Optimum Surface Roughness Prediction in Face Milling of High Silicon Stainless Steel

M. Farahnakian, M.R. Razfar, and S. Elhami-Joosheghan

Abstract—This paper presents an approach for the determination of the optimal cutting parameters (spindle speed, feed rate, depth of cut and engagement) leading to minimum surface roughness in face milling of high silicon stainless steel by coupling neural network (NN) and Electromagnetism-like Algorithm (EM). In this regard, the advantages of statistical experimental design technique, experimental measurements, artificial neural network, and Electromagnetism-like optimization method are exploited in an integrated manner. To this end, numerous experiments on this stainless steel were conducted to obtain surface roughness values.

A predictive model for surface roughness is created by using a back propogation neural network, then the optimization problem was solved by using EM optimization. Additional experiments were performed to validate optimum surface roughness value predicted by EM algorithm. It is clearly seen that a good agreement is observed between the predicted values by EM coupled with feed forward neural network and experimental measurements.

The obtained results show that the EM algorithm coupled with back propogation neural network is an efficient and accurate method in approaching the global minimum of surface roughness in face milling.

Keywords—cutting parameters, face milling, surface roughness, artificial neural network, Electromagnetism-like algorithm,

I. INTRODUCTION

HUMAN operators can select optimal operating conditions after they learn the characteristics of a system through trial and error. But in modern industry the goal is to manufacture low cost, high quality products in short time. Automated and flexible manufacturing systems are employed for that purpose along with CNC machines that are capable of achieving high accuracy and very low processing time. Therefore, it is beneficial to have a computer program that is capable of learning the complex characteristics of the system from experimental data and selecting the optimal conditions.A number of studies have been carried out to estimate optimal surface roughness. Sağlam and ¨Un¨ uvar [1] Used an artificial neural network model for future selection in order to estimate the flank wear of tool and surface roughness during face milling depending on cutting speed, feed rate, depth of cut, feed force and vertical force.

[2] did research to obtain optimal cutting parameters such as cutting speed, feed per tooth, and cutting depth for surface roughness in down face milling operations by using duplex (ferritic/austenitic) stainless steel and carbon steel compositions.

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Topal et al. [3] proposed an ANN model for predicting the surface roughness from machining parameters such as cutting speed, feed rate, and depth of cut in milling of AISI 1040 steel. Dhokia et al. [4] developed a model based on neural network for prediction surface roughness behavior of the surface roughness for machined polypropylene products. Onwubolu [5] presented a hybrid modeling approach, based on the group method of data handling and the differential evolution population-based algorithm, for modeling and predicting surface roughness in turning operations. Most of the time, it is very difficult to find the related analytical or empirical expressions and proper coefficients to calculate the optimal cutting conditions for the considered material and tool. Recently analytical and empirical models have been developed by using neural network and response surface methodology in order to calculate surface roughness for several materials [6-8]. Also the neural network model coupled with the GA is proposed to determine the optimal machining for surface roughness [9-11].
Electromagnetism-like algorithm (EM) is a population-based meta-heuristic method for solving optimization problems. Experimental results show that EM algorithm is capable of finding good solution. Experimental results show that EM algorithm is capable of finding good solution [12].
A meta-heuristic algorithm, based on electromagnetism-like mechanism (EM), has been successfully implemented in a few combinatorial problems. Debels et al. used a meta-heuristic algorithm capable of providing near-optimal heuristic solutions to solve the resource-constrained project scheduling problem, for relatively large instances [13].
In this study, an ANN model based on experimental data was developed to predict surface roughness in face milling. The factors considered in the experiment were cutting speed, feed per tooth, depth of cut, and engagement. The developed ANN model includes more cutting parameters, which are more effective on surface roughness, than those in the literature. EM algorithm was used to find optimum cutting parameters leading to minimum surface roughness.

II. EXPERIMENTAL PROCEDURE AND DATA COLLECTION

A. Material

Durcomet 5 is a cast austenitic stainless steel containing a significant amount of silicon (see Table I). The unusual composition of this alloy imparts excellent corrosion resistance to very strongly oxidizing environments, such as concentrated nitric acid. In addition to its notable corrosion resistance, Durcomet 5 possesses mechanical properties superior to the 18-8 stainless steels. Durcomet 5 will find use in very strongly oxidizing services like hot, concentrated resistance nitric acid, concentrated sulfuric acid, and chromic acid [14].

