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Optimization of Surface Roughness When Turning Polyamide Using ANN-IHSA Approach

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Abstract

This study presents an approach by coupling artificial neural network (ANN) and improved harmony search algorithm (IHSA) to determine the optimum cutting parameter settings for minimizing surface roughness when turning of polyamide material. An ANN model surface roughness was developed in terms of cutting speed, feed rate, depth of cut, and tool nose radius using the data from the turning experiment conducted according to Taguchi's L_{27} orthogonal array. The optimal cutting parameter settings were determined by applying the IHSA to the developed ANN surface roughness model. The results show that the proposed optimization approach can be efficiently used for optimization of cutting parameter settings when turning polyamides. Although determining ANN and IHSA parameters is quite complex and problem dependent, it can be simplified by using Taguchi's experimental design as in this study.

Keywords: *artificial neural networks, improved harmony search algorithm, optimization, polyamides, turning*

1 Introduction

As a basic machining process, turning is one of the most widely used metal removal processes in industry. Surface roughness is an important measure of the technological quality of a turned part and a factor that influences machining cost. The mechanism behind the formation of surface roughness is very dynamic, complicated, and process dependent [1]. Surface roughness in turning process has been found to be influenced in varying amounts by a number of factors such as cutting parameters, cutting fluid, and workpiece hardness [2].

Many investigations on surface roughness of various metallic materials have been carried out but very few on soft materials such as polymers. The polymers require machining operations at the final assembly stage in order to get the finished components, even though they are produced as near net shapes [3]. Nevertheless, the knowledge regarding the machining of polyamides is limited. Hence the machining of polymers often presents challenges to engineers in terms of close tolerances, their unusual geometry, and softness, which means that it behaves differently as compared with conventional metal cutting [4]. Among various types of polymers, the polyamides have attracted a great deal of interest over the last few years. Modeling the correlation between cutting parameters and process parameters in machining of polyamides is of prime interest. Besides traditional empirical modeling using regression analysis (RA), the artificial neural network (ANN) based modeling is increasingly becoming popular.

To ensure the quality of machining products, and to reduce the machining costs and increase the machining effectiveness, it is very important to select the optimal machining parameters [5]. The selection of cutting tool and process parameters is very much essential in machining of polymers [6]. In machining practice, most of the time the optimal cutting conditions are determined using Taguchi method and by coupling empirical models based on RA and ANNs with different optimization algorithms.

This study was inspired by the very limited work on the application of ANNs in modeling the relationship between cutting parameters and surface roughness during turning of polyamide, as well as determining the optimal cutting conditions for minimizing surface roughness. The surface roughness model was developed in terms of cutting speed, feed rate, depth of cut, and tool nose radius using the data from the turning experiments conducted according to Taguchi's L_{27} orthogonal array (OA). The optimal cutting parameter settings were determined by applying the harmony search algorithm (HSA) [7] to the developed mathematical model of surface roughness based on ANN. The HSA has fewer parameters and is easier to implement than the widely used genetic algorithm. Successful applications of HSA to some optimization problems [7-8] have demonstrated its potential.

2 Experimental Procedure

The work material used in the study was unreinforced polyamide PA-6 (commercially DOCAMID 6E) produced by Quattroplast Ltd. (Hungary). The mechanical properties of the work material are given in Table 1. The longitudinal turning experiment was carried out in 100 *mm* length and 92 *mm* diameter workpiece on the universal lathe machine "Potisje PA-C30" with a 11 *kW* power, speed range n = 20÷2000 *rpm*, and longitudinal feed rate range f = 0.04÷9.16 *mm/rev*. Cutting tool was SANDVIK Coromant tool holder SVJBR 3225P 16 with inserts VCGX 16 04 04-AL (H10) and VCGX 16 04 08-AL (H10). The tool geometry was: rake angle γ = 7º, clearance angle α = 7º, cutting edge angle χ = 93º, and cutting edge inclination angle λ = 0º.

