Modelling and Optimization of Surface Roughness Parameters of Stainless Steel by Artificial Intelligence Methods

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Abstract. The objective of this study is to examine the influence of machining parameters on surface finish in turning of medical steel. A new approach in modeling surface roughness which uses design of experiments is described in this paper. The values of surface roughness predicted by different models are then compared. Used were adaptive-neuro-fuzzy-inference system (ANFIS). The results showed that the proposed system 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 modeling technique can be effectively used for the prediction of the surface roughness for medical steel difficult to machining. Optimizations of surface roughness parameters was done by use of ant colony method.

Keywords: Turning · Stainless steel · ANFIS modelling · Ant Colony Optimization · Surface roughness

1 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 [3–5].

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].

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Nonlinear regression analysis, with logarithmic data transformation is applied in development of 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 parameters in the precision turning with a diamond cutting tool is presented in [7].

Recently, some initial investigations in applying the basic artificial intelligence approach to model 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 studies [11–14]. 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 modeled. This can be seen in the work where the neural network is based on the face milling machining processes where is aimed to produce the relationship of cutting force versus instantaneous angle φ in [16]. Use of Coolant and Lubricatio agents in Hard Machining is 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.

2 Material and Experimental Procedure

The aim of the experiment was to carry out the monitoring of machining surface roughness for different cutting regime used. The terms of the experimental study:

(a) Cutting operation was performed on Vertical turning machine for hard turning VL5 (Fig. 1). Machine control unit was Fanuc 18i-TB. Number of Axes: 2 to 3, cutting diameter: 127 to 200 mm, cutting length: 119 mm, tool Stations: 12, spindles: 1, motor power: 20.88 Kw, spindle speed: 4500 rpm.

Fig. 1. Vertical turning machine for hard turning

(b) Tool: The survey was used interchangeable plates tags WNMG 080408-QM, manufacturer SANDVIK Coromant, analogous to the ISO standard (EN ISO 9001:2000, EN ISO 14001:2004) with P30-50. Tool holder for external processing PWLNL 2525 M08 H4 was used.
(c) Equipment for cooling and lubrication was used ALUSOL of Castrol, conc. 6–10%. Castrol Alusol™ RAL BF is a high-performance soluble metalworking fluid which is boron and chlorine free. It contains a unique additive package that works in synergy to enhance machining performance and surface finish, provide excellent product stability, improve bio-resistance properties and lower the overall operations costs.
(d) Workpiece material used in tests was steel IDM 8365 (EN X30CrNi2520+1.3Nb) it has a large degree of elongation, toughness due to the high content of Ni, corrosion resistance due to the presence Cr and Ni, belong to the group of stainless steel and high-alloy steels. Also, mechanical properties of processed materials are given in Table 1. Testing show that the microstructure shall consist of interdendritic eutectic chromium carbides in an austenitic matrix, Fig. 2. This was performed and morphological examination of material microscope, “Leitz” Aristomet QI 01297/“OLYMPUS BH” optical Japan QI 01298 and 01298/1.
(e) For measuring the surface roughness was used Surftest Mitutoyo SJ-301, the needle of the diamond, and the radius of curvature at the top of the needle 5 microns. Path length measured was 3.7 mm. The measured values of: R_a, R_{max}. The measurement results are given in Table 2.

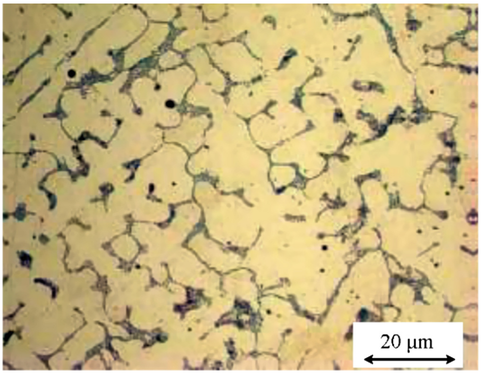

Fig. 2. The microstructure shall consist of interdendritic eutectic chromium carbides in an austenitic matrix

