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ADVANCED MODELING OF SURFACE ROUGHNESS WITH ARTIFICIAL NEURAL NETWORK, TAGUCHI METHOD AND GENETIC ALGORITHM

POKROČILÉ MODELOVÁNÍ POVRCHOVÉ DRSNOSTI POMOCÍ NEURONOVÝCH SÍTÍ, TAGUCHIHO METODY A GENETICKÉHO ALGORITMU

Abstract

Modern manufacturing requires reliable and accurate models for the prediction of machining performance. Predicting surface roughness before actual machining plays a very important role in machining practice. This paper presents the modeling methodology for predicting the surface roughness in turning of unreinforced polyamide based on artificial neural networks (ANNs), Taguchi method and genetic algorithm (GA). The machining experiment was conducted based on Taguchi's experimental design using L_{27} orthogonal array. Input variables consisted of cutting speed, feed rate, depth of cut and tool nose radius, while surface roughness (R_a) was considered as output variable. To systematically identify optimum settings of ANN design and training parameters, Taguchi method was applied. Furthermore, a simple procedure based on GA for enhancing the ANN model prediction accuracy was applied. Statistically assessed as an accurate model, ANN model equation was graphically presented in the form of contour plots to study the effect of the cutting parameters on the surface roughness.

Abstrakt

Moderní výroba vyžaduje spolehlivé a přesné modely pro predikci výkonu zpracování. Předvídání drsnost povrchu před vlastním zpracováním hraje velmi důležitou roli v obráběcí praxi. Tato práce představuje modelovou metodiku pro odhad drsnosti povrchu při soustružení z prostého polyamidu na bázi umělé inteligence neuronových sítí (ANNs), Taguchiho metodě a genetických algoritmů (GA). Obráběcí experiment byl proveden na základě experimentálního Taguchiho návrhu pomocí L27 ortogonální pole. Vstupními proměnnými jsou řezná rychlost, posuv, hloubka řezu a poloměru břitu, zatímco drsnost povrchu (Ra) je považována za výstupní proměnnou. Pro systematickou identifikaci optimálního nastavení ANN návrhu a odborné přípravy parametrů byla použita metoda Taguchi. Dále byl použit jednoduchý postup, založený na GA pro zvýšení přesnosti modelu ANN predikce. Statisticky vyhodnocený přesný model ANN rovnice byl graficky prezentován ve formě obrysů pro studium vlivu řezných parametrů na drsnost povrchu.

1 INTRODUCTION

Among various machining processes, turning is one of the most fundamental and most applied metal removal operations in the industry. Surface roughness is an important measure of the technological quality of a turned part. Machined surface characteristics greatly affect functional attributes, overall performance of mechanical parts and production costs.

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Many investigations on surface roughness in turning of various metallic materials were carried out, but very few on soft materials such as polymers. Gaitonde et al. [2] developed second-order mathematical models for analyzing the influence of the cutting speed and feed rate on the machining force, cutting power, and specific cutting pressure during turning of unreinforced polyamide, and reinforced polyamide with 30% of glass fibers. In another work, Gaitonde et al. [3] analyzed the effects of the process parameters (work material, type of cutting tool, cutting speed, and feed rate) on the machinability characteristics (machining force, power and specific cutting force) during turning of unreinforced polyamide, and reinforced polyamide with 30% of glass fiber through artificial neural network (ANN) modeling. Marin [7] analyzed the effects of the cutting speed, feed rate, and depth of cut on the main cutting force in turning of PA 66 polyamide. Based on experiments, conducted according to Taguchi's L_{12} orthogonal array (OA) experimental plan, the regression equation for main cutting force was developed. Eriksen [1] examined the influence of the cutting parameters (feed rate, cutting speed and tool nose radius) and the fiber orientation on the surface roughness in turning of short fiber reinforced thermoplastic.

A prerequisite for achieving desired surface quality are accurate mathematical predictive models. To this aim, various methods are proposed, whereas empirical models using regression analysis and the artificial neural network (ANN) are one of the most used.

ANNs offer a number of attractive features which makes them one of the most popular nonlinear modeling methods applied in a variety of machining process analysis, modeling and optimization.

