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Identification Optimization Cutting Parameters Based on ICA Method in Peripheral Milling of a Thin Wall

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Abstract: In the today's competitive world, all of the companies for overcoming economical problems have increased the quality of their production. Surface quality of products is one of the most important factors to evaluate the quality of machining process. The suitable surface roughness cannot be achieved due to thin wall of workpiece during machining processes. In this paper effects of cutting parameters on surface roughness of a low immersion milling are determined. Afterward the optimum points of workspace based on multi-objective function and given constrains for manufacturing variables are determined by G.A. and ICA algorithms. Finally, the results of two methods are compared and efficiency of ICA algorithm is demonstrated.

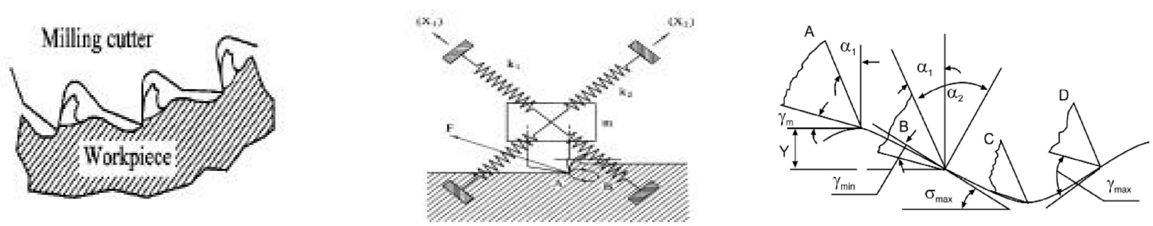
Key words: Cutting parameters · Surface roughness · ICA algorithm

INTRODUCTION

Increasing productivity is one of worries in the global competitions so each companies attempt to find new approaches for decreasing costs and increasing quality of the production. Therefore, we have observed a lot of new product process since three decade ago. Automated manufacturing systems are widely employed in machining along with computer numerical control (C.N.C) machines to achieve such goals so that effects of operators on processes are eliminated. So only the cutting conditions are determined quality of product. Usually quality of product is related to surface roughness of workpiece. This parameter correlated to cutting parameters as well as depth of out, spindle speed with of cut and feed rate. The relation between these parameters can be defined stability or instability of milling dynamic systems which their effects in surface roughness of workpiece is appeared.

The appearance of vibration can be observed in form the displacement of tool or workpiece and sometime with noise during machining. This appearance is generated by, mode coupling, wave regeneration and damping process. These events show in Fig. 1.

With time, as complexity in dynamics of cutting processes increased substantially, researchers and practitioners have focused on mathematical modeling techniques to determine optimal or near-optimal cutting condition(s) with respect to various objective criteria [1]. Several modeling techniques proposed and implemented are based on statistical regression [2], artificial neural network [3] and fuzzy set theory [4]. Optimization tools and techniques proposed are also based on Taguchi method [5], response surface design [6], mathematical programming [7], genetic algorithm [8], Tabu search [9] and simulated annealing [10]. Despite numerous studies on process optimization problems, there exists no



(a) Regeneration wave (b) mode coupling (c) process damping

Fig. 1: Kind of source of vibration on machinery processes

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universal input–output and in process parameter relationship model, which is applicable to all kinds of metal cutting processes [11]. Luong *et al.* [12] claim a lack of basic mathematical model that can predict cutting behavior over a wide range of cutting conditions. Optimization techniques also have certain constraints, assumptions and limitations for implementation in real-life cutting process problems. Some of these limitations and assumptions are discussed in the literature [13].

El-Mounayri *et al.* [14] used swarm intelligence to find proper values of coefficients in a widely accepted model representing a relationship between roughness and spindle speed, feed rate and depth of cut. Wang *et al.* [15] investigated the influence of micro-end milling cutting conditions on roughness (Ra) of a brass surface using RSM. Reddy and Rao [16] developed a mathematical model for surface roughness considering the cutting parameters and tool geometry during end milling of medium carbon steel using RSM. Recently, Ozcelik and Bayramoglu [17] have modelled Ra in high speed flat end milling of steel including total tool operating time along with other machining variables such as spindle speed, feed rate, depth of cut and step over. Bagci and Aykut [18] used the Taguchi optimization method for low surface roughness value (Ra) in terms of cutting parameters in CNC face milling of Cobalt based alloy. Prakasvudhisarn *et al.* [19] demonstrated that the combined SVM and PSO could be applied to effectively and efficiently predict surface roughness and determine optimal cutting condition for the roughness specification.