TABLE I
CHEMICAL AND MECHANICAL PROPERTIES OF DURCOMET5

Cr (%)	N (%)	Si (%)	C (%)	Mn (%)	S (%)	P (%)
19.75 -22	15-17	4 - 6	0.025 max	1.5 max	0.04 max	0.04 max

Yield strength (MPa)		Tensile strength (MPa)		Elongation (%)		Hardness (Brinel)
275		620		30		175

B. Tool and Machine tool

The experiments were performed in a Vertical milling machine (Tabriz co.) with a maximum spindle speed of 2500 rpm and 630 mm/min maximum feed rate. The machine had a 4.4 KW spindle motor. The actual machining operation is illustrated in Fig. 1.

Fig. 1 actual machining operation

Cutting experiments were carried out in a block of Durcomet 5 with dimensions of 235 mm (length)×120 mm (width) ×20 mm (height). The ranges of cutting parameters were selected based on recommendation of SANDVIK Tools Catalogue as listed in Table II [15]. The diameter of cutter was 60 mm with three inserts. The cutter inserts were from SANDVIK designated as type ISO-TPMR 16 03 12 and the holder type was R220.17-0063-22 from SECO Company.

TABLE II
RANG OF CUTTING PARAMETERS AND FACTOR LEVEL

Level	Feedrate fz (mm/tooth)	Depth of cut ap (mm)	Spindle speed (rpm)	Engagement ae (%)
Low	0.033	0.4	250	30
Medium	0.066	0.8	315	60
High	0.13	1.2	500	100

C. Surface roughness measurement

Surtronic3+ was used in the experimental work to measure surface roughness. The tools measure surface roughness with probes, measure, and control in appropriate length and circumferences. To do this, three small regions on the machined surface are determined for measurements. Measurements in these regions are conducted and the average value is recorded as the Ra. The tracing velocity and the cut-off lengths were fixed at 0.5 mm/sec and 2.5 mm, respectively.

D. Design of experiment

In order to determine the influence of control factors of face milling operation, four of input parameters were selected: feederate (fz), depth of cut (ap), cutting speed (Vc), and engagement (ae). For each factor three levels were considered. Briefly we employed the L27 orthogonal array. The output parameter is average surface roughness (Ra). Cutting parameters for each of 27 experiments can be seen in Table III.

TABLE III
EXPERIMENTAL RESULTS OBTAINED FROM MACHINED SURFACES AND CUTTING PARAMETERS

No	Engagemet (percent)	Spindle speed (rpm)	Feed (tooth/min)	Depth (mm)	Roughness (µm)
1	30	250	0.033	0.4	0.43
2	30	250	0.066	0.8	1.20
3	30	250	0.13	1.2	3.32
4	30	315	0.033	0.8	0.72
5	30	315	0.066	1.2	0.57
6	30	315	0.13	0.4	3.05
7	30	500	0.033	1.2	0.46
8	30	500	0.066	0.4	0.82
9	30	500	0.13	0.8	2.64
10	60	250	0.033	0.8	0.46
11	60	250	0.066	1.2	1.30
12	60	250	0.13	0.4	2.75
13	60	315	0.033	1.2	1.39
14	60	315	0.066	0.4	0.76
15	60	315	0.13	0.8	2.23
16	60	500	0.033	0.4	0.61
17	60	500	0.066	0.8	1.16
18	60	500	0.13	1.2	3.19
19	100	250	0.033	1.2	0.56
20	100	250	0.066	0.4	0.92
21	100	250	0.13	0.8	1.90
22	100	315	0.033	0.4	0.72
23	100	315	0.066	0.8	1.32
24	100	315	0.13	1.2	3.30
25	100	500	0.033	0.8	0.62
26	100	500	0.066	1.2	1.05
27	100	500	0.13	0.4	3.18

III. SURFACE ROUGHNESS MODELING BY BACK PROPAGATION NEURAL NETWORK

Neural network is a logical structure with multi-processing elements, which are connected through interconnection weights. The knowledge is presented by the interconnection weights, which are adjusted during the learning phase. In minimizing surface roughness, mathematical models that express surface roughness in terms of cutting parameters are

needed. The mathematical model in this study is established using Artificial Neural Networks (ANNs).