Table 1. Mechanical properties of workpiece material

	Mark:	Unit	Limits	Size
Tensile strength	R_m	MPa	Min 450	486
Prof stress	$R_{p0,2}$	MPa	Min 240	351
Elongation:	A	%	Min 10	10,3
Brinell hardness	HBW 5/750		162–229	207

Table 2. The experimental and modeled values

No.	Factor			Surface roughness			
	v[m/s]	f[mm/rev]	a[mm]	R_a[μm]	R_{max}[μm]	R_a model[μm]	R_{max} model[μm]
1.	3.0	0.12	0.5	0.86	5.22	0.76	5.11
2.	4.33	0.12	0.5	0.88	6.07	0.80	5.78
3.	3.0	0.187	0.5	1.58	10.03	1.86	10.32
4.	4.33	0.187	0.5	1.8	11.06	1.95	11.67
5.	3.0	0.12	1.4	0.97	6.39	0.89	5.46
6.	4.33	0.12	1.4	0.97	6.63	0.94	6.18
7.	3.0	0.187	1.4	2.17	11.04	2.17	11.03
8.	4.33	0.187	1.4	2.4	12.03	2.28	12.47
9.	3.6	0.15	0.84	1.33	6.86	1.32	8.00
10.	3.6	0.15	0.84	1.16	7.58	1.32	8.00
11.	3.6	0.15	0.84	1.17	6.71	1.32	8.00
12.	3.6	0.15	0.84	1.29	7.78	1.32	8.00
13.	2.5	0.15	0.84	1.18	6.87	1.26	7.08
14.	5.22	0.15	0.84	1.25	8.43	1.39	9.06
15.	3.6	0.096	0.84	0.81	4.94	0.54	3.94
16.	3.6	0.234	0.84	3.49	16.26	3.22	16.18
17.	3.6	0.15	0.3	1.105	7.83	1.13	7.48
18.	3.6	0.15	2.34	1.34	8.09	1.54	8.55
19.	2.5	0.15	0.84	1.037	6.72	1.26	7.08
20.	5.22	0.15	0.84	1.082	8.45	1.39	9.06
21.	3.6	0.096	0.84	0.74	5.01	0.54	3.94
22.	3.6	0.234	0.84	3.05	14.92	3.22	16.18
23.	3.6	0.15	0.3	1.34	8.11	1.13	7.48
24.	3.6	0.15	2.34	1.48	8.21	1.54	8.55

3 Implementation of Factorial Experimental Plan

The modeled results by factorial experimental plan are shown in Table 2. In the Table 3 are given results of dispersion analyses, adequacy of models and significance of parameters. Equations for surface roughness modeling determined by central compositional plan design of experiment:

$$R_a = 50.92 \cdot \mathrm{v}^{0.135} \cdot \mathrm{f}^{2.002} \cdot \mathrm{a}^{0.150} \tag{1}$$

$$R_{max} = 106.3 \cdot \mathrm{v}^{0.335} . \mathrm{f}^{1.585} \cdot \mathrm{a}^{0.065} \tag{2}$$

Table 3. Adequacy of models and significance of parameters

Model adequacy		R_a	R_{max}
		F_a = 3.23658	F_a = 3.09891
Significance	218.57	218.57	218.57
	1.17	1.17	1.17
	375.76	375.76	375.76
	11.38	11.38	11.38

4 Implementation of ANFIS

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 ill-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 parameters R_a or R_{max}).

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

Calculation of percentual deviation for measured and model surface roughness values was performed according next formula:

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

where are: Ri_{exp} - experimental value, Ri_m - model value.

