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Prediction of Surface Roughness by Hybrid Artificial Neural Network and Evolutionary Algorithms in End Milling

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Machining processes such as end milling are the main steps of production which have major effect on the quality and cost of products. Surface roughness is one of the considerable factors that production managers tend to implement in their decisions. In this study, an artificial neural network is proposed to minimize the surface roughness by tuning the conditions of machining process such as cutting speed, feed rate and depth of cut. The proposed network is tested by many test problems of Ghani et al.[1] study and the weights of network are optimized by using three meta-heuristics, genetic algorithm (GA), imperialist competitive algorithm (ICA). The results show the efficiency and accuracy of the proposed network.

Keywords: End milling, Genetic algorithm, Imperialist competitive algorithm, Surface roughness, Artificial neural network

1 Introduction

Machining processes such as end milling are the main steps of production which have major effect on the quality and cost of products. In recent decades, many studies have been made to evaluate the quality of the machined parts such as surface roughness. Some of them considered the optimization of parameters of cutting problem and many researches were done on the prediction of parameters setting. Ghani et al. [1] applied the Taguchi methodology for tuning of the parameters of end milling operation. The prediction of surface roughness is a function of many variables like cutting speed, depth of cut, step over ratio and etc. In such situation, because the surface roughness estimation is a complex function of like cutting speed, depth of cut, step over ratio and other variables. The setting of these controllable parameters or variables for minimizing roughness of surface is an NP-hard problem. Artificial neural network as an intelligent tool has been extensively studied to find the optimum levels by many researchers. Shiuh et al. [2] proposed two different kinds of neural networks for online determination of optimal cutting conditions. Suk-Hwan and Yang-Soo [3] formulated the rough cut tool path planning problem into a travelling sales man problem that the powerful neural network method can be effectively applied. Benardos and Vosniakos [4] presented a feed forward neural network model for the prediction of surface roughness. They considered the depth of cut, the feed rate per tooth, the cutting speed, the engagement and

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wear of the cutting tool and etc. data as control factors. Oktem et al. [5] determined the best cutting parameters leading to surface roughness in end milling by coupling neural network and genetic algorithm. Tandon et al. [6] proposed a new evolutionary computation technique, particle swarm optimization (PSO), to optimize multiple machining parameters. In another study, Zuperl et al. [7] applied a neural adaptive control strategy to the problem of cutting force control in high speed end milling operations. It is designed to adaptively maximize the feed rate subject to allowable cutting force on the tool. Song et al. [8] studied the signals of cutting force in end milling by using multilayer perceptron and self-organizing feature map. In a novel study, Lebbal et al,[9] developed a new technique of optimization for dry machining refractory titanium alloys. They considered two objective functions which the first function measures the volume of material removal produced during the cutting tool life and the second function evaluates the surface roughness.
In comparison with the previous works, most of the studies considered some known factors as shown in table (1). According to table (1), it is clear that, cutting speed, feed rate and depth of cut are the most common factors applied for end milling setting. On the other hand, the performance of end milling processes mostly is measured by many criteria which a detail of them is listed in table (2). According to table (2) surface roughness is one of the critical issues that researchers are mentioned.

In this study, an artificial neural network (ANN) is implemented to set the parameters of end milling process which the roughness of surface is minimized. The proposed model consists of factors that are implemented by Ghani et a1. [1]. Many problems are applied by proposed ANN and are compared by Taguchi method.

2 The proposed artificial neural network

In recent decades, because of increasing the competition and the complexity of systems, the optimization decision will be necessary for managers. On other hand, the objectives of systems are nonlinear functions of decision variables as controllable inputs. Artificial neural networks (ANN) as an intelligent tools are computational models of nervous systems which are applied for prediction of relations between inputs and outputs of systems.

Table 1 Important factors of end milling

Factor	References
Feed rate	[10, 11,12]
Speed of cut	[10, 11]
Depth of cut	[10,11, 12]
Step over	[11]
Machining tolerance	[5]
Inclination angles	[12]

Table 2 Performance criteria of end milling

Output	References
Surface roughness	[5]
Dimensional quality	[12]
Friction coefficient	[12]
Tool Wear	[12]

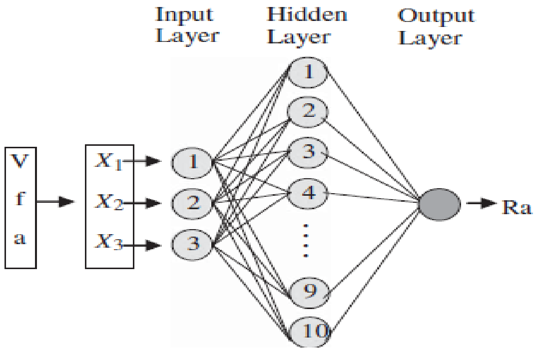

Figure 1 The ANN structure used in this

2.1 Neural network architecture

The proposed ANN consists of an input layer, two hidden layers and an output layer as shown in Figure (1) the input layer represents the cutting speed, feed rate and depth of cut and the output layer represents the surface roughness. A hidden layer is tested by three to ten neurons which the best is found by four neurons and a logistic sigmoid (logsig) transfer function has been used for these neurons. The pure line transfer function is defined for output layer.