The efficiency of ANN based modeling depends highly on proper selection of ANN design and training parameters. With very limited practical guidelines which could be generally applied, until now, trial and error method has been the most prevailing. In order to take advantage of the full potential of ANNs for modeling, more effort should be spent on efficient network design [9]. Taguchi method [8] provides a systematic, efficient and easy-to-use optimization approach, therefore, it can be applied for selection of optimal ANN design and training parameters [5].

Another issue that needs attention is the analysis of developed ANN model and means to improve the ANN model performance in terms of accuracy, precision, and generalization capability [11]. To this aim, a simple procedure based on genetic algorithm (GA) for enhancing the ANN model performance was proposed.

In this paper, ANN model was developed for predicting the surface roughness in dry turning of polyamide in terms of cutting speed, feed rate, depth of cut and tool nose radius. For conducting the experiment, Taguchi's L_{27} OA was used where cutting parameters were arranged. ANN design and training procedure was optimized by using Taguchi method, and furthermore, the ANN model performance was enhanced using the GA. Finally, the contour plots were generated to study the effect of the cutting parameters on the surface roughness.

2 EXPERIMENTAL STUDY

The work material used in the study was unreinforced polyamide PA-6. The mechanical properties of the work material are: density = 1.14 g/cm^3, tensile strength = 80 N/mm^2, module of elasticity = 3200 N/mm^2, Charpy impact resistance > 3 KJ/m^2.

The longitudinal turning experiment was carried out in 100 mm length and 92 mm diameter workpiece on the universal lathe machine "Potisje PA-C30" (11 kW power, spindle speed range n = 20÷2000 rpm, and longitudinal feed rate range f = 0.04÷9.16 mm/rev) under dry conditions. The workpiece was fixed in the lathe with a three-jaw chuck. Cutting tool was SANDVIK Coromant tool holder SVJBR 3225P 16 with insert VCGX 16 04 08-AL (H10). The tool geometry was: rake angle γ = 7°, clearance angle α = 7°, cutting edge angle χ = 93°, and cutting edge inclination angle λ = 0°. Test sample was centered and cleaned by removing a 1 mm depth of cut (a_p) from the outside surface, prior to actual machining.

In the present study, four cutting parameters, namely, cutting speed (v), feed rate (f), depth of cut (a_p) and tool nose radius (r) were considered. Other parameters were kept constant for the scope of this research. The average surface roughness (R_a) was chosen as the target function.

Since it was obvious that the effects of the cutting parameters on the selected function were nonlinear, the experiment was set up with parameters at three levels. The cutting parameter ranges were chosen based on machining guidelines provided by tool manufacturer's recommendation, previous researches by Gaitonde et al. [2] and the possibility of mechanical system was also taken into account. The cutting parameters and their levels are illustrated in Table 1.

Tab. 1. Cutting parameters and levels.

Coded	Cutting parameter	Level 1	Level 2	Level 3
A	cutting speed, v (m/min)	65.03	115.61	213.88
B	feed rate, f (mm/rev)	0.049	0.098	0.196
C	depth of cut, a_p (mm)	1	2	4
D	tool nose radius, r (mm)	0.4	0.8	-

Based on the selected parameters and their levels, a design matrix was constructed in accordance with the standard L_{27} (3^{13}) Taguchi's OA (Table 2). Cutting parameters v, f and a_p were assigned to columns 1, 2 and 5, respectively. Cutting parameter r was assigned to column 12. As it had only two levels, the dummy-level technique [8] was used to reassign level 3 to level 1. This design provided uniform distribution of experimental points within the selected experimental hyper-space and the experiment with high resolution.

The cutting parameters in experiment were changed according to different cutting conditions for each trial. All of the trials were conducted on the same machine tool, with the same tool type and the same other cutting conditions. To consider system variations, a replicate number of two was considered.

The average surface roughness (R_a) of machined workpieces was measured using Surfrest SJ-301 (Mitutoyo) profilometer. The average surface roughness values shown in Table 2 are the arithmetical mean of two measurements. Trials were performed at random order to avoid systematic errors.