Backpropagation (BP) is one of the basic and most frequently used ANNs. A user determines the number of inputs, outputs, hidden layers, and nodes at the hidden layers. In most applications, each node is connected to all the nodes of the next layer. The hidden and output layer nodes multiply the incoming values by weight, and process the result with a transfer function. Sigmoid is the most commonly used transfer function. Linear, Gaussian, and various hyperbolic functions are also used depending on the need. The network starts to process the incoming training signals with arbitrary parameters. The error is calculated by comparing the output of the network with the provided data of the training file. All the nodal weights are adjusted by back propagating the errors through the network. All the weights of the network should be adjusted at each training iteration. This process is repeated many times until the network's output errors are reduced to a minimum. The speed and stability of the network is controlled by the learning rate and momentum selected by the user, respectively. Adding a number of hidden layers may decrease network error and bring about a precise result, but at the same time the topology of the network also becomes complicated, which leads to an increase in the training time needed for finding values for the network weights. In this study, the Bayesian regularization back propagation based on Levenberg-Marquardt algorithm is selected for training the ANNs. It minimizes a combination of squared errors and weights, and then determines the correct combination so as to produce a network that generalizes well. Optimal neural network architecture is designed using MATLAB Neural Network Toolbox. It includes two hidden layers with four inputs and two outputs have been used to model the process. The four most important input parameters are feed rate, depth of cut, spindle speed and end mill flutes. The output parameters are average surface roughness. In the network, each neuron receives total input from all of the neuron in the previous layer as:

$$net_j = \sum_{j=0}^{n} w_{ij} x_i \qquad (1)$$

where netj is the total or net input and n is the number of inputs to the jth neuron in the hidden layer. wij is the weight of the connection from the ith neuron in the forward layer to the jth neuron in the hidden layer and xi is the input from the ith neuron in the preceding layer. A neuron in the network produces its output (outj) by processing the net input through a transfer function f, such as tangent sigmoid function chosen in this study as below:

$$Out_j = f(net_j) = \frac{1 - 2\exp(-2net_j)}{1 + 2\exp(-2net_j)}, \qquad (2)$$

The input and output parameters have been normalized between -1 and 1 by:

$$x_i = 2\left(\frac{x - x_{min}}{x_{max} - x_{min}}\right) - 1, \qquad (3)$$

and initial weight values have been chosen randomly between 0.1 and 0.9.

The experimental data consist of 27 groups of data as shown in Table 3, one for each repetition, which associate the levels of each factor considered in the experiment with two values for the surface roughness (Ra). The distribution of these groups was done so as for the training subset to include 23 groups or 85(%) of the data and the testing subset to include 4 groups or 15(%) of the data. levenberg-marquardt algorithm has been used for the training of the network. In order to find out the suitable architecture of the network, different architectures have been studied. The model with 4-6-4-2 architecture is found to be the most suitable for the task and mean square error (MSE), for training data is calculated as 10^{-5} after 300 iterations. The MSE of every test is shows in Fig. 2.
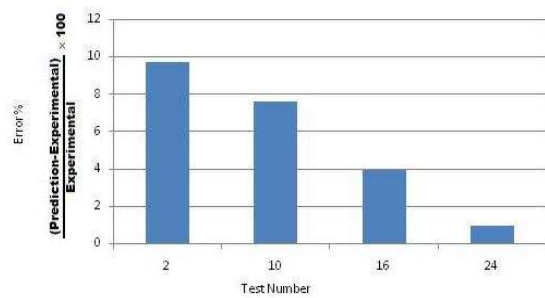

Fig. 2 The MSE of every test

IV. OPTIMIZATION METHODOLOGY

Most of the researchers have used traditional optimization techniques for solving machining problems [16]. The traditional methods of optimization and search do not fare well over a broad spectrum of problem domains. Traditional techniques are not efficient when practical search space is too large. These algorithms are not robust. Numerous parameters and constrains make the machining optimization problem more complicated. Traditional techniques such as geometric programming, dynamic programming, branch and bound techniques and quadratic programming found it hard to solve these problems. And they are inclined to obtain a local optimal solution.

A. Introduction to Electromagnetism-like Algorithm

Taking advantage of the attraction repulsion mechanism of electromagnetic theory, EM type algorithm has been widely used for optimization problems. In fact, EM algorithm is relating a new population-based meta-heuristic method simulating coulomb's law. The approach starts with a random population of points (particles) from the feasible region. Each particle stands for a solution, and its charge represents the quality of solution it relates to. In other words, in maximization (minimization) problems, a better solution has a higher (lower) charge. A better solution attracts neighbor particles in order to converge to that point, while a bad solution pushes them. The following equation represents the relation between the charge of particles and the objective function to be optimized.

$$q^i = \exp(-n \frac{f(x^i) - f(x^{best})}{\sum_{k=1}^{m}(f(x^k) - f(x^{best}))}) \tag{4}$$

where q^i is the charge of particle i, $f(x^{best})$ is the objective function of the best solution of population, $f(x^i)$ is the value of the objective function x^i, m is the population size, and the number of components of the position vector is denoted by n.

