Research Journal of Applied Sciences, Engineering and Technology 7(14): 2908-2913, 2014
DOI:10.19026/rjaset.7.620
ISSN: 2040-7459; e-ISSN: 2040-7467

Submitted: May 16, 2013 Accepted: October 19, 2013 Published: April 12, 2014

Research Article

Prediction and Optimization Approaches for Modeling and Selection of Optimum Machining Parameters in CNC down Milling Operation

[1, 3]Asaad A. Abdullah, [1]Caihua Xiong, [1]Xiaojian Zhang, [1]Zhuang Kejia and [2]Nasseer K. Bachache
[1]School of Mechanical Science and Engineering,
[2]College of Electrical and Electronic Engineering, Huazhong University of Science and Technology, Wuhan, Hubei 430074, China
[3]Department of Material Engineering, College of Engineering, University of Basrah, Basrah, Iraq

Abstract: In this study, we suggested intelligent approach to predict and optimize the cutting parameters when down milling of 45# steel material with cutting tool PTHK- (Ø10*20C*10D*75L) -4F-1.0R under dry condition. The experiments were performed statistically according to four factors with three levels in Taguchi experimental design method. Adaptive Neuro-fuzzy inference system is utilized to establish the relationship between the inputs and output parameter exploiting the Taguchi orthogonal array L27. The Particle Swarm Optimized-Adaptive Neuro-Fuzzy Inference System (PSOANFIS) is suggested to select the best cutting parameters providing the lower surface through from the experimental data using ANFIS models to predict objective functions. The PSOANFIS optimization approach that improves the surface quality from 0.212 to 0.202, as well as the cutting time is also reduced from 7.5 to 4.78 sec according to machining parameters before and after optimization process. From these results, it can be readily achieved that the advanced study is trusted and suitable for solving other problems encountered in metal cutting operations and the same surface roughness.

Keywords: ANFIS, down milling process, Particle Swarm Optimization (PSO), surface roughness

INTRODUCTION

Milling is processed for removal of unwanted material from the work-pieces using the rotating cutting tool, to reach a specified dimension and to produce a smooth finish on the part. This process aims at minimizing of the led time and improves product quality in conventional manufacturing.

In the last years, the surface roughness modeling in cutting operations has received considerable attention by researchers. Several authors used neural network, fuzzy logic, Response Surface Methodology (RSM) and Taguchi design Method (TM) to develop the analytical and empirical models. These techniques were used to predict the response-cutting variable and determine the optimal process parametric conditions. Adaptive Neuro-Fuzzy Inference System (ANFIS) is used in the recent years by several researchers to develop the predication the response of various applications (Tsourveloudis, 2010; Fischer and Kwon, 2002; Dweiri *et al*., 2003; Dong and Wang, 2011; Abburi and Dixit, 2006). Artificial Neural Network (ANN) is developed for estimation the surface Roughness (Ra) models in milling process of various materials in terms of cutting parameters as input and the surface roughness as output (Yazdi and Chavoshi, 2010; Sharma *et al*., 2008; Nalbant *et al*., 2009; Chavoshi and Tajdari, 2010; Aykut *et al*., 2007). Saglam *et al*. (2007) studied the employing of the Taguchi approach for the effect of cutting tool geometries (rake angle and entering angle) and cutting speed on cutting force components and the temperature generated at the tool tip in turning of AISI 1040 steel. Bhattacharya *et al*. (2009) investigated the influence of cutting parameters on the surface finish and power consumption using Taguchi design and analysis of variance. Ding *et al*. (2010) investigated the influence of cutting parameters on cutting forces and surface roughness, established the empirical model to estimate cutting forces and surface roughness and selected the optimal cutting parameters for minimal cutting forces and surface roughness in hard milling of AISI H13 steel.