Finally, there are a lot of theoretically methods for modeling of the above dynamic systems but they haven't succeeded for presenting a comprehensive model that including all of variation sources. One of the main problems in modeling process of low immersion milling is determining process damping. This phenomenon can be created the nonlinearity behavior of system. However a lot of researcher studied on improving these mathematical models, but some researchers for obtaining the better modeling for correlation between cutting parameters and surface roughness, used the experimental approaches.

In this paper, firstly cutting parameters, dimension properties of workpiece and tool and setup of experimental test are defined. In the next section, the results of measuring roughness at two path tool directions are presented. Afterward, nonlinear regression applied for generating a model of system based on cutting parameters such as width of cut, feed rate and spindle speed. Thus G.A. and ICA algorithms used for determining optimum points of workspace subjected to given constrains and multi objective functions.

Response Surface Method: The basic idea of nonlinear regression is the same as that of linear regression, namely to relate a response Y to a vector of predictor variables x $=(x_1,..., x_k)^T$. Nonlinear regression is characterized by the fact that the prediction equation depends nonlinearly on one or more unknown parameters.

Response surface method (RSM) adopts both mathematical and statistical techniques which are useful for the modeling and analysis of problems in which a response of interest is influenced by several variables and the objective is to optimize the response [20]. In most of the RSM problems, the form of the relationship between the response and the independent variables is unknown. Thus the first step in RSM is to find a suitable approximation for the true functional relationship between response of interest 'y' and a set of controllable variables $\{x_1, x_2, ...x_n\}$. Usually when the response function is not known or non-linear, a second-order model is utilized [20] in the form:

$$y = b_0 + \sum_{i=1}^{n} b_i x_i + \sum_{i=1}^{n} b_i x_i^2 + \sum_{i<j}\sum b_i x_i x_j + \varepsilon$$

Where, ε represents the noise or error observed in the response y such that the expected response is $(y(x_i))$ and b_i factors are the regression coefficients to be estimated. The least square technique is being used to fit a model equation containing the input variables by minimizing the residual error measured by the sum of square deviations between the actual and estimated responses. The calculated coefficients or the model equations, however, need to be tested for statistical significance. Analysis of variance (ANOVA) is used to check the adequacy of the model for the responses in the experimentation. ANOVA calculates the F-ratio, which is the ratio between the regression mean square and the mean square error. If the calculated value of F-ratio is higher than the tabulated value of F-ratio for roughness, then the model is adequate at desired significance level α to represent the relationship between machining response and the machining parameters. For testing the significance of individual model coefficients, the model is optimized by adding or deleting coefficients through backward elimination, forward addition or stepwise elimination or addition. It involves the determination of P- value or probability of significance that relates the risk of falsely rejecting a given hypothesis. If the P-value is less or equal to the selected α-level, then the effect of the variable is significant. If the P-value is greater than the selected α-value, then it is considered that the variable is not significant. Sometimes the individual variables may not be significant. If the effect of interaction terms is significant, then the effect of each factor is different at different levels of the other factors. In the present study, ANOVA for different response variables is carried out using commercial software Minitab [21] with confidence level set at 95%, i.e., the α-level is set at 0.05. To have an assessment of pure error and model fitting error, some of the experimental trials are replicated. The adequacy of the models is also investigated by the examination of residuals [20]. The residuals, which are the difference between the respective observed responses and the predicted responses, are examined using the normal probability plots of the residuals and the plots of the residuals versus the predicted response. If the model is adequate, the points on the normal probability plots of the residuals should form a straight line. On the other hand, the plots of the residuals versus the predicted response should be structure less, i.e., they should contain no obvious pattern.

Experimental Details

Design of Experiment: The design of experiments technique is a very powerful tool, which permits us to carry out the modeling and analysis of the influence of process variables on the response variables. The response variable is an unknown function of the process variables, which are known as design factors. There are a large number of factors that can be considered for machining of a particular material in end milling. In the present study width of cut (W, mm), spindle speed (S, rpm) and feed rate (f, mm/min) are selected as design factors while other parameters have been assumed to be constant over the experimental domain. Therefore the independent and dependent effects of each manufacturing variables can be investigated on the response function. For this study manufacturing variables considered according Table 1. So the numbers of experiments for each direction of tool path consisting of 108 sets are considered. The number of test run can be calculated by $W_{num} \times S_{num} \times f_{num}$ ($4 \times 9 \times 3 = 108$). Due to the limitation in carrying out these tests, only two variables for calculating error are considered. Note that the center line average roughness (Ra, ìm) is considered for measuring surface roughness.