Apparently, the charge of particle determines the magnitude of force exerted on neighbor points. Particles move in the resultant force F^i direction exerted on them. The following equation calculates the resultant force F^i.

$$q^i = \exp(-n \frac{f(x^i) - f(x^{best})}{\sum_{k=1}^{m}(f(x^k) - f(x^{best}))}) \tag{5}$$

It can be seen that the force between two particles is inversely proportionate to the square of distance between the points and directly proportionate to particle charges.

According to the (5), particle i is moved to a new position after calculating the resultant force exerted on it:

$$x^i = x^i + \lambda \frac{F^i}{\|F^i\|} \begin{cases} (U - x^i), & if \ F^i > 0 \\ (x^i - L), & if \ F^i \le 0 \end{cases} \tag{6}$$

Where, for each component k in search space, U^k and L^k are upper bound and lower bound of coordinates of position vector for particle i. λ is a random step length ($0 \le \lambda \le 1$) to guarantee a non-zero probability for moving the particle to unvisited points. The underlying procedures of EM include five steps: initialization, local search, total force calculation, particles movement and particles evaluation.

The following shows a general pseudo-code for the EM:

1. Initialize ()
While (has not met stop criterion) do
2. Local Search ()
3. Calculate total force F ()
4. Move particle by F ()
5. Evaluate particles ()
 End while

In this algorithm, at the first step an initial random population is generated. Procedures like local search, calculation of the force applied to each particle by other particles, particle motion in force direction(s), and particles evaluation are iterated until stop criteria is reached [17-19].

B. Objective and constrain

The main goal of the present study is to determine the optimal machining parameters that minimize the surface roughness. For this purpose, face milling process is defined in the standard optimization problem format that can be solved by a numerical optimization algorithm. Standard optimization problem definition requires an objective function to be minimized and constraint functions to be satisfied in terms of optimization parameters. For machining of Durcomet 5, optimization problem can be defined as below:

$$\text{Objective: Min } Ra \ (V_c, f_z, a_p, a_e) \tag{7}$$

The input parameters including permissible range of cutting conditions according to the Table II:

$$f_{z \min} \le f_z \le f_{z \max} \tag{8}$$

$$a_{p \min} \le a_p \le a_{p \max} \tag{9}$$

$$v_{c \min} \le v_c \le v_{c \max} \tag{10}$$

$$a_{e \min} \le a_e \le a_{e \max} \tag{11}$$

These equations indicated the range of permissible changes in input parameters (Vc, fz, ap, ae) during optimization process.

In GONNS first a predictive model for surface roughness is created using a conventional neural network (backpropagation based on Levenberg–Marquardt algorithm) exploiting experimental data then the optimization problem was solved by an effective Electromagnetism-like algorithm (coupling conventional Neural Network and Genetic Algorithm).

C. Optimization by EM

Optimization problem in (7) was solved with effective Electromagnetism-like algorithm codes that was written in MATLAB and the optimization result are shown in table IV In doing this, block of Durcomet 5 was machined again by using optimum value predicted by EA. Additional measurement were then performed to validate the optimum values and their corresponding to roughness value obtain from EM program. In this study the critical parameters in EM such as population size (40), and the number of generations (100), are employed.

TABLE IV
RANG OF CUTTING PARAMETERS AND FACTOR LEVEL

Condition		Ra pre.	Ra exp.	Error (%)
Spindle speed (rpm)	316.5			
fz (tooth/min)	0.033	0.42	0.44	4.7
ap(mm)	0.04			
ae(%)	35.78			

V. CONCLUSION

This study have discussed application of neural network and Electromagnetism-like Algorithm method for determining optimum cutting parameters leading to minimum surface roughness value in the face milling of Durcomet 5 material. *The results that were drawn from this study can be summarized in the following points:*

Feed forward artificial neural networks can be used reliably, successfully and very accurately for the modeling of the surface roughness formation mechanism and the prediction of its value in face milling.

Neural network model coupled with the EM was proposed for selection of the optimal cutting conditions in specialized machining operations from the experimental data without developing any analytical or empirical models. NNs were trained by using a series of experimental results to represent the relationship between the machining parameters and the cutting-related value such as, surface roughness. EM determined the optimal cutting conditions to minimize one of the machining-related values.