Hwang *et al*. (2009) studied the effect of machine tools, cooling lubrication environments and machining parameters on the surface roughness and cutting force and select combination of machining parameters led to minimize the effect of machine tool variables on the dispersion of cutting force and surface roughness utilizing Taguchi method. Asiltürk and Akkuş (2011) utilized the ANOVA and Taguchi approach for

Corresponding Author: Caihua Xiong, School of Mechanical Science and Engineering, Huazhong University of Science and Technology, Wuhan, Hubei 430074, China, Tel.: + 86-27-8755 7843; Fax: + 86-27-8755 7843

obtaining effects of cutting parameters on the surface roughness and optimum cutting parameters, respectively. They machined hardened AISI 4140 (51 HRC) with coated carbide cutting tools. Experiments have been conducted using the L9 orthogonal array in a CNC turning machine. Moshat *et al*. (2010) used Taguchi method to determine optimum cutting parameters for providing a good surface finish as well as a high Material Removal Rate (MRR). Liu (2012) used Particle Swarm Optimization (PSO) for estimation of the unknown heat flux on the inner surface of a crystal tube from the knowledge of temperature measurements determined at the outer surface. Venkata and Pawar (2010) investigated the optimal machining parameters of multi-pass milling operations for minimization of total production time with the constraints of arbor strength, arbor deflection and cutting power employing non-traditional optimization algorithms. Yildiz (2013) established a novel hybrid differential evolution algorithm to solve optimization problems for the selection of optimal machining parameters in milling operations. Hsieh and Chu (2013) considered Advanced Particle Swarm Optimization (APSO) and Fully Informed Particle Swarm optimization (FIPS) algorithms for optimization of tool path planning in 5-axis flank milling of ruled surfaces with machining error as an objective.

In the current study, the PSO and Adaptive Neuro-Fuzzy Inference System (ANFIS) were hybridized to optimize cutting parameters for down milling process. Taguchi's design approach was applied to refine the set of design parameters. After completing the experimental test according to Taguchi's orthogonal array L27, the experimental data used to training the ANFIS model. Meanwhile, another experimental data employed to testing ANFIS model. ANFIS used to establish the relationship between the cutting parameters and surface roughness. Meanwhile, the Particle Swarm Optimization (PSO) employed to determine the best combination of the cutting parameters.

Particle Swarm Optimization (PSO): Essentially the Particle swarm optimization PSO algorithm is identified thru understanding the analogy of birds flock or bee swarm during their search for foods. Particle swarm optimization has introduced and discussed in the numerous researches (Robinson and Rahmat, 2004). Following briefly defined within the PSO environment:

- Create initiation particles
- Evaluate the fitness of each particle
- Update individual and global best fitness's and positions as Eq. (1):

$$v_{k+1}^{i} = v_{k}^{i} + c_1 r_1 \left(p_{k}^{i} - x_{k}^{i}\right) + c_2 r_2 \left(p_{k}^{g} - x_{k}^{i}\right) \tag{1}$$

where,
x_k^i = Particle position

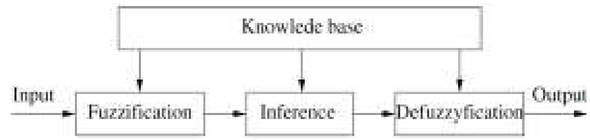

Fig. 1: Shows the construction of FIS

v_k^i = Particle velocity
p_k^i = Best "remembered" individual particle position
p_k^g = Best "remembered" swarm position
c_1, c_2 = Cognitive and social parameters
r_1, r_2 = Random numbers between 0 and 1

- Update velocity and position of each particle. The position of individual particles updated as Eq. (2), repeat step 2:

$$x_{k+1}^{i} = x_{k}^{i} + v_{k+1}^{i} \tag{2}$$

Adaptive Neuro-Fuzzy Inference System (ANFIS): This acquaintance has two parts:

Fuzzy inference system: The fuzzy inference system is considered the following stages as shown in Fig. 1:

- Fuzzification comprises the input characteristics (input membership functions)
- Knowledge Base (KB) encompasses the rules of Input membership function, which characterized the decision maker of output characteristic functions
- Defuzzyfication calculate a single-valued for output

Learning and inference: Model learning and inference through ANFIS are trailing the subsequent points:

- The parameters can be adjusted automatically depending on the data of the model.
- Suppose the data already have a collection of input/output and would like to build a fuzzy inference model/system approximate that data.
- This model would consist of a number of membership functions and rules with adjustable parameters similarly to that of neural networks.
- Rather than choosing the parameters associated with a given membership function arbitrarily, these parameters could be chosen as fitting of input/output membership functions in order to account the types of variations in the data values.
- The Neuro-adaptive learning techniques are afford a method for the fuzzy modeling procedure to learn information about a data set, in order to compute the membership function parameters, which allows the associated fuzzy inference system to track the given input/output data effectively.