Fig. 2: Setup of experimental test

Experimental Setup and Equipments: The machine used for the milling tests is a ‘VMC 850’ CNC end milling machine having the control system Siemens with a vertical milling head and equipped with maximum spindle speed of 8000 rpm, maximum feed rate 10 m/min, 10 kW driver motor and accuracy 0.001mm.

Roughness measurement was done using a portable stylustype profilometer, Talysurf (Taylor Hobson, Surtronic 3+). The profilometer was set to a cut-off length of 0.8 mm, filter 2CR, traverse speed 1 mm/sec and 4 mm evaluation length. Roughness measurements, in the transverse direction, on the workpieces were repeated three times and average of three measurements of them was recorded.

All of workpieces were selected from 6061-T4 aluminum with dimension of 20mm×10mm×2mm. Also Cutting tools used are coated carbide. Table 2 present the information of used cutting tools. Figure 2 shows the setup of experiment during machining.

RESULTS AND DISCUSSION

In this study the workpiece considered with thin wall. Therefore vibration of workpiece due to thickness of wall along motion of tool is very various. On the other hand vibration of workpiece can be effected on the amount of surface roughness. So, we considered two direction of tool path of cutting tool in feed direction for illustrating surface roughness. Figure 2 shows both directions. Also, Table 3 is presented levels of designs of experiment.

Table 1: Cutting tool properties

Width of cut (mm)	Spindle speed (rpm)	Feed rate (mm/min)
0.1-0.3-0.6-1	50-250-500-630-1000-12501600-2000-2500	8-20-25

Table 2: Cutting tool properties

D (mm)	N (flute)	Lflute (mm)	Overhang (mm)	Helix angle
8	4	28	67	30

Table 3: Complete experimental results for milling of aluminum

	Spindle speed (rpm)										
Width of cut =0.1mm	Feed (mm/min)	Toolpass (mm)	50	250	500	630	1000	1250	1600	2000	2500
	8	5	1.62	1.26	0.48	0.58	0.8	0.5	0.46	0.44	0.8
		10	0.66	0.5	0.46	0.34	0.32	0.26	0.3	0.36	0.68
	20	5	1.7	0.44	0.48	0.4	0.42	0.64	0.78	0.42	0.66
		10	1.9	0.4	0.32	0.4	0.34	0.5	0.76	0.48	0.52
	25	5	1.52	0.46	0.58	0.74	0.58	0.5	0.56	0.6	0.46
		10	1.24	0.46	0.62	0.5	0.48	0.58	0.54	0.6	0.5
Width of cut=0.6mm			50	250	500	630	1000	1250	1600	2000	2500
	8	5	0.8	0.4	0.4	0.4	0.4	0.4	0.6	0.8	0.8
		10	0.6	0.4	0.4	0.2	0.2	0.4	0.4	0.4	0.6
	20	5	1	0.4	0.6	0.4	0.4	0.58	0.36	0.72	0.56
		10	1.6	0.8	0.4	0.4	0.2	0.44	0.36	0.6	0.46
	25	5	1.38	0.56	0.86	0.42	0.44	0.4	0.36	0.42	0.5
		10	1.38	0.46	0.52	0.3	0.28	0.4	0.28	0.4	0.4
Width of cut=0.6mm			50	250	500	630	1000	1250	1600	2000	2500
	8	5	0.4	0.54	0.28	0.36	0.48	0.92	0.54	0.66	0.34
		10	0.78	0.54	0.28	0.3	0.4	0.82	0.38	0.54	0.5
	20	5	1.28	0.64	0.58	0.36	0.44	0.54	0.62	0.56	0.28
		10	1.38	0.44	0.32	0.44	0.4	0.5	0.36	0.34	0.32
	25	5	1.7	0.38	0.3	0.38	0.36	0.56	0.56	0.66	0.36
		10	1.84	0.34	0.38	0.28	0.48	0.7	0.56	0.56	0.32
Width of cut=1mm			50	250	500	630	1000	1250	1600	2000	2500
	8	5	1.18	0.34	0.64	0.54	0.56	0.84	0.56	1	1.26
		10	1.48	0.64	0.62	0.52	0.62	0.92	0.52	1.1	1.3
	20	5	1.38	0.36	0.28	0.26	0.34	0.36	0.32	0.34	0.5
		10	1.68	0.46	0.36	0.28	0.34	0.24	0.46	0.54	0.5
	25	5	3.26	0.42	0.26	0.32	0.4	0.8	0.54	0.7	0.52
		10	1.96	0.48	0.48	0.32	0.48	1.5	0.46	0.46	0.52