Table 1: Mechanical properties of PA-6 polyamide

Density, g/cm^3	1.14
Tensile strength, N/mm^2	80
Module of elasticity, N/mm^2	3200
Charpy impact resistance, KJ/m^2	>3
Hardness (Shore D), N/mm^2	82

In the study, the average surface roughness (R_a) was considered. The machined surface was measured at three equally spaced positions around the circumference of the workpiece using the surface profilometer Surftest Mitutoyo SJ-301.
To develop mathematical model based on ANN that relates the cutting parameters and average surface roughness (R_a), a plan of experiment is needed. The classical design of experiment (DOE) is sometimes too complex, time consuming and not easy to use [9]. Hence, in the present investigation, the Taguchi's DOE [10] was applied.
Four cutting parameters, namely, cutting speed (V), feed rate (f), depth of cut (a), and tool nose radius (r) were considered. The cutting parameter ranges were selected based on preliminary investigations and previous research by Gaitonde et al. [11]. The cutting parameters were arranged in standard Taguchi's L_{27} (3^{13}) OA. Cutting parameters V, f and a 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 [10] was used to reassign level 1 to level 3. The plan of experiment layout to obtain average surface roughness (R_a) is shown in Table 2. Experiment trials were performed at random order to avoid systematic errors.

3 Artificial Neural Networks: An Overview

Artificial neural networks (ANNs) originally developed to mimic basic biological neural systems, are parallel-distributed architectures with a large number of neurons and connections [12]. An ANN has a multilayered architecture where neurons are grouped into three layers i.e. input, hidden, and output layer. The j-th hidden neuron receives an activation signal which is the weighted sum from the neurons in the input layer:

$$h_j = \sum_i w_{ji} \cdot x_i + b_j \tag{1}$$

Table 2: Mechanical properties of PA-6 polyamide

Trial no.	Cutting parameter levels				Actual cutting parameter values				Experimental results		
	V	f	a	r	V	f	a	r	R_a		$\bar{R}_a$
					m/min	mm/rev	mm	mm	µm		µm
1	1	1	1	1	65.03	0.049	1	0.4	1	1.07	1.035
2	1	1	2	2	65.03	0.049	2	0.8	0.95	0.86	0.905
3	**1**	**1**	**3**	**1**	**65.03**	**0.049**	**4**	**0.4**	**1.31**	**1.42**	**1.365**
4	1	2	1	1	65.03	0.098	1	0.4	1.39	1.51	1.450
5	1	2	2	1	65.03	0.098	2	0.4	2.05	1.4	1.725
6	1	2	3	2	65.03	0.098	4	0.8	2.09	1.67	1.880
7	**1**	**3**	**1**	**2**	**65.03**	**0.196**	**1**	**0.8**	**3.78**	**3.56**	**3.670**
8	1	3	2	1	65.03	0.196	2	0.4	3.46	3.34	3.400
9	1	3	3	1	65.03	0.196	4	0.4	3.61	3.51	3.560
10	**2**	**1**	**1**	**2**	**115.61**	**0.049**	**1**	**0.8**	**1.04**	**1.4**	**1.220**
11	2	1	2	1	115.61	0.049	2	0.4	1.04	1.01	1.025
12	2	1	3	1	115.61	0.049	4	0.4	1.22	1.12	1.170
13	**2**	**2**	**1**	**1**	**115.61**	**0.098**	**1**	**0.4**	**1.43**	**1.29**	**1.360**
14	2	2	2	2	115.61	0.098	2	0.8	1.25	1.44	1.345
15	2	2	3	1	115.61	0.098	4	0.4	1.78	1.63	1.705
16	**2**	**3**	**1**	**1**	**115.61**	**0.196**	**1**	**0.4**	**3.41**	**3.23**	**3.320**
17	2	3	2	1	115.61	0.196	2	0.4	3.41	3.39	3.400
18	2	3	3	2	115.61	0.196	4	0.8	6.03	5.74	5.885
19	**3**	**1**	**1**	**1**	**213.88**	**0.049**	**1**	**0.4**	**0.85**	**0.69**	**0.770**
20	3	1	2	1	213.88	0.049	2	0.4	1.04	1.16	1.100
21	3	1	3	2	213.88	0.049	4	0.8	1.45	1.36	1.405
22	3	2	1	2	213.88	0.098	1	0.8	1.37	1.59	1.480
23	3	2	2	1	213.88	0.098	2	0.4	1.24	1.45	1.345
24	**3**	**2**	**3**	**1**	**213.88**	**0.098**	**4**	**0.4**	**1.7**	**1.54**	**1.620**
25	3	3	1	1	213.88	0.196	1	0.4	3.33	3.1	3.215
26	3	3	2	2	213.88	0.196	2	0.8	5.53	4.94	5.235
27	3	3	3	1	213.88	0.196	4	0.4	3.61	3.45	3.530