3 ARTIFICIAL NEURAL NETWORKS

3.1 Overview

Artificial neural networks (ANNs) are massive parallel systems made up of simple processing units (neurons) that are linked with weighted connections. A capability to learn from examples and to describe non-linear dependences is a big advantage of ANNs [4]. Among different types of ANNs, the feed-forward neural networks are the most used because of their simplicity and their capability of universal function approximation. The feed-forward ANN is a nonlinear mapping system composed of many interconnected neurons which are grouped into input, hidden, and output layers. The input neurons are used to feed the ANN with the input data. Through neurons interconnections each input data is processed with weights to be used in the hidden layer. With the transfer (activation) functions used in hidden and output layer, the nonlinear data processing is enabled. In feed-forward architecture, information processing is only in the forward direction, i.e. from input to output neurons. Accordingly, the functioning of a three-layer feed-forward ANN can be expressed as:

$$\hat{y}_k(X) = g\left(\sum_j w_{kj} \cdot f\left(\sum_i w_{ji} \cdot x_i + b_j\right) + b_k\right) \tag{1}$$

where:

$\hat{y}(X)$ – k-th computed ANN output (prediction) for the input $X=\{x_1,...,x_i\}$,
b_j and b_k – biases of the hidden and output neurons, respectively,
w_{kj} and w_{ji} – hidden to output and input to hidden neuron weights, respectively,
f and g – transfer functions of the hidden and output neurons, respectively.

The weights and biases are initially assigned to random continuous (real) values, and are determined during the ANN training process. The ANN training represents a process of adjusting weights and biases on the basis of comparing the output values with the desired (target) ones for the same input ones. Training is a continuous process, which is repeated until the ANN is stabilized or overall error is reduced below a previously defined threshold. The most common training algorithm for ANNs is the backpropagation (BP) algorithm and its variants. Generally, BP is a procedure which minimizes a squared error by back propagating the error from the output layer, through hidden layers(s), to the input layer.

Tab. 2. Taguchi's L_{27} OA as experimental plan and surface roughness results.

Trial no.	Coded cutting parameters				Actual cutting parameter values				Experimental results
	A	B	C	D	v	f	a_p	r	$\overline{R}_a$
					m/min	mm/rev	mm	mm	µm
1	1	1	1	1	65.03	0.049	1	0.4	1.035
2	1	1	2	2	65.03	0.049	2	0.8	0.905
3	**1**	**1**	**3**	**1**	**65.03**	**0.049**	**4**	**0.4**	**1.365**
4	1	2	1	1	65.03	0.098	1	0.4	1.450
5	1	2	2	1	65.03	0.098	2	0.4	1.725
6	1	2	3	2	65.03	0.098	4	0.8	1.880
7	**1**	**3**	**1**	**2**	**65.03**	**0.196**	**1**	**0.8**	**3.670**
8	1	3	2	1	65.03	0.196	2	0.4	3.400
9	1	3	3	1	65.03	0.196	4	0.4	3.560
10	2	1	1	2	115.61	0.049	1	0.8	1.220
11	2	1	2	1	115.61	0.049	2	0.4	1.025
12	2	1	3	1	115.61	0.049	4	0.4	1.170
13	2	2	1	1	115.61	0.098	1	0.4	1.360
14	2	2	2	2	115.61	0.098	2	0.8	1.345
15	2	2	3	1	115.61	0.098	4	0.4	1.705
16	**2**	**3**	**1**	**1**	**115.61**	**0.196**	**1**	**0.4**	**3.320**
17	2	3	2	1	115.61	0.196	2	0.4	3.400
18	2	3	3	2	115.61	0.196	4	0.8	5.885
19	**3**	**1**	**1**	**1**	**213.88**	**0.049**	**1**	**0.4**	**0.770**
20	3	1	2	1	213.88	0.049	2	0.4	1.100
21	3	1	3	2	213.88	0.049	4	0.8	1.405
22	3	2	1	2	213.88	0.098	1	0.8	1.480
23	3	2	2	1	213.88	0.098	2	0.4	1.345
24	**3**	**2**	**3**	**1**	**213.88**	**0.098**	**4**	**0.4**	**1.620**
25	3	3	1	1	213.88	0.196	1	0.4	3.215
26	3	3	2	2	213.88	0.196	2	0.8	5.235
27	3	3	3	1	213.88	0.196	4	0.4	3.530
Bolded rows represent data for testing the ANN model									

3.2 ANN design and training

Besides many advantages that ANNs offer, there are some drawbacks and limitations related to ANN design and training process. In order to develop an ANN which generalizes well and is robust, one has to take into consideration a number of issues, particularly related to ANN architecture and training parameters. The ANN parameters that largely affect the ANN model performance are illustrated in Figure 1.