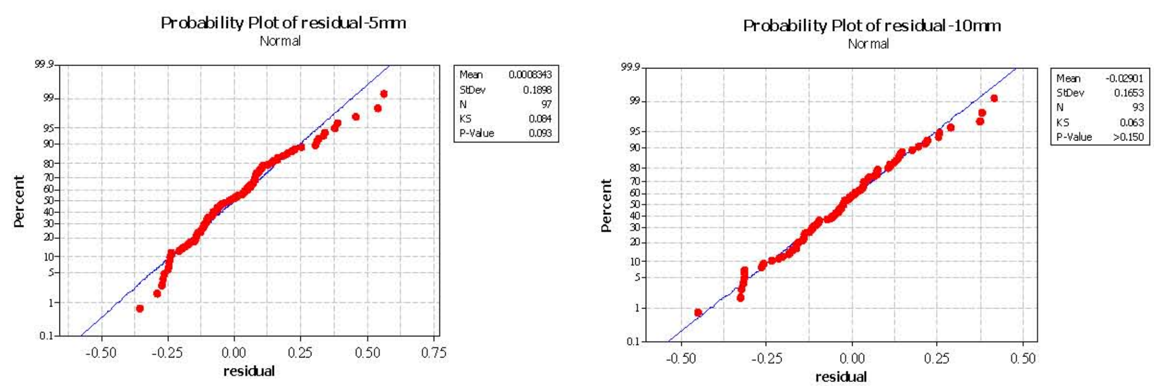
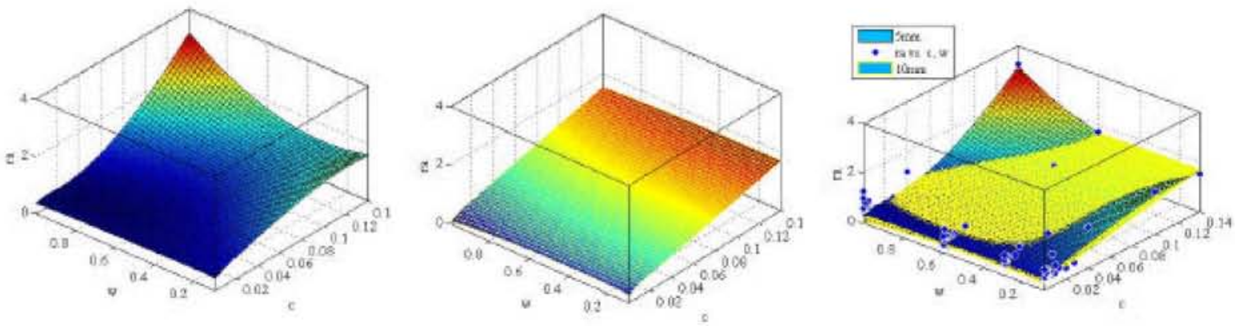


Fig. 3: Kormogrov-Smirov test for confiding nonlinearity regression



(a) Direction of 5mm (b) Direction of 10mm (c) Mixed two direction

Fig. 4: Variation of roughness in different direction

According to above table, two functions are determined for illustrating Ra in each direction that presented in Eqs. (2-3). Accuracy of these functions isevaluated by P-value of the Kormogrov-Smirov test. If the p-value of this test is less than our chosen α-level, we can reject our null hypothesis and conclude that the population is non-normal. Figure 3 shows diagram of this test. In these equations feed per tooth (mm/tooth min) is considered instead of feed rate and spindle speed. Figure 4 shows plots of objective functions. Since there are two objective functions is a multi objective problem with two variables. This variation can make clear explanation graphically for optimization problem. On the other hand constrains are defined on feed rate, spindle speed and width of cut. In addition to lower bound for objective functions. Constrains and multi-objective function presented in following equations.