where w_{ji} is input to hidden neurons weights, b_j biases (thresholds) of hidden neurons, and i and j are the number of input and hidden neurons, respectively. This sum is then passed through an activation function (f) to produce the neurons output (H_j). The activation function in the hidden layer is most commonly a sigmoid function whose general form is given as:

$$H_j = f(h_j) = \frac{1}{1 + e^{-h_j}} \tag{2}$$

Finally, the output neurons receive the following signals from the hidden neurons:

$$y_k = \sum_j w_{kj} \cdot H_j + b_k \tag{3}$$

where w_{kj} are the weights of the connection between hidden and output neurons, and b_k biases of output neurons. These activation signals can be transformed again, using the sigmoid transfer function to give the outputs of the ANN. However, for prediction, it is sufficient to use the linear activation function (identity) for output neurons. The ANN output is then as in Eq. (3) which are predicted values for the given inputs. Accordingly, the functioning of a three-layer feed-forward ANN, can be expressed as:

$$\hat{y}(X) = \left(\sum_j w_{kj} \cdot f\left(\sum_i w_{ji} \cdot x_i + b_j \right) + b_k \right) \tag{4}$$

where $\hat{y}$ is the ANN estimated output (prediction) for the input $X=\{x_1 ,..., x_i\}$. The weights and biases are initially assigned to random continuous (real) values, and are determined during ANN training. 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.

4 ANN Model for Surface Roughness

4.1 ANN design and training

The experimental data in Table 2 were taken for ANN model development. The entire data were randomly divided into a data for ANN training (N_{tr} = 40), and data for testing model performance (N_{ts} = 14, bolded rows in Table 2). In order to stabilize and enhance ANN training the input and output data was normalized between -1 and 1.

MATLAB software was used for ANN modeling of average surface roughness (R_a) in terms of cutting parameters (V, f, a, r). The quality of the developed ANN model is highly dependable on training process and ANN architecture.

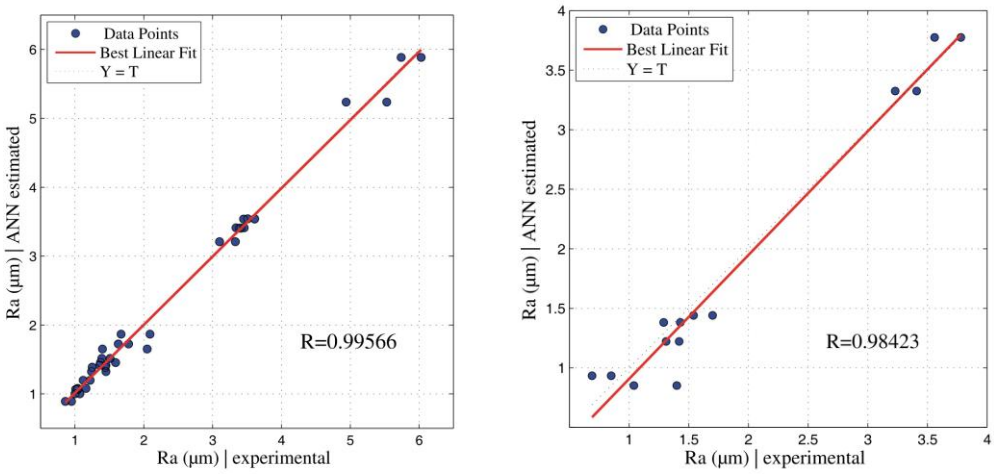
In this study, the gradient descent with momentum [13] algorithm was selected for ANN training. Learning rate η and momentum μ are two parameters which control the speed and stability of the training algorithm, and usually take values between 0 and 1 [14].