Table 4. Experimental values and values obtained and percentage deviation

No.	Factor			R_i - experimental roughness		R_i - modeled roughness		Deviation E %	
	v[m/s]	f[mm/rev]	a[mm]	R_a[μm]	R_{max}[μm]	R_a[μm]	R_{max}[μm]	R_a[μm]	R_{max}[μm]
1.	3.6	0.15	0.5	1.373	9.321	1.358	9.255	1.105	0.708
2.	3.6	0.15	1.4	1.878	15.950	1.866	15.871	0.643	0.495
3.	3.6	0.12	0.84	1.236	8.413	1.244	8.291	0.643	1.451
4.	3.6	0.187	0.84	2.018	13.138	2.031	13.119	0.640	0.144
5.	3.0	0.15	0.84	2.379	17.754	2.291	17.689	3.841	0.366
6.	4.33	0.15	0.84	2.486	24.334	2.476	23.159	0.404	4.828
	Average deviation							1.213	1.332

In Fig. 3 showed the correlation between the experimental and expected values of surface roughness (R_a, R_{max}). From the diagram can be seen that the regression line is approximately in the direction of the angle of 45° degrees or regression factor for all three sizes is close to the number one (1).

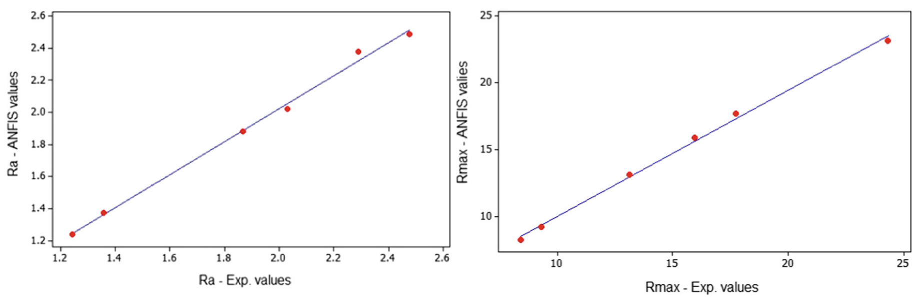

Fig. 3. Correlation between experimental and obtained values of roughness Ra and Rmax

5 Implementation of ANTS Algorithm

The term Ant Colony Optimization (ACO) is then introduced by Marco Dorigo [22], as a result of research on combinatorial optimization approaches. Initially, the algorithm applied to the problem of a commercial passenger and the problem of joining the quadrant. Since 1995 Dorigo and others have worked on various extended versions of the initial idea.

Ants have the ability to find the shortest path that leads from ants to a food source without the use of a visual sign. This ability of the ants is realized by leaving a certain amount of a chemical known as a pheromone by its movement along the ground. In addition, they have the ability to adapt to the new changes around them. For example, when they find the shortest path to a food source, in the event of a barrier on the road or in the concealment of the road, they find a new shortest path, Fig. 4.

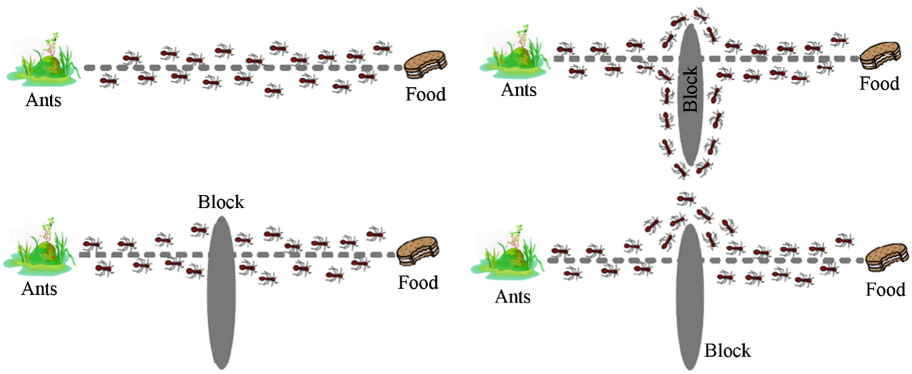

Fig. 4. Finding the shortest path on the road with an obstacle

The ants, although they are blind, can find the shortest path to the food source. This feature of ants is available to solve real problems using certain features and some supplements. Characteristics of ants created by artificial ant are:

- Communication between ants using the chemical pheromone.
- Preferred roads with a higher number of pheromones.
- Faster increase of pheromones on shorter paths than on longer ones.

Characteristics added to real ants:

- Live in an environment where time is calculated discreetly.
- They are completely blind and can access the details of the problem.
- I can retain information to solve a particular problem with a certain amount of memory.