Objective functions are:

$$F(c,w)= 7.717+1492.32\, c^3w -7.243cw-533.405c^3 \quad (2)$$

$$F(c,w)=0.357+9.575c-0.176w^4 \quad (3)$$

And Constrains are:

$$F_5 \geq 0.4 \quad (4)$$

$$F_{10} \geq 0.4 \quad (5)$$

$$0.01 \leq C \leq 0.14 \quad (6)$$

$$0.1 \leq \text{Width of cut} \leq 1 \quad (7)$$

Investigation of Fig. 4 has shown that there are some points which in both of directions have equal roughness. For determining them, G.A and ICA Algorithms are used.

Optimization Procedure Set-up and Analysis Results

Genetic Algorithm: These are the algorithms based on mechanics of natural selection and natural genetics, which are more robust and more likely to locate global optimum. It is because of this feature that GA goes through solution space starting from a group of points and not from a single point. The cutting conditions are encoded as genes by binary encoding to apply GA in optimization of machining parameters. A set of genes is combined together to form chromosomes, used to perform the basic mechanisms in GA, such as crossover and mutation. Crossover is the operation to exchange some part of two chromosomes to generate new offspring, which is important when exploring the whole search space rapidly. Mutation is applied after crossover to provide a small randomness to the new chromosomes. To evaluate each individual or chromosome, the encoded cutting conditions are decoded from the chromosomes and are used to predict machining performance measures. Fitness or objective function is a function needed in the optimization process and selection of next generation in genetic algorithm. Optimum results of cutting conditions are obtained by comparison of values of objective functions among all individuals after a number of iterations. Besides weighting factors and constraints, suitable parameters of GA are required to operate efficiently. (Optimization of machining techniques – A retrospective and literature review).

According to above discussion, a multi-objective optimization procedure, based on genetic algorithms, to obtaining the optimum cutting conditions (width of cut, feed rate and cutting speed) in milling, is presented. Therefore, the problem of optimizing the cutting conditions is confined in obtaining the optimum feed rate,

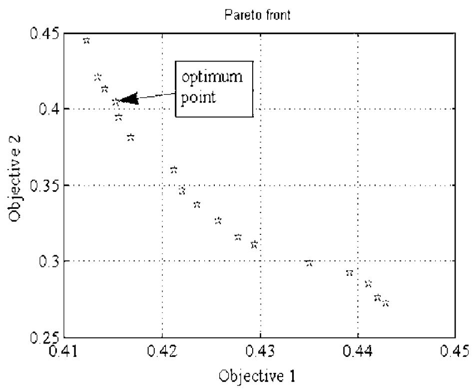


Fig. 5: Optimum points by G.A. method

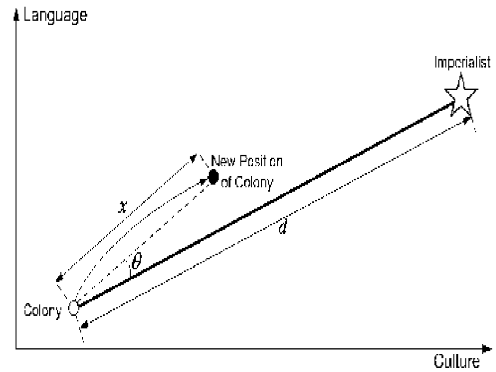


Fig. 6: The movement of a colony towards an imperialist

cutting speed and width of cut. On the other hand the roughness functions obtained from nonlinear sections that show variation of it based on variation of width of cut and feed per tooth parameters.

The calculation of G.A. is done by parameters are shown below;

Population size	100
Length of chromosome	200
Crossover operator	single point operator
Crossover probability	0.9
Mutation probability	0.01
Fitness parameter	0.4

The results of G.A. presented in Table 4. Also Figure 5 shows optimum points by G.A. method.

Imperialist Competitive Algorithm: In this work, a new algorithm is being used for optimization which is called Imperialist Competitive Algorithm (ICA). This algorithm suggested by Atashpaz *et al*. [22-23]. This method is inspired from a social-Human phenomenon.

This algorithm, like the other evolutionary methods, is started with a primary population. In this algorithm, each population element is named as a "country". The countries are divided into two groups; colonies and imperialists. These colonies along with the imperialist form the empire.