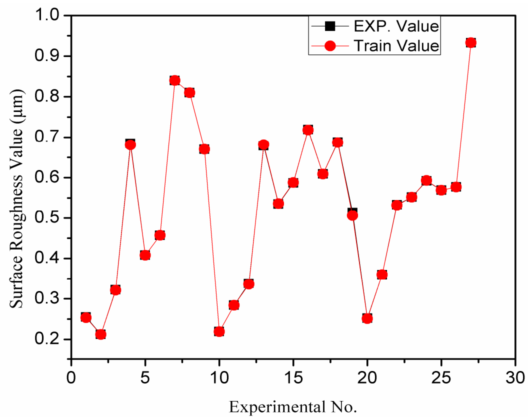

Fig. 2: Comparison between the experimental results with the prediction of Ra values at training stage

Table 1: Range of cutting parameters

Cutting parameter	Level 1	Level 2	Level 3
Cutting speed Sp (rev/min)	4000	6000	8000
Feed rate fe (mm)	0.05	0.09	0.12
Cutting depth dp (mm)	3.50	4	4.50
Axial feed rate ae (mm)	0.50	1	1.50

Table 2: Experimental results based on the Taguchi orthogonal array L27

No.	Sp	fe	dp	ae	V*fe*Z	Ra
1	4000	0.05	3.5	0.50	800	0.255
2	4000	0.05	4.0	1.00	800	0.212
3	4000	0.05	4.5	1.50	800	0.322
4	4000	0.09	3.5	0.50	1440	0.685
5	4000	0.09	4.0	1.00	1440	0.408
6	4000	0.09	4.5	1.50	1440	0.457
7	4000	0.12	3.5	0.50	1920	0.840
8	4000	0.12	4.0	1.00	1920	0.810
9	4000	0.12	4.5	1.50	1920	0.670
10	6000	0.05	3.5	1.00	1200	0.219
11	6000	0.05	4.0	1.50	1200	0.284
12	6000	0.05	4.5	0.50	1200	0.338
13	6000	0.09	3.5	1.00	2160	0.679
14	6000	0.09	4.0	1.50	2160	0.535
15	6000	0.09	4.5	0.50	2160	0.587
16	6000	0.12	3.5	1.00	2880	0.719
17	6000	0.12	4.0	1.50	2880	0.609
18	6000	0.12	4.5	0.50	2880	0.688
19	8000	0.05	3.5	1.50	1600	0.514
20	8000	0.05	4.0	0.50	1600	0.252
21	8000	0.05	4.5	1.00	1600	0.360
22	8000	0.09	3.5	1.50	2880	0.533
23	8000	0.09	4.0	0.50	2880	0.552
24	8000	0.09	4.5	1.00	2880	0.592
25	8000	0.12	3.5	1.50	3840	0.569
26	8000	0.12	4.0	0.50	3840	0.577
27	8000	0.12	4.5	1.00	3840	0.933

Finally, a toolbox function ANFIS can be used for a given input/output data set, this toolbox constructs of a Fuzzy Inference System (FIS) whose membership function parameters are tuned (adjusted) using either a back-propagation algorithm alone, or combined with a least squares method.

Investigation of the experimental data: The present experimental research, 45# steel block as shown in Fig. 2 was milled in the Micron UCP 800 5-axis Computer Numerical Control (CNC) milling machine having a maximum spindle speed of 20000 RPM and a maximum power of 15 kW by cutting tool PTHK-(Ø10*20C*10D*75L) -4F-1.0R under dry conditions. The experimental parameters are listed in Table 1, the ranges of the cutting parameters were selected according to a machine milling practice. Work-piece surface roughness are measured by utilizing a portable surface roughness tester (Mitatoyu Surftest 301).