According to additional measurement results, a good correlation is obtained between the value of surface roughness predicted by the EM and that of surface roughness obtained from experimental measurements. This indicates that the neural network model coupled with the EM can be effectively utilized to find the optimum cutting parameters values for a specific cutting condition in face milling Durcomet 5 material.

REFERENCES

[1]   Sağlam, H., and ̈Un̈uvar, A. Tool condition monitoring in milling based on cutting forces by a neural network. Int J Prod Res, 2003, 41, 1519–1532.

[2]   Bouzid, W., Zghal, A., and Sai, L. Taguchi method for design optimization of milled surface roughness, J. Mater. processing Technol, 2004, 19 (3), 159– 162.

[3]   Topal, ES., Sinanoglu, C., Gercekcioglu, E., and Yildizli,K. Neural Network Prediction of Surface Roughness in Milling of AISI 1040 Steel, J Balkan Trib Assoc, 2007, 13, 18–23.

[4]   Dhokia, V G., Kumar, S., Vichare, P., Newman S T., and Allen, R D. Surface   roughness prediction model for CNC machining of polypropylene. Proc. IMechE Part B: J. Engineering Manufacture, 2008, 222, 137-157.

[5]   Onwubolu, G. C. Modelling and predicting surface roughness in turning operations using hybrid differential evolution and the group method of data handling networks, Proc IMechE, Part B: J. Engineering Manufacture, 2008, 222(B7), 785-795.

[6]   Benardos, PG., and Vosniakos, GC. Prediction of surface roughness in CNC face milling using neural networks and Taguchi's design of experiments. Robot Comput Integr Manuf, 2002, 18, 343–354.

[7]   Oktema, H., Erzurumlu, T., and Kurtaran, H. Application of response surface   methodology in the optimization of cutting conditions for surface roughness, J. Mater. processing Technol, 2005, 170, 11–16.

[8]   Krimpenis, A., and Fousekis, A. Assessment of sculptured surface milling strategies using design of experiments, Int J Adv Manuf Technol, 2005, 25, 444–453.

[9]   Tansela, I.N.,   Ozcelikb, B., Baoa, W.Y., Chena, P., Rincona, D., Yanga, S.Y.,   and Yenilmezc, A. Selection of   optimal cutting conditions by using GONNS, Machine Tools Mf. J., 2006, 46, 26–35.

[10] Razfar, M. R., and Zanjani Zadeh, M. R. Optimum damage and surface roughness prediction in end milling Glass fiber-reinforced plastics, using neural network and genetic algorithm, proc. IMechE, Part B: J.Eng-ineering Manufacture, 2009, 223, 653–664.

[11] Oktem, Hasan., Erzurumlu, Tuncay., and Erzincanli, Fehmi. Prediction of minimum surface roughness in end milling mold parts using neural network and genetic algorithm, Mater Design, 2006, 27, 735–744.

[12] Birbil, S. I., and Fang, S.C., An Electromagnetism-like Mechanismfor Global Optimization. J Global Optim, 2003, 25,263–282.

[13] Debels, D., Reyck, B. D., Leus, R., & Vanhoucke, M., A hybrid scatter search/electromagnetism meta-heuristic for project scheduling. Eur J Oper Res, 2006, 169, 638–653.

[14] Durcomet 5 data sheet, Flowserve Corporation, P.O. Box 8820, Dayton, Ohio 45401-8820, (937) 226-4000

[15] Sandvik Milling. Catalogue & technical guide, Sandvik Coromant, Sweden, 2007.

[16] Agapiou, J. S. "The optimization of machining operations based on a combined criteria, part: 1: the use of combined objectives in single pass operations", Trans. ASME J. Eng. Ind., 114 , (1992).

[17] Chang, P., Chen., S., and Fan, C., A hybrid electromagnetism-like algorithm for single machine scheduling problem, Expert Sys Appl, 2009, 36, 1259–1267

[18] Naderi, B., Tavakkoli-Moghaddam, R., and Khalili, M., Electromagnetism-like mechanism and simulated annealing algorithms for flowshop scheduling problems minimizing the total weighted tardiness and makespan, Knowledge-Based Systems 23 (2010) 77–85

[19] [Yurtkuran, A., and Emel, E., A new Hybrid Electromagnetism-like Algorithm for capacitated vehicle routing problems, Expert Sys Appl, 2010, 37, 3427–3433

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