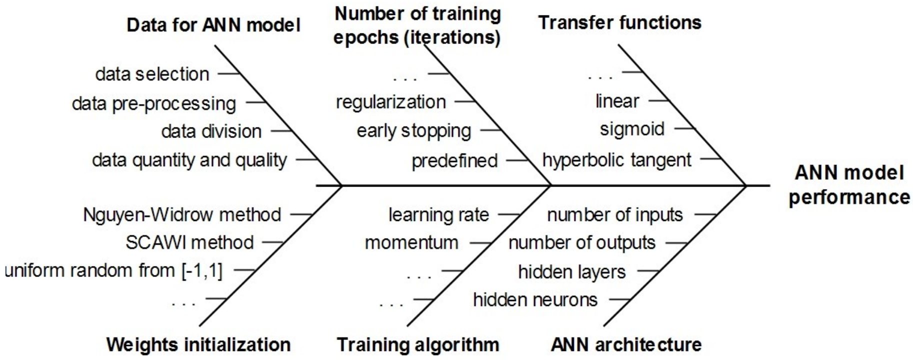


Fig. 1. Fishbone diagram for the ANN model performance.

The selection of ANN architecture followed by selection of training algorithm and related parameters is rather a matter of the designer past experience since there are no practical rules which could be generally applied. The experience, intuition and experiments are also important for the optimization of the neural network [4]. With very limited practical guidelines which could be generally applied, these parameters are typically determined in trial-and-error procedure. Pontes et al. [9] pointed to the fact that trial-and-error still remains the most frequent technique for ANN design selection. This is usually a very time consuming procedure where a number of ANNs are designed and compared to one another. Above all, the design of optimal ANN is not guaranteed. It is unrealistic to analyze all combination of ANN parameters and parameter's levels effects on the ANN performance. To deal economically with the many possible combinations, one can apply the Taguchi method [8]. Taguchi method provides a systematic, efficient and easy-to-use optimization approach [6], therefore it was applied for selection of optimal ANN design and training parameters. In such a way one can develop an ANN model of high performance in a systematic way with a relatively small and time-saving experiment, thereby avoiding the lengthy trial-and-error procedure [5].

4 TAGUCHI OPTIMIZED ANN MODEL

MATLAB software was used for development of thrANN model for average surface roughness (R_a) in terms of cutting parameters (v, f, a_p, r). The ANN architecture consisted of four input neurons, each to represent v, f, a_p and r, and one output neuron for estimating R_a (Figure 2).

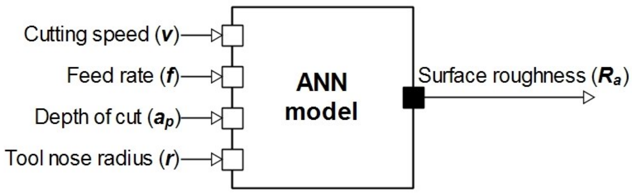


Fig. 2. Schematic ANN model for prediction of surface roughness.

It has been widely reported that ANNs with single hidden layer are able to approximate any arbitrary function to a given accuracy. Therefore, the selection of ANN architecture can be reduced to finding the "optimal" number of hidden neurons (N_h). The number of hidden neurons is data-dependent. The number of weights is equal to the sum of the product between the numbers of neurons in each layer. Therefore, the upper limit of number of hidden neurons is restricted by the number of available data for training.

Linear transfer function (*purelin*) and hyperbolic tangent sigmoid activation function (*tansig*) were used in the output and hidden layer, respectively.

Prior to ANN training, the initial values of weights were set according to Nguyen-Widrow method. In order to stabilize and enhance ANN training, the input and output data was normalized in [-1, 1] range using the following equation:

$$p_{norm} = 2 \cdot \frac{(p_i - p_{min})}{(p_{max} - p_{min})} - 1 \tag{2}$$

where:

p_{norm} and p_i – normalized and original (raw) i-th data,

p_{min} and p_{max} – minimum and maximum values of the original data.

In this study, the gradient descent with momentum algorithm was selected for ANN training. This algorithm has two main parameters that control the speed and convergence of the ANN. These are learning rate (α) and momentum (μ), and usually take values between 0 and 1 [10]. Training was terminated after a maximum number of epochs (10000) or when no further improvement in the mean squared error (MSE) was achieved.