To define the algorithm, first of all, initial countries of size $N_{Country}$ are produced. Then, some of the best countries (with the size of N_{imp}) in the population are selected to be the imperialist states. Therefore the rest with the size N_{col} will form the colonies that belong to imperialists. Then, the colonies are divided among imperialists according to their power which are inversely proportional to their cost [23].

After dividing all colonies among imperialists and creating the initial empires, these colonies start moving toward their relevant imperialist country. This movement is a simple model of assimilation policy. This policy is shown in Figure 6. In this movement θ and X are random numbers with uniform distribution and d is the distance between the imperialist and the colony [23].

$$x \sim U(0, \beta \times d) \tag{8}$$

$$\theta \sim U(-\gamma . \gamma) \tag{9}$$

Also, β and γ are arbitrary numbers that modify the area that colonies randomly search around the imperialist. In our implementation β and γ are 2 and π/4 (Rad) respectively [23]. During any movement, if a colony reaches a better point than an imperialist, they will be replaced by each other.

Also, total power of an empire is defined by the sum of the powers of the imperialist and some percentage of the mean power of its colonies. Any empire that is not able to succeed in imperialist competition and cannot increase its power (or at least prevent decreasing its power) will be eliminated [23].

According to imperialist competition, the weakest colony of the weakest empire is chosen by other empires and the imperialist competition is started on possessing this colony. So the weak empires will slowly lose their power by the time and getting weak and at last, they will vanish and at the end, there will remain just one empire that govern the whole colonies. This happens only if the imperialist competitive algorithm stops, by reaching the optimum point [23].

The Algorithm: TO construct the algorithm following steps should be taken:

- Choose some random points on the function and create the primary empires.
- Move the colonies towards the imperialist country (the assimilation policy).
- If in an empire, a colony has less cost than an imperialist, exchange the positions of that colony and the imperialist.
- Compute the total cost of an empire, regarding the cost of the imperialist and the colony.
- Choose a colony from the weakest empire and then give it to the empire with the most possibility of possession (the imperialistic competition).
- If an empire doesn't have any colonies, we will eliminate this empire.
- If there is just one empire, s top, if not go to step 2.

In the initial population is equal to 50. The number of the imperialist countries is considered 4. Table 4 presents a comparison of G.A. with ICA results. These results selected based on maximum