Specifying ANN architecture requires determining the number of neurons in input, output and hidden layers, and the choice of activation functions in hidden and output layers. The number of input neurons was set to four to represent four cutting parameters (V, f, a, r), while there was one output neuron for estimating the R_a. It has been widely reported that ANNs with a single hidden layer are able to approximate any arbitrary function to a given accuracy. Therefore, the choice of ANN architecture can be reduced to selection of the “optimal” number of neurons in the hidden layer. Linear transfer function (*purelin*) and hyperbolic tangent sigmoid activation function (*tansig*) were used in the output and hidden layer, respectively.

Using the Taguchi method [10] optimal ANN architecture, 4-4-1 was developed so that the ANN model was successfully trained after 5000 epochs with optimal settings of training algorithm parameters [15].

4.2 ANN testing

The performance capability of the developed ANN model for estimating the R_a was examined based on the correlation coefficient between the ANN predictions and the experimental values using the training and testing data (Fig. 2).



(a) (b)

Fig. 2. Comparison of ANN estimations with experimental values: (a) for training data set (b) for testing data set

It can be seen that ANN predictions are in good agreement with the experimental results. Therefore the ANN model can be used to perform reliable estimation of average surface roughness (R_a), and furthermore can be used as an objective function for optimization purpose.

5 Optimization Methodology

Over the last decades, a large number of methods and algorithms have been developed to solve various engineering optimization problems. Traditional optimization methods and algorithm include mathematical iterative search methods, regression analysis, response surface methods and Taguchi method. These optimization methods provide a useful strategy to get the global solution [16]. However, many engineering optimization problems are very complicated in nature and quite difficult to solve using these methods. In recent years, meta-heuristics algorithm such as genetic algorithm, simulated annealing, tabu search, particle swarm optimization, have been increasingly used by many researches.

HSA, developed by Geem et al. [7] in 2001, was conceptualized using the musical process of searching for a perfect state of harmony. The HSA is simple in concept, few in parameters, and easy in implementation [8], and has several advantages over other meta-heuristic algorithms [7].

Optimizations procedure of the HSA includes five steps [7, 17]: (1) initialize the parameters of optimization; (2) initialize the harmony memory (HM); (3) improvise a new harmony from the HM; (4) update the HM; (5) repeat steps 3 and 4 until the termination criterion is satisfied.

Step 1. *Parameters initialization*. In this step, the optimization problem is specified as follows:

$$\begin{aligned}&\textit{Minimize } f(x)\\&\textit{subject to}: x_i \in X_i,\ i = 1,2,\ldots,N.\end{aligned} \tag{5}$$

where *f(x)* is the objective function, x_i is the set of each design variable, X_i is the set of the possible range of values for each design variable, that is $X_i = \{x_i(1), x_i(2), \ldots, x_i(K)\}$, N is the number of design variables and K is the number of candidate values for the discrete decision variables. The HSA parameters are also specified in this step: harmony memory size (HMS), harmony memory considering rate (HMCR), pitch adjusting rate (PAR), and the number of improvisations (maximal number of searches). These algorithm parameters are explained in the following steps.

Step 2. *Initialize the HM*. In this step, the HM matrix, as shown in Eq. (6), is filled with randomly generated solution vectors and sorted by the values of the objective function *f(x)*.

$$HM = \begin{bmatrix} x_1^1 & x_2^1 & \cdots & x_N^1 \\ x_1^2 & x_2^2 & \cdots & x_N^2 \\ \vdots & \vdots & & \vdots \\ x_1^{HMS} & x_2^{HMS} & \cdots & x_N^{HMS} \end{bmatrix} \tag{6}$$

Step 3. *Improvise a new harmony from the HM*. In this step, a new harmony vector $x' = x_1', x_2', \ldots, x_N'$ is improvised by following three rules: HM consideration, pitch adjustment and random selection. As a musician plays any pitch out of the preferred pitches in his/her memory, the value of decision variable is chosen from any pitches stored in HM ({ $x_i^1, x_i^2, \ldots, x_i^{HMS}$ }) with a probability of HMCR (0 ≤ HMCR ≤ 1) while it is randomly chosen with a probability of (1-HMCR) in random selection process as:

$$x_i' \leftarrow \begin{Bmatrix} x_i' \in \{x_i^1, x_i^2, \ldots x_i^{HMS}\} & w.p.\ HMCR \times PAR \\ x_i' \in X_i & w.p.\ HMCR \times (1 - PAR) \end{Bmatrix} \tag{7}$$