2.2 Training

One of the most popular learning algorithms is the back-propagation algorithm which the mean square error (MSE) function is used by relation (1) to minimize the sum of square of errors:

(1)

where *N* is the number of training samples, y_i is the desired output of *ith* sample and $\overline{y_i}$ is the network output for the *ith* sample. In this work, supervised learning, in which the network is presented with inputs along with the target outputs together with adjusted weighting, are employed. The training samples are gained from the research is done by Ghani et al [1].
Relation (1) updates the weights of network and because of the complexity of this function will be increased by increasing the number of inputs and layers.
Evolutionary algorithm is one of the hybrid type solutions which combines the human interaction and machine calculation and solves the complicated problems. Hence, two type of meta-heuristics based genetic algorithm (GA) and imperialist competitive algorithm (ICA) are applied to estimate the optimal weights of network.

2.3 Evolutionary learning
2.3.1 Hybrid GA-ANN

General genetic algorithms (GAs) are a bio-inspired optimization method that was first used by Holland. In this method, a population of strings that called chromosome, which encode candidate solutions to an optimization problem, evolves toward better solutions. The GA method also was used to solve a lot of scheduling problems. In this work, the weights of neurons are formed as a matrix and are updated based on genetic operators.

$$\begin{bmatrix} w_{11} & w_{1i} & w_{16} \\ w_{21} & w_{2i} & w_{26} \\ .w_{31} & w_{3i} & w_{36} \\ & . & \\ & . & \end{bmatrix}$$

Figure 2 Presentation of solution

2.3.1.1. Chromosome encoding

Each solution of weights is presented in form of a matrix. Figure (2) shows a typical solution which w_{ij} indicates the weight of *ith* input and *jth* neuron.

2.3.1.2 Genetic operators

In this study after generation of population, the cross over operator will be applied on each solution based on cross rate (c_r).Figure (3) shows this operator.

2.3.1.3. Mutation operators

In this step, for each solution after cross over is mutated with m_r rate. For this reason a random number between 1 and the last column number will produced and the values of the selected column will be changed randomly. Figure (4) shows a typical of this operator.

0.7	0.4	0.5	0.6	0.2	0.9
0.8	0.6	0.3	0.3	0.1	0.6

0.6	0.4	0.5	0.7	0.2	0.9
0.3	0.6	0.3	0.8	0.1	0.6

Figure 3 Cross over operator

0.7	0.4	0.5	0.6	0.2	0.9
0.8	0.6	0.3	0.3	0.1	0.6

0.7	0.4	0.5	0.1	0.2	0.9
0.8	0.6	0.3	0.9	0.1	0.6

Figure 4 Mutation operator

2.3.2. Hybrid ICA-ANN

ICA is one of the newest methods in Meta-heuristic field that was suggested and developed by Atashpaz and Lucas [13]. This method is based on human social and political behavior. Similar to GA, the ICA is a population based algorithm and the population is consisted of some countries which are classified in two categories: imperialists and colonies. Imperialist is a country that rules a number of countries which are called colonies. In other word the policies, culture, religion and other social measurements of a colony is delineated by the imperialist in power.
After producing initial population randomly, at first step each country must be specified to either imperialist or colony. The counties have several attributes including culture, language, religion, economic policy; etc and are shown by vector F:

$$F= [f1, f2\ldots f_N] \tag{2}$$

In which f_i indicates *i'th* attribute of a country.

Next, the fitness value of countries will be calculated and those with lowest cost are determined as imperialists and other countries will be considered as colonies.

3 Experimental design

In this section, the many test problems which are applied by Ghani [1] are tested by three proposed ANN. The first network weights are updated by gradient method, the second by GA and the last by ICA. The result is reported in table (3).

4 Discussion and Analysis

In the defined problem, three techniques of data analysis have been used for predicting the roughness of surface. All proposed techniques are designed based on ANN, the first technique used traditional ANN, in the second technique ANN is mixed by GA and in third technique ANN is mixed by ICA. As shown in figure (5), the efficiency of ANN-GA outperformed the other algorithms. Therefore the ANN-GA algorithm can predict the best setting of parameters for minimizing the roughness of surface.