In order to find the optimal architecture and training parameters so that an accurate and robust ANN model could be developed, the Taguchi method was applied.

The performance of each ANN model is evaluated using a proposed performance index (P_I):

$$P_I = \frac{MSE_{tr} + MSE_{ts}}{2} \tag{3}$$

where:

MSE_{tr} *and* MSE_{ts} – mean squared errors on training and testing, respectively.

Therefore, the ANN accuracy belongs to a smaller-the-better type problem. The corresponding objective function to be maximized is represented by the following equation:

$$\eta \equiv S/N = -10 log\left(\frac{1}{n}\sum_{i=1}^{n} y_i^2\right) \tag{4}$$

where:

η – signal-to-noise ratio (*S/N*) for ANN performance,

y_i – i-th observed value of the response,

n – number of observations in a trial.

The identified ANN architectural and training parameters and their corresponding levels were arranged in Taguchi L_9 orthogonal array. The nine ANN models were developed and trained, and the yielded results for P_I are given in Table 3.

Tab. 3. L_9 OA for ANN model optimization.

ANN model	N_h	α	μ	P_I	*S/N*
I	2	0.2	0.2	0.262647	11.6126
II	2	0.5	0.5	0.304664	10.3236
III	2	0.8	0.8	0.144282	16.8158
IV	3	0.2	0.5	0.140477	17.0479
V	**3**	**0.5**	**0.8**	**0.030092**	**30.4310**
VI	3	0.8	0.2	0.983889	0.1411
VII	4	0.2	0.8	0.528639	5.5368
VIII	4	0.5	0.2	0.337936	9.4233
IX	4	0.8	0.5	0.068556	23.2791

In order to find optimal levels for the ANN parameters, the S/N of each parameter was analyzed by using the analysis of means (ANOM). The ANOM is a statistical approach that is based on determining the mean *S/N* ratios for each design factor and each of its levels. For example, the mean *S/N* ratio of factor Q at level k can be calculated as:

$$\overline{\eta}_{Qk} = average(S/N)_{Qk} = \frac{1}{n_{Qk}} \sum_{l=1}^{n_{Qk}} \left[(S/N)_{Qk} \right]_l \qquad (5)$$

where:

n_{Qk} – number of appearances of factor Q at level k in Taguchi's OA,

$(S/N)_{Qk}$ – *S/N* ratio related to factor Q at level k.

The optimum level for a parameter is the level that gives the highest value of *S/N* in the experimental region [8]. The ANOM results are shown in Figure 3 from which the optimal ANN parameter levels can be identified.

ANN model having 3 neurons in the hidden layer, and trained with BP algorithm using learning rate α=0.5 and momentum μ=0.8, can be selected as the optimal ANN model. The optimal combination of ANN training and design parameters corresponds to the ANN model V, therefore, no confirmation model was developed. The proposed P_I of this ANN model is smaller compared to other models in Table 3. The Taguchi optimized ANN was trained at 10000 epochs yielding MSE of 8.679 10^{-4}.

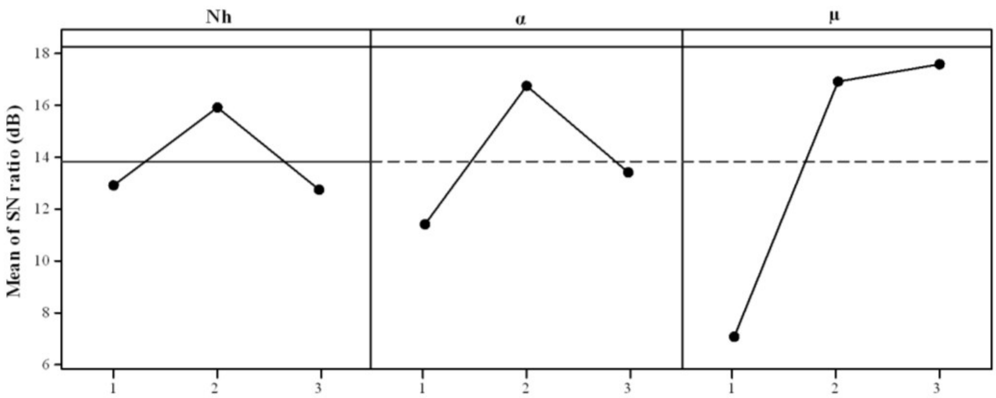


Fig. 3. ANOM for ANN design and training parameters.