The basic idea of algorithms based on an ant colony is that artificial intelligence agents, using a simple mechanism of communication, can produce solutions to many complex problems [22].

The way in which the algorithm functions is shown is a pseudocode, Table 5.

Table 5. Algorithm: pseudocode – ACO metaheuristic

```
PROCEDURE ACO metaheuristic
        Set parameters
            Initialize pheromone trails
                WHILE (termination condition not met)
                    Construct Ant solutions
                    Deamon actions
                    Update pheromones
                END WHILE
END PROCEDURE
```

The optimization is performed for the target function surface roughness parameters (R_a and R_{max}) minimum, based on the input parameters shown in Table 6 with limit values.

Table 6. Optimal values for R_A and R_{max}

Parameter	Minimal value	Maximal value
Speed v[m/s]	2.5	5.22
Feed f[mm/o]	0.096	0.234
Depth of cut a[mm]	0.3	2.34

The display of the optimization process is shown through the following images. Where are with card acor shown parameters of ant algorithm and problem definition. Until with card criterion are input parameters (v, f and a) with their limited values and input function (R_a and R_{max}) min defined. The results obtained by optimizing the cutting process using an ant algorithm are shown in the Fig. 5. Under the BestSol card, the obtained optimization results are displayed, as well as the value (R_a) min. The results of optimization of surface roughness parameters are shown in Table 7.

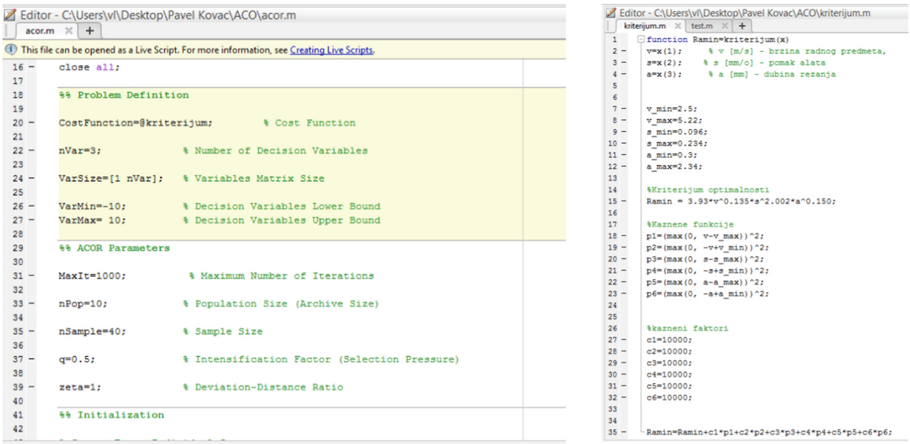

Fig. 5. Display of the optimization ANTS process

Table 7. The results of optimization of surface roughness parameters

Outputs		Input parameters		
Surface roughness parameters [µm]		v[m/s]	f[mm/rev]	a[mm]
R_a	0.440	2.500	0.096	0.300
R_{max}	3.28	2.500	0.096	0.300

6 Conclusion

Intelligent optimization techniques give the influence of cutting conditions on machining surface quality during turning medical steel difficult to machine, 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, which consist of the pertinent process parameters, for predicting the surface roughness parameters of workpiece. Diagrams on Fig. 3 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. Optimal values of surface roughness parameters were successfully determined by ant colony method.