Table 3 Comparison of proposed algorithms

Test Problem	Network	Network-GA	Network-ICA
1	0.613	0.594	0.635
2	0.690	0.575	0.618
3	0.542	0.581	0.592
4	0.886	0.511	0.625
5	0.764	0.483	0.618
6	0.641	0.487	0.532
7	0.507	0.558	0.596
8	0.753	0.515	0.659
9	0.836	0.581	0.586
10	0.558	0.518	0.666
MSE	0.127	0.098	0.107

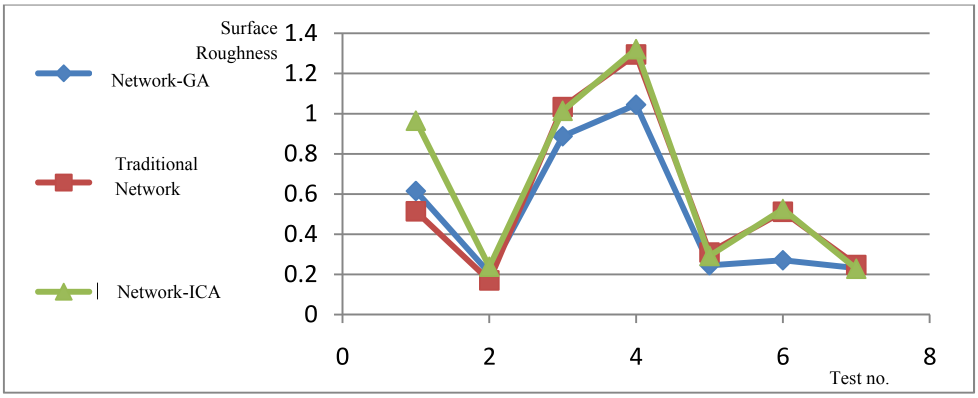

Figure 5 Comparison of proposed algorithms

On the other hand, it seems to be necessary the benchmark of proposed ANN-GA. For this reason, the results of ANN-GA are compared by results achieved by Taguchi method which proposed by Ghani et al.[1]. This comparison is shown in table (4). According to Ghani's study for each test problem three factors A, B and C which represent cutting speed, feed rate and depth of cut are considered as controllable variable. The best combinations of these factors are searched by all algorithms to minimize surface roughness. It is noticeable that the Taguchi method satisfies more objectives than surface roughness but the value of surface roughness of Taguchi is valuable for measuring the efficiency of the proposed algorithms. The results are listed in table (4).

Base on the table (4), the Gap shows the relative difference between the values obtained by Taguchi and ANN-GA. The results show that ANN-GA obtains better values than Taguchi except problems 10 and 11. In these exception values the difference is least. Hence, it is inferable that the ANN-GA outperformed all algorithms.

Table 4 Surface Roughness Values of proposed algorithms

Problem No.	Factor			Taguchi	ANN	ANN-GA	ANN-ICA	Gap %
	A	B	C					
1	224	0.1	0.3	0.207	0.1682	0.164342	0.1664	25.95685
2	224	0.16	0.5	0.169	0.1698	0.168999	0.174	0.000592
3	224	0.25	0.8	0.513	0.512	0.509123	0.514	0.761506
4	280	0.1	0.3	0.245	0.247	0.240872	0.248	1.713773
5	280	0.16	0.5	0.252	0.255	0.247866	0.249	1.667837
6	224	0.16	0.8	0.448	0.45	0.408610	0.445	9.639999
7	224	0.25	0.3	0.418	0.42	0.417787	0.419	0.050983
8	280	0.1	0.5	0.203	0.21	0.187229	0.188	8.423375
9	280	0.16	0.8	0.671	0.674	0.670063	0.68	0.139838
10	280	0.25	0.3	0.234	0.263	0.258912	0.2634	-9.621802
11	224	0.25	0.5	0.872	0.892	0.893044	0.895	-2.356435
12	280	0.1	0.8	1.424	1.35	1.383108	1.384	2.95653
13	280	0.16	0.3	0.872	0.876	0.872760	0.878	0.08708
14	280	0.25	0.5	0.888	0.889	0.884839	0.8885	0.35724
15	355	0.1	0.8	1.392	1.398	1.391317	1.396	0.04909

5 Conclusion

In this study, the operation of end milling is investigated. The depth of cut, speed and feed rate as effective parameters are considered on this machining operation and the level of roughness. This parameters are tuned by Taguchi method and an ANN is designed two predict the value of roughness. The ANN network is hybridized by two meta-heuristics algorithms and the results show that the ANN hybridized with GA gives better MSE.

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چکیده

عملیات های ماشینکاری مانند فرزکاری یکی از گام های مهم تولید می باشد که بر روی هزینه و کیفیت محصولات موثر هستند. در این راستا زبری سطح یکی از فاکتورهای قابل توجه می باشد که مدیران تولید علاقمند به کنترل آن می باشند. در این تحقیق یک شبکه عصبی مصنوعی برای حداقل نمودن زبری سطح با تنظیم شرایط عملیات ماشین کاری نظیر سرعت باربرداری، نرخ باربرداری و عمق برش پیشنهاد شده است. شبکه پیشنهادی با مسائل نمونه تحقیق قانی [1] مورد آزمایش قرار گرفته و اوزان با الگوریتم های ژنتیک و رقابت استعماری تنظیم شدند. نتایج نشان دهنده کارایی شبکه پیشنهادی می باشد.