Once the ANN is trained, the input to hidden neurons weights (w_{ji}) and hidden to output neuron weights (w_{kj}), as well as hidden neurons biases (b_j) and output neurons biases (b_k), are determined. The weights and the biases of the trained ANN are presented in Table 4.

Tab. 4. The weights and biases of the developed ANN model.

Weights, (w_{ji})				Weights, (w_{kj})	Biases	
					b_j	b_k
0.88088	-0.55173	-0.55173	-0.21819	0.58713	3.1142	-0.94984
-0.31591	-1.0143	-0.4633	0.92854	1.2256	1.0154	-
-0.18638	-1.0021	-0.35343	0.35219	-1.8575	0.52016	-

Regarding the architecture of the developed ANN, the used transfer functions, and by using the weights and biases from Table 4, the mathematical model for surface roughness can be expressed by the following equation:

$$R_{a|norm} = \left[\frac{2}{1+e^{-2\left(X \cdot w_{ji} + b_j\right)}} - 1 \right] \cdot w_{kj} + b_k \tag{6}$$

where:

X – column vector which contains normalized values of v, f, a_p, and r,

$R_{a|norm}$ – normalized value for the average surface roughness (R_a).

In order to obtain the actual values for the average surface roughness (R_a), one needs to perform denormalization by the following equation:

$$R_{a|actual} = \frac{1}{2} \cdot \left(R_{a|norm} + 1\right) \cdot \left(p_{max} - p_{min}\right) + p_{min} \tag{7}$$

5 ENHANCING ANN MODEL PREDICTION ACCURACY USING GA

Using Eqs. (6) and (7) the average surface roughness predicted values are calculated and are compared with experimental values in Figure 4.

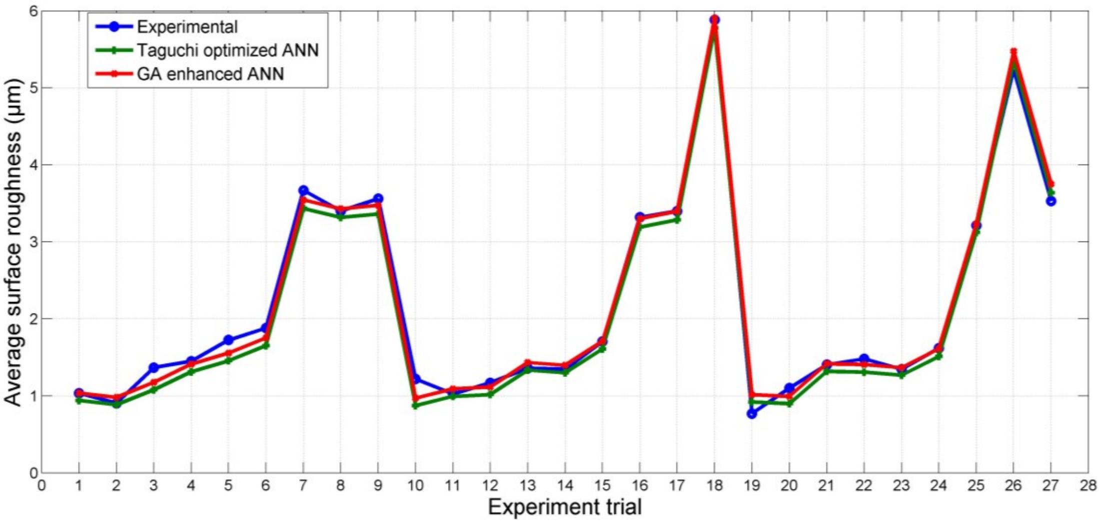


Fig. 4. Comparison between experimental values of surface roughness, Taguchi optimized and GA enhanced ANN model.

As it could be seen, in most cases, the ANN model underestimates the experimental values for surface roughness. In order to enhance the ANN model prediction accuracy, without ANN retraining, a simple method involving calculation of correction coefficients was applied. It is based on the assumption that the following relation exists between ANN model predictions and actual values for surface roughness:

$$R_{a|experimental} = x \cdot ANN_{predicted} + y \tag{8}$$

The correction coefficients x and y were determined by GA to minimize the following objective function:

$$E = \sum_{i=1}^{N} \left| e_i - ANN_i \right| \tag{9}$$

where:
N – number of data,
e_i and ANN_i – experimental value and ANN predicted value for surface roughness, respectively.