Experimental data determined from the down milled surface are shown in Table 2. The table results included 27 groups of data according to Taguchi orthogonal array L27 from three level Taguchi experimental methods for four machining parameters. From Table 3, the seventh column represented the surface roughness values. These data are used in the training of adaptive neural-fuzzy inference system model and optimization operation. Also from the table, it was cleared that the surface roughness values do not follow a consistent frequency at the difference of the parameter value sets.

ANFIS models for surface roughness: In single objective optimization, there is a need for a mathematical model that represents objective functions in terms of machining conditions. The objective functions in this research are established by employing Adaptive Neuro-Fuzzy Inference system (ANFI). ANFIS models serve as predictive models. The best adaptive Neuro-fuzzy inference system architectures employed in this research is designed utilizing MATLAB ANFIS Toolbox.

The experimental data were determined to create the prediction model based on the ANFIS and to optimize the machining variable during down milling process of 45# steel work-piece. Twenty-seven Ra values measured from experiments were carried out from the work-piece by utilizing cutting parameters according to Taguchi orthogonal array L27. The 27 Ra experimental values were used to train the ANFIS models. Training process conducted for (3 4 2 2) Gausses membership function with maximum iterations of 50 epochs until they were getting the best performance. Meanwhile, another five experimental data for Ra values were utilized to test the trained ANFIS in 'MATLAB' Toolbox.

Optimization problem solution: During the down milling operation, the aim of the optimization process is to appropriate selection of the machining parameters to improve the product quality and reduced process cost. In this study, the optimal machining parameters in a

Table 3: Best machining parameters combination after optimization process

PSOANFIS	Machining parameters: Sp (rev/min)	fe (mm)	dp (mm)	ae (mm)	Surface roughness Ra (μm)
Best combination	5808.7	0.054	3.77	0.54	0.202

certain range in Table 1 are identified by employing an optimization technique. For this purpose, it was suggested the using of the hybrid optimization method. Which consist of ANFIS models as objective functions and particle swarm optimization method for selecting the optimum cutting parameters leading to minimum surface roughness. Because the down milling process of a complex nature, objectives that are surface roughness and machining time are usually in conflict with each other. The cutting time was determined by taking advantage of the machining parameters as well as the best combinations of cutting parameters before and after optimization process based on an analytical formula in Eq. 4, respectively.

The current optimization problem is accorded as follows:
Select cutting parameters:

$$Sp, ae, de, a$$

To minimize:

$$Ra$$

Range of cutting parameters.
Subject to cutting parameters:

$$\begin{aligned} &4000 \le Sp \le 8000 \\ &0.05(mm) \le fe \le 0.15(mm) \\ &3.5(mm) \le de \le 4.5(mm) \\ &0.5(mm) \le ar \le 1.5(mm) \end{aligned} \tag{3}$$

$$Tc = \frac{S}{fe * Sp * z} \tag{4}$$

where, Tc is the cutting time (sec), Sp is cutting speed (rev/min), fe is the feed rate per tooth (mm/tooth), z is the number of tooth and S is cutting distance (mm). Before optimization process, according to experimental result the minimum Ra value of (0.212 μm) the cutting speed (4000 rev/min), feed rate (0.05), cutting depth (4 mm), radial feed rate (1 mm) and cutting time (7.5 sec) was determined by application of the Eq. (5). After optimization process, the cutting time was calculated by utilizing the best combinations of machining parameters (cutting speed (5808.7 rev/min), feed rate (0.054), cutting depth (3.77 mm), radial feed rate (0.54 mm)) leading to minimum Ra value of 0.204 μm determined by PSO program.
Before optimization process:

$$Tc1 = \frac{100}{800} * 60 = 7.5 Sec$$

After optimization process:

$$Tc2 = \frac{100}{1254.67} * 60 = 4.78 Sec$$

As a result of cutting time values of $Tc1$ and $Tc2$, the percentage of reduction can be determined as follow:

$$Time\ Reduction = \frac{Tc1 - Tc2}{Tc1} * 100 \tag{5}$$

$$Time\ Reduction = 37.3\%$$

RESULTS AND DISCUSSION

The experimental data were determined to create the prediction model based on the ANFIS and to optimize the machining variable during down milling process of 45# steel work-piece. Twenty seven Ra values measured from experiments were carried out from the work-piece by utilizing cutting parameters according to Taguchi orthogonal array L27. Figure 2 illustrates the relationship between the training data (27 Ra values measured from experiments) and those that predicted from the ANFIS model. On the other hand, from Fig. 2, it can also be inferred that an excellent match between the experiment and the prediction results. The ANFIS model has Root Mean Square Error (RMSE) of 0.0019189 in the training stage.

Meanwhile, another five experimental data for Ra values were utilized to test the trained ANFIS in 'MATLAB' Toolbox. Figure 3 indicates a comparison between measured and predicted values area during the test phase. In Fig. 3, it can be conclude that there is a good agreement between the measured and predicted of Ra values. Whereas, Table 4, illustrates the results determined from the testing of the predicted ANFIS models. It can be seen from this table that the RMSE is 0.050978.

To solve the optimization problems stated in Eq. (3) PSO that combined with the ANFIS models was developed to determine the optimum machining parameters combinations to lead the lower surface roughness with high prediction efficiency as well as computational time. The optimum machining

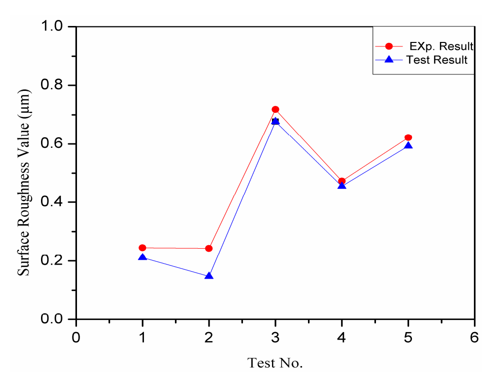

Fig. 3: Comparison between the experimental results with the prediction of Ra values at testing stage

Table 4: The Ra value resulted from the testing of the trained ANFIS

Cutting parameters					
Sp	fe	dp	ae	Exp. res. of Ra	Predict res. of Ra
5000	0.05	3.5	1.00	0.245	0.211
7000	0.05	3.5	0.50	0.243	0.147
6000	0.10	3.5	0.75	0.718	0.677
7500	0.09	3.5	0.50	0.473	0.455
8000	0.10	4.5	1.00	0.622	0.593

parameters combinations determined by PSO technique for the lower surface roughness is indicated in Table 3. From Table 3, it is to say that the PSO reduces surface roughness value, which is reduced in the experimental measurements, from 0.212 to 0.202 μm by approximately 4.7% improvement. By application the machining parameters that obtained with and without optimization operation, cutting time fell from 7.5 to 4.78 sec by about 37.3% saving time.

CONCLUSION

The following conclusions can be extraction based on the results refereed from the prediction model and optimization approach. The experiments were statistically performed according to four factors with three levels in Taguchi experimental design method. The AFIS model was trained and tested to establish the prediction model for surface Roughness (Ra). An effective model of the PSO adapted with the ANFIS was utilized to obtain the best combinations of machining parameters while leading the minimum surface roughness:

- ANFIS has been employed to predict the surface roughness based on four machining parameters as input variable. Results of Ra predicted the ANFIS model were very agreement with that of the experimental results for training and testing steps.
- PSO combined with the tested ANFIS model were used to determine the optimum combinations of machining parameter for producing the best surface quality. From optimization approach results, it can be achieved by improves the Ra value, from 0.212 to 0.202 μm, by about 4.7%.
- The cutting time was dropped about 37.3% reduction. Consequently, this result, it can be concluded that the machining time decreased as well as improved the surface quality due to increase in the table feed rate and cutting speed.
- As a result, the suggested optimization method is effective and sufficient to establish the better solutions of optimization problems in down milling process.

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