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Prediction of surface roughness in the ball-end milling process using response surface methodology, genetic algorithms, and grey wolf optimizer algorithm

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A B S T R A C T

In this research study proposed are a response surface methodology (RSM), genetic algorithm (GA) and a grey wolf optimizer (GWO) algorithm for prediction of surface roughness in ball-end milling of hardened steel. The RSM is a conventional predicting approach, GA is an evolutionary algorithm and GWO is a new swarm intelligence-based algorithm. Spindle speed, feed per tooth, axial depth and radial depth of cut were selected as input parameters. Experiments were performed on a CNC milling center and experimental data were collected based on a four-factor-five-level central composite design (CCD). RSM was applied for establishing the basic relationship between input parameters and surface roughness. After that analysis of variance (ANOVA) was conducted for the evaluation of the proposed mathematical model. A predefined reduced quadratic model was used as a reference model for a build-up of predictive models using GA and GWO algorithm. Predicted values of RSM, GA and GWO models are compared with experimental results. In the comparison of model performance for all the three models it was found that GWO model is the best solution. The model accuracy was found to be at 91.80 % and 89.58 % for training and testing data, respectively, which showed the effectiveness of the GWO algorithm for modeling machining processes.

A R T I C L E I N F O

Keywords:
Ball-end milling;
Surface roughness;
Response surface methodology (RSM);
Genetic algorithm (GA);
Grey wolf optimizer algorithm (GWO)

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1. Introduction

The primary objective of machining operations modeling is developing a predictive capability for machining performance in order to facilitate effective planning of machining operations to achieve optimum productivity, quality, and cost [1]. Modeling of output machining performances, fundamental variables (cutting forces, cutting temperature, stress, etc.), and output performances which are relevant for machine industry (tool life, surface roughness, surface integrity, chip form, etc.) is very important due to the fact that conventional machining processes still occupy the dominant part of all production processes [2]. The development of advanced predictive models enables the selection optimal cutting conditions, cooling (kinds of cutting fluids, pressure, flow), cutting tool material (coatings) and its geometry, machine tools and other. Predictive models also help manufacturing engineers to plan and manage machining processes more efficiently and use the sophisticated simulation tools to check the effects of projected process performances far beyond the actual production of any particular product(s).

Since the conventional machine tools era to the present times of CNC multi-tasking machine tools, the prediction of machining performances and optimization of cutting conditions have been interesting research areas. Modeling of output machining performances is mainly a very difficult task due to complexity and stochastic nature of most machining processes. Despite both past and present numerous attempts to analyze metal cutting, the basic relationship between the various variables has still remained unexplained [3]. In the last 60 years, metal cutting researchers have applied many methods or techniques for modeling the output machining performances. Predictive models in practice can be analytical, empirical, numerical, Artificial Intelligence (AI) based, and hybrid, too [2]. Each of these approaches has its advantages and disadvantages, or capabilities and constraints. For example, response surface methodology (RSM) is used for empirical models building. In recent years the research in the area of machining process modeling is oriented towards the use of methods based on Artificial Intelligence. Artificial Intelligence-based models are commonly founded on either a biological, molecular, or neurological phenomenon that resembles the metaphor of natural biological evolution and/or the social behavior of different species of natural organisms [4].

These models have been developed thanks to the rapid advancement of computer technology over the past two decades and are often called nature-inspired algorithms. Nature-inspired algorithms could be classified into three wide groups: physics-based algorithms (PBA), chemistry-based algorithms (CBA) and biology-based algorithms (BBA) [5]. Physics-based algorithms (PBA) actually apply the basic principles of physics, for instance, Newton's laws of gravitation, laws of motion and the like.

Biology-based algorithms (BBA) present a special group of algorithms within algorithms inspired by nature and those can learn and adapt similar to biological organisms [6]. These algorithms can be put into three categories: evolutionary algorithms (EA), bio-inspired algorithms (BIA) and swarm intelligence-based algorithms (SIA) [5]. Biology-based algorithms try to mimic the way in which biological organisms or sub-organisms (e.g., bacteria or neurons) function, so as to achieve a high level of efficiency [6]. Evolutionary algorithms (EA) are based on Darwin's theory of evolution and among them are most famous genetic algorithm (GA) and genetic programming (GP).