Using the Matlab optimization toolbox and by taking the default parameter settings for GA operators, the objective function optimum value converged to 2.32786, and at the same time the unknown correction coefficient values were obtained. Substituting the determined correction coefficients values in Eq. (6), the GA enhanced ANN prediction model was obtained as:

$$R_{a|enhanced} = 2.57342\left(\left[\frac{2}{1+e^{-2\left(X\cdot w_{ji}+b_j\right)}}-1\right]\cdot w_{kj}+b_k\right)+3.43867 \tag{10}$$

The correction coefficients were determined so there was no need to perform denormalization, hence Eq. 10 could be used solely for surface roughness calculation. Surface roughness predictions of ANN enhanced model are compared in Figure 4. As it can be seen, ANN predictions are in very good agreement with experimental values.

To test the validity of proposed approach the statistical method of absolute percent error (APE) was calculated as one of the most stringent criteria for assessing the accuracy of the mathematical model. Table 5 shows the comparison between Taguchi optimized ANN model and GA enhanced ANN model with experimental results.

Tab. 5. Comparison of the ANN models for surface roughness.

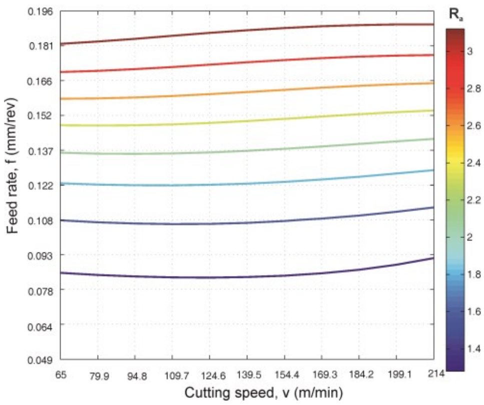
Model	APE		
	min	max	average
Taguchi optimized ANN	1.816	28.415	8.323
GA enhanced ANN	0.093	31.946	5.6

From Table 5, one can see that using the proposed approach prediction accuracy of the initial Taguchi optimized ANN model was improved for more than 30 % in terms of APE. Therefore, GA enhanced ANN model can be efficiently used for analyzing the effect of cutting parameters on the average surface roughness.

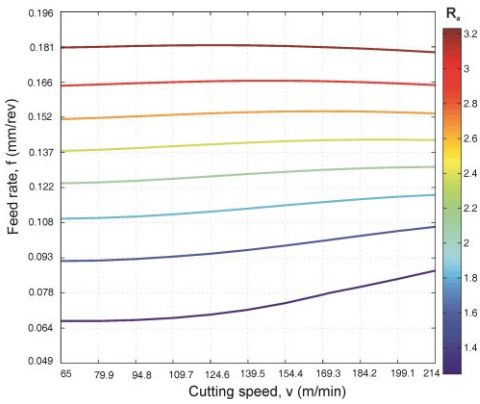
5 CONTOUR PLOTS

The influence of the cutting parameters on the average surface roughness can be studied using the GA enhanced ANN model. To this aim, Eq. 10 was plotted in Figure 5(a)–(f) as surface roughness contours (sections) for each of response surfaces at two selected levels of tool nose radius along with three constant depth of cuts.

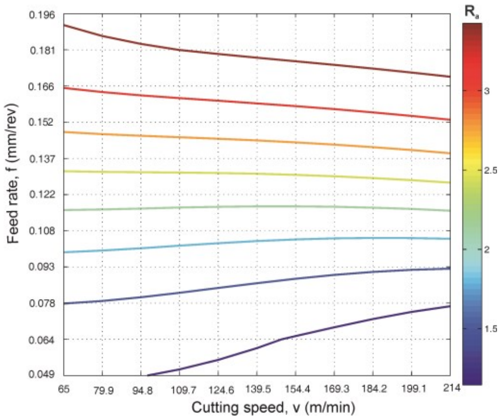
It can be seen from Figure 5 that the surface roughness decreases with an increase in the cutting speed, and increases as feed rate increases. It could be also observed that the surface roughness is directly proportional to the depth of cut. On the other hand, for a_p = 2 mm and a_p = 4 mm an increase in tool nose radius, increased surface roughness, whereas for a_p = 1 mm the influence of tool nose radius is negligible. Good surface roughness can be achieved when cutting speed and depth of cut are set nearer to their low level of the experimental range (65 m/min and 1 mm) and feed rate is at low level of the experimental range (0.049 mm/rev). From Figure 5 it is clear that there is no significant interaction between the cutting speed and feed rate.