In the pitch adjusting process when one pitch is obtained in HM consideration, a musician can further adjust the pitch to neighboring pitches with a probability of HMCR x PAR (0 ≤ PAR ≤ 1) while the original pitch obtained in HM consideration is just kept with a probability of HMCR x (1-PAR) as:

$$x_i' \leftarrow \begin{Bmatrix} x_i(k+m) & w.p.\ HMCR \times PAR \\ x_i' & w.p.\ HMCR \times (1 - PAR) \end{Bmatrix} \tag{8}$$

where x_i' obtained in HM consideration and $x_i(k)$ (the k-th element in X_i) are identical, m ($m \in$ {..., - 2, -1, 1, 2, ...}) is a neighboring index used for discrete decision variables.

Step 4. *Update the HM*. In this step, if the new harmony vector $x' = x_1', x_2', \ldots, x_N'$ is better than the worst harmony in the HM in terms of the objective function value, the new harmony is included in the HM and the existing worst harmony is excluded from the HM. The HM is then sorted by the objective function value.

Step 5. *Repeat steps 3 and 4 until the termination criterion is satisfied*. This is the final step where the computations are terminated when the termination criterion is satisfied. Otherwise, steps 3 and 4 are repeated.

Mahdavi et al. proposed an improved HSA (IHSA) [18] that employs a novel method generating new solution vectors with enhanced accuracy and convergence speed. In this paper IHSA was selected for solving the optimization problem.

5.1 Optimization Problem Formulation

The main goal of the present study is to determine the optimal cutting parameters settings that minimize the average surface roughness (R_a). In turning of polyamide PA-6, the optimization problem can be defined as:

$$\textit{Objective}: \textit{Minimize}\ R_a(V, f, a, r) \tag{9a}$$

subject to permisable range of cuting parameters:

$$65.03 \le V \le 213.88\ (\text{m/min}) \tag{9b}$$

$$0.049 \le f \le 0.196\ (\text{mm/rev}) \tag{9c}$$

$$1 \le a \le 4\ (mm) \tag{9d}$$

$$r = \{0.4, 0.8\}\ (\text{mm}) \tag{9e}$$

For calculating R_a in Eq. (9) the mathematical function based on developed ANN in preceding section was employed.

5.2 Optimization Results

The optimization problem in Eq. 9 was solved with IHSA written in MATLAB. The following IHSA parameters were used: HMS = 50, HMCR = 0.9, PAR = 0.35, number of improvisations = 5.000. As discussed in [19], Taguchi experimental design method was applied to assist in determining the IHSA parameter values. The obtained optimization results are given in Table 3.

Table 3: Optimization result and comparison

Optimal cutting parameter settings				R_a (µm)	$\bar{R}_a$ (µm)
V (m/min)	f (mm/rev)	a (mm)	r (mm)	ANN+IHSA	Experiment
65.03	0.049	1	0.8	0.6507	0.7274

To verify the optimization result, one needs to perform the experiment under the optimal cutting conditions. Since the optimal combination of cutting parameters was not included in the OA (Table 2), the verification test was conducted. The comparison of optimal value obtained by IHSA with experimental value is given in Table 3. From the obtained result, it is clear that IHSA can find optimum solution with high accuracy and efficiency. Small differences between prediction and experimental result arise from mathematical simplifications applied when developing ANN model.

6 Conclusions

This paper discussed the application of artificial neural network and improved harmony search algorithm for optimization of surface roughness when turning of polyamide. Experiment trials were performed according to Taguchi's experimental design method and the obtained data were used for developing ANN model for average surface roughness in terms of cutting speed, feed rate, depth of cut, and tool nose radius. The developed model was the used as an objective function in harmony search algorithm, and the optimum cutting parameter settings yielding minimum average surface roughness were obtained. The optimization results were then experimentally validated. The proposed approach indicates that ANNs can be efficiently used for mathematical modeling, whereas IHSA can be utilized effectively to find the optimum cutting parameter settings. Although determining ANN and IHSA parameters is quite complex and problem dependent, it can be simplified by using Taguchi's experimental design as in this study.

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