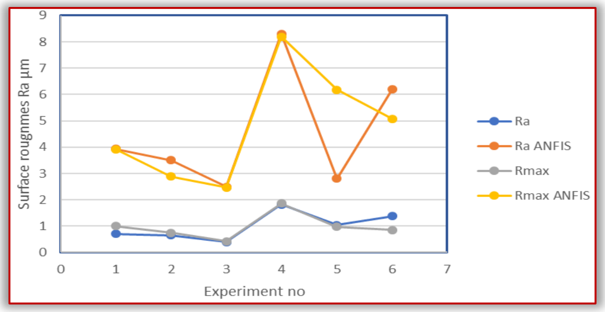

Figure 6. Deviation of 6 testing numbers of ANFIS

The surface roughness parameters (Ra, Rmax) versus cutting speed is in Fig 7, versus feed in Fig. 8 and versus depth of cut in Fig 9.

Any change in the cutting speed leads to a slowly corresponding change in the value of surface roughness. The cutting speed has a small and decreasing effect Fig 7. Influence of feed on value surface roughness is higher than the cutting speed effect. Increasing feed increase surface roughness Fig 8.

Depth of cut at least influences the wear on the flank surface and surface roughness values slightly, Fig 9.

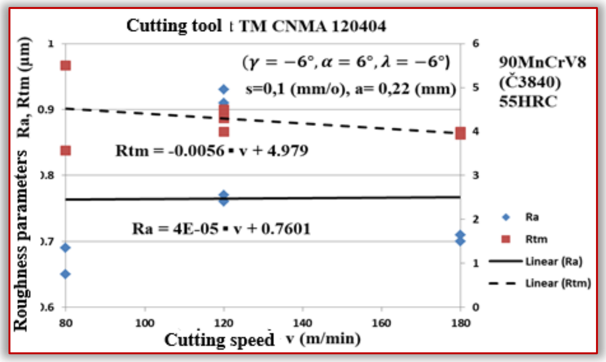

Figure 7. The surface roughness (Ra, Rmax) versus cutting speed

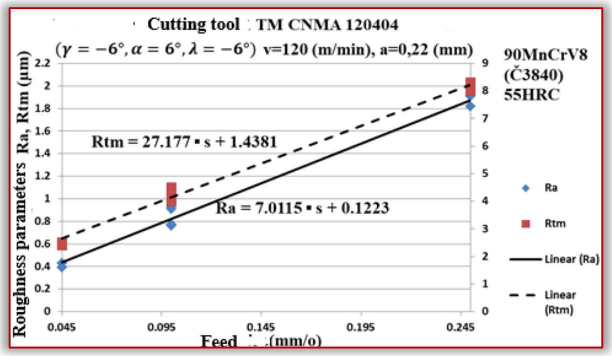

Figure 8. The surface roughness (Ra, Rmax) versus feed per revolution

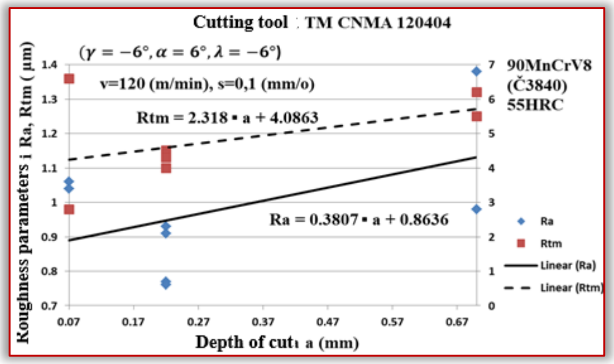

Figure 9. The surface roughness (Ra, Rmax) versus the cutting depth

CONCLUSION

Intelligent optimization techniques give the influence of cutting conditions on machining surface quality during turning hard material, are investigated through experimental verification. The investigation results confirm the highly consent of experimental research and intelligent techniques modeling. The intelligent optimization techniques and experimental results show some good information which could be used by future researches for optimal control of machining conditions. This paper has successfully established ANFIS model, for predicting the workpiece surface roughness parameters. Figures 4 and 5 shows the compared predicted values obtained by experiment and estimated by ANFIS shows a good comparison with those obtained experimentally. The average deviations of models are checked and are found to be adequate. The model adequacy can be further improved by considering more variables and ranges of parameters.

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