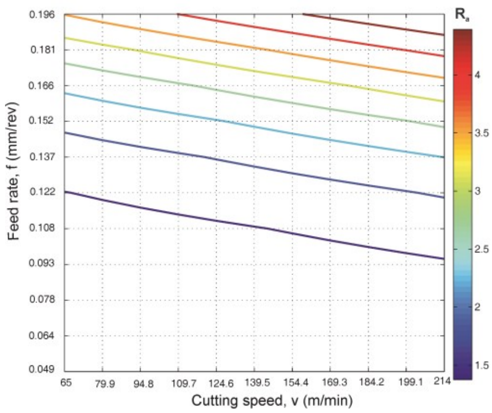
a) r= 0.4 mm, a_p = 1 mm



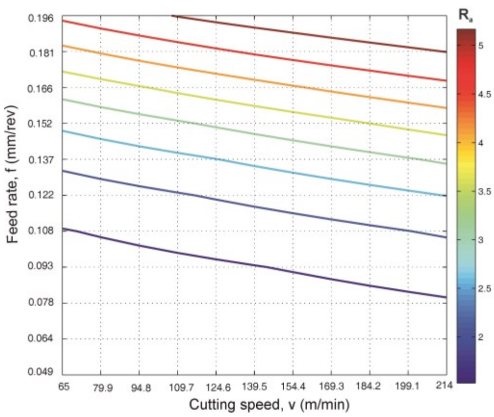
b) r= 0.8 mm, a_p = 1 mm



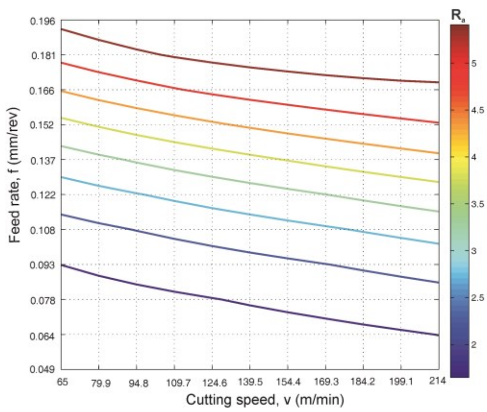
c) r= 0.4 mm, a_p = 2 mm



d) r= 0.8 mm, a_p = 2 mm



e) r= 0.4 mm, a_p = 4 mm



f) r= 0.8 mm, a_p = 4 mm

Fig. 5. Surface roughness contour in cutting speed and feed rate plane at different a_p and *r*.

It can be seen from Figure 5 that the surface roughness decreases with an increase in the cutting speed, and increases as feed rate increases. It could be also observed that the surface roughness is directly proportional to the depth of cut. On the other hand, for a_p = 2 mm and a_p = 4 mm an increase in tool nose radius, increased surface roughness, whereas for a_p = 1 mm the influence of tool nose radius is negligible. Good surface roughness can be achieved when cutting speed and depth of cut are set nearer to their low level of the experimental range (65 m/min and 1 mm) and feed rate is at low level of the experimental range (0.049 mm/rev). From Figure 5 it is clear that there is no significant interaction between the cutting speed and feed rate.

6 CONCLUSIONS

This paper presented empirical modeling of surface roughness based on artificial neural network (ANN) approach. Turning experiment was conducted according to Taguchi's experimental design and the obtained data was used for developing ANN surface roughness model in terms of cutting speed, feed rate, depth of cut, and tool nose radius. In order to optimize the selection of ANN design and training parameters, Taguchi method was applied. It was observed that performance of ANN dramatically changes with small changes in design and training parameters. Although determining architectural and training parameters of an ANN is complex, it was shown that Taguchi method is one of the appropriate methods for developing high performance ANN models. Furthermore, it was shown that the prediction accuracy of the developed ANN model can be enhanced using the simple procedure based on genetic algorithm.

Finally using the ANN surface roughness model, contour plots were generated from which one can select the cutting parameters for providing the desired surface roughness.

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