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References

1. Chen, J.C., Savage, M.: A fuzzy-net-based multilevel in-process surface roughness recognition system in milling operations. Int. J. Adv. Manuf. Technol. **17**, 670–676 (2001)
2. Quintana, G., Garcia-Romeu, M.L., Ciurana, J.: Surface roughness monitoring application based on artificial neural networks for ball-end milling operations. J. Intell. Manuf. **22**, 607–617 (2009)
3. Sivarao, Castillo, Taufik: Machining quality predictions: comparative analysis of neural network and fuzzy logic. Int. J. Electr. Comput. Sci. IJECS **9**, 451–456 (2000)
4. Drégelyi-Kiss, Á., Horváth, R., Mikó, B.: Design of experiments (DOE) in investigation of cutting technologies, Development in Machining Technology DIM, Cracow, pp. 20–34 (2013)
5. Maňková, I., Vrabeľ, M., Beňo, J., Kovač, P., Gostimirovic, M.: Application of Taguchi method and surface response methodology to evaluate of mathematical models for chip deformation when drilling with coated and uncoated twist drills. Manuf. Technol. **13**(4), 492–499 (2013)
6. Hadi, Y., Ahmed, S.G.: Assessment of surface roughness model for turning process. In: Knowledge Enterprise: Intelligent Strategies in Product Design, Manufacturing, and Management. International Federation for Information Processing (IFIP), vol. 207, pp. 152–158 (2006)
7. Chen, C.C., Chiang, K.T., Chou, C.C., Liao, Y.C.: The use of D-optimal design for modeling and analyzing the vibration and surface roughness in the precision turning with a diamond cutting tool. Int. J. Adv. Manuf. Technol. **54**, 465–478 (2011)
8. Choudhary, A., Harding, J., Tiwari, M.: Data mining in manufacturing: A review based on the kind of knowledge. J. Intell. Manuf. **20**(5), 501–521 (2009)

9. Grzenda, M., Bustillo, A., Zawistowski, P.: A soft computing system using intelligent imputation strategies for roughness prediction in deep drilling. J. Intell. Manuf. **23**, 1733–1743 (2012)
10. Balic, J., Korosec, M.: Intelligent tool path generation for milling of free surfaces using neural networks. Int. J. Mach. Tools Manuf. **42**, 1171–1179 (2002)
11. Pérez, C.J.L.: Surface roughness modeling considering uncertainty in measurements. Int. J. Prod. Res. **40**(10), 2245–2268 (2002)
12. Azouzi, R., Gullot, M.: On-line prediction of surface finish and dimensional deviation in turning using neural network based sensor fusion. Int. J. Mach. Tools Manuf. **37**(9), 1201–1217 (1997)
13. Ho, S.Y., Lee, K.C., Chen, S.S., Ho, S.J.: Accurate modeling and prediction of surface roughness by computer vision in turning operations using an adaptive neuro-fuzzy inference system. Int. J. Mach. Tools Manuf. **42**(13), 1441–1446 (2002)
14. Zębala, W., Gawlik, J., Matras, A., Struzikiewicz, G., Ślusarczyk, Ł.: Research of surface finish during titanium alloy turning. Key Eng. Mater. **581**, 409–414 (2014)
15. Rajasekaran, T., Palanikumar, K., Vinayagam, B.K.: Application of fuzzy logic for modeling surface roughness in turning CFRP composites using CBN tool. Prod. Process. **5**(2), 191–199 (2011)
16. Savković, B., Kovač, P., Gerić, K., Sekulić, M., Rokosz, K.: Application of neural network for determination of cutting force changes versus instantaneous angle in face milling. J. Prod. Eng. **16**(2), 25–28 (2013)
17. Kundrák, J., Varga, G.: Use of coolants and lubricants in hard machining. Tech. Gaz. **20**(6), 1081–1086 (2013)
18. Kovac, P., Rodic, D., Pucovsky, V., Savkovic, B., Gostimirovic, M.: Application of fuzzy logic and regression analysis for modeling surface roughness in face milling. J. Intell. Manuf. **24**(4), 755–762 (2013)
19. Jang, J.S.R., Sun, C.T.: Neuro-fuzzy modeling and control. Proc. IEEE **83**, 378–406 (1995)
20. Ying, L.C., Pan, M.C.: Using adaptive network based fuzzy inference system to forecast regional electricity loads. Energy Conversat. Manag. **49**, 205–211 (2008)
21. Avci, E.: Comparison of wavelet families for texture classification by using wavelet packet entropy adaptive network based fuzzy inference system. Appl. Soft Comput. **8**, 225–231 (2008)
22. Dorigo, M., Maniezzo, V., Colorni, A.: Ant system: optimization by a colony of cooperating agents. IEEE Trans. Syst. Man Cybern. Part B Cybern. **26**(1), 29–41 (1996)