Table 4: Results of G.A. method

	F_{5mm}	F_{10mm}	c	w
G.A.	0.415	0.404	0.021	0.914
I.C.A	0.404	0.404	0.0208	0.936

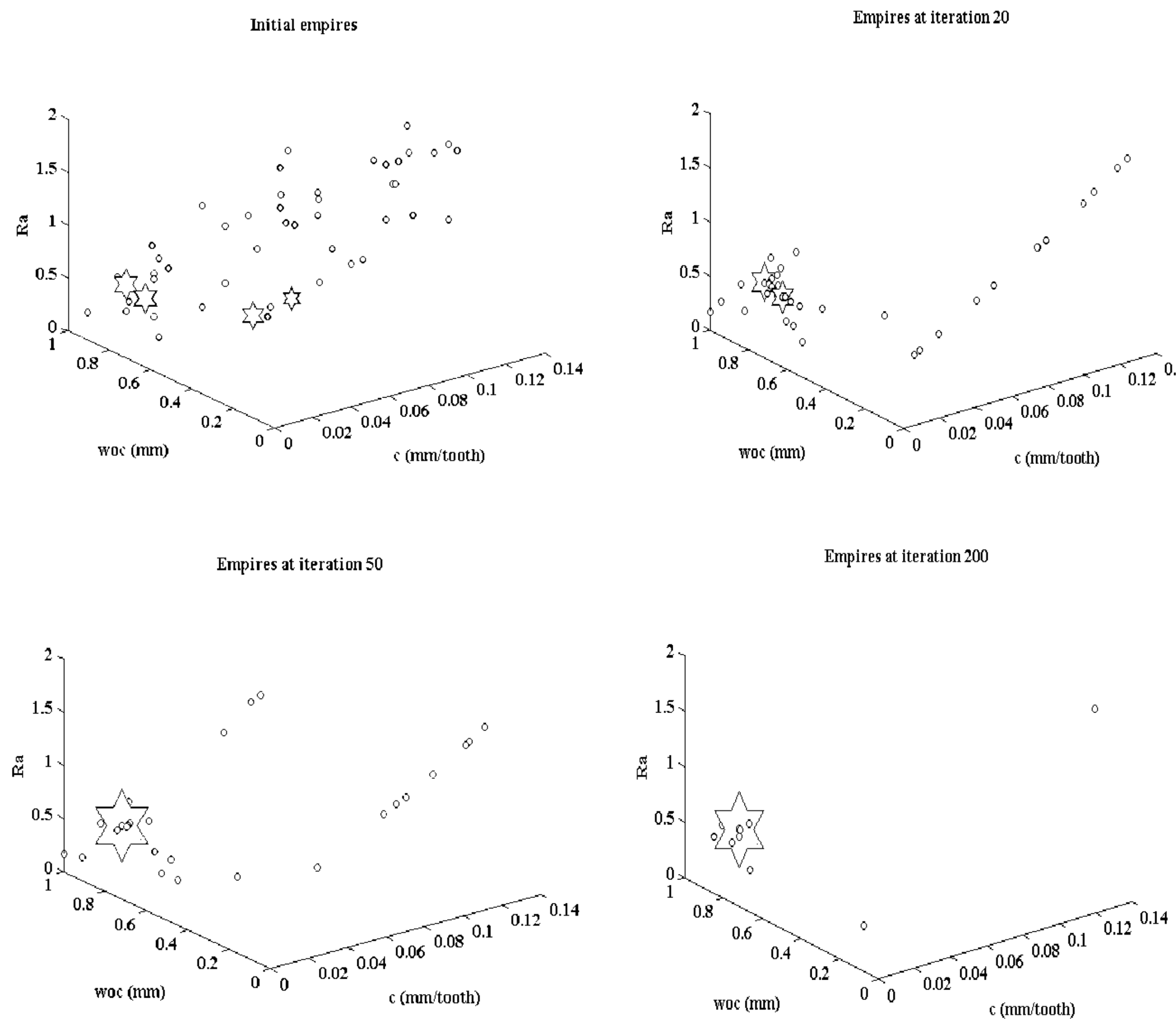


Fig. 7: Process of determining of optimum point by ICA method

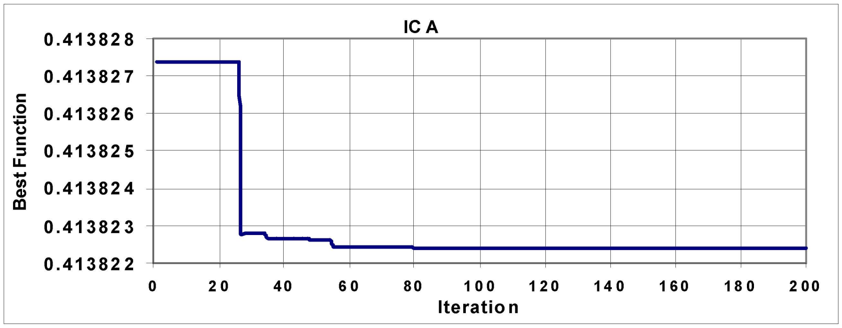


Fig. 8: Number of iterations in ICA method

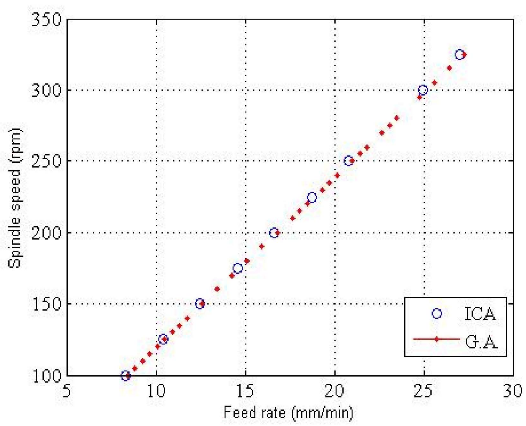


Fig. 9: Comparison of different compounds of feed rate and spindle speed for optimum surface roughness

width of cut that can be prepared. Also Figure 9 shows comparison of different compounds of spindle speed and feed rate for both of methods.

CONCLUSION

In this paper a new optimization method is employed for determining optimum points of surface roughness with multi-objective function. Results of this method compared with G.A. method and shows that this method has better efficiency and high accuracy with respect to G.A. method. The obtained optimum points for roughness in using ICA method is not only more accurate but also are the same. In the other hand the achieved width of cut of ICA method is more than the G.A. method.

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