Bio-inspired algorithms (BIA) are built on the idea of a commonly observed phenomenon in some animal species and ordered, natural movement of organisms. Flocks of birds and shoal of fish are amazing examples of self-organized coordination. For example, Particle Swarm Optimisation (PSO) simulates the social behavior of birds. In PSO, each solution in search for space is actually analogous to a bird and it is called "a particle". The system is started with a population of random particles (called a swarm) and their searches for optimum value continues by updating new generations. Each particle in the swarm tries to reach a possible solution, whereby the group attempts to meet the collective objective of the group, all that based on the actual feedback from the other members.

Swarm intelligence-based algorithms (SIA) use the fact that collective intelligence of swarm is more than a sum of individual intelligences. Each agent of the swarm may be considered as unintelligent, but it follows some simple rules, so that the whole swarm may show some self-organization behavior and thus can behave like some kind of collective intelligence. These algorithms began from observing the collective behaviors of insects living in colonies such as ants, bees, wasps, termites, respectively and also the collective behaviors of some animal species, such as cuckoos, lions, wolves, etc. The most famous algorithms based on swarm intelligence are Artificial Bee Colony (ABC), Ant Colony Optimization (ACO), Cuckoo search (CS).

The aim of this work is to present the various approaches to predict surface roughness in ball-end milling process and developing a predictive model to obtain surface roughness as a function of machining parameters: spindle speed (n), feed per tooth (f_z), axial depth of cut (a_p) and radial depth of cut (a_e), using response surface methodology (RSM), genetic algorithm (GA) and grey wolf optimizer (GWO) algorithm. RSM is conventional modeling approach, GA is a part of evolutionary algorithms and GWO is new swarm intelligence-based algorithm. GWO is a recently developed algorithm inspired by grey wolves and their life in nature (as for example leadership hierarchy and hunting mechanism) and has been successfully applied for solving different problems. As the grey wolf optimizer (GWO) is a real novelty, there is no study in the literature about the application of this algorithm for modeling and optimization of machining operations, in other words for prediction of output machining performances.

2. Literature review

One of the most important machining performances is surface roughness, particularly so in finish milling operations [7]. When referencing to the already published papers, obviously there have been a lot of researches regarding the prediction of surface roughness in face, but also end milling process. For this purpose, a number of statistical methods were used such as RSM and soft computing techniques or bio-inspired computing (ANN, GA, GP, ANFIS).

Numerous researchers have studied the influence of input cutting parameters on surface roughness for practical end milling. Most of the research proposal is the multiple regression method to predict surface roughness [8, 9], some research applied ANN, fuzzy logic, ANFIS, GA and grey-fuzzy approaches for surface roughness prediction in end milling process [10-15], everyone proposed GP, namely RSM to predict surface roughness in end milling [16, 15].

Ball-end milling is a type of milling process where ball-end mill is used with the goal to generate 3D free formed sculptured products. In reality, die, mold and aerospace industries mostly apply that type of process. There is a far smaller number of published references dealing with the prediction of the surface roughness for this type of end milling process.

Dhokia *at al*. [17] used GA for predicting of surface roughness in ball-end milling of polypropylene. Establishing a relationship between surface roughness and the process parameters such as feed, speed, and depth of cut for the ball-end milling of polypropylene was the most significant goal for the surface roughness model. The experimental tests were carried out according to the orthogonal array design L_{16}. The mean deviation of R_a obtained by surface roughness model over the validation dataset was obtained as 8.43 %.

In their study Vakondios *at al*. [18] addressed the influence of milling strategy on the surface roughness in ball end milling of the aluminum alloy Al7075-T6. Different strategies were analyzed (vertical, push, pull, oblique, oblique push and oblique pull). A mathematical model of the surface roughness was established for each of them, considering both the down and up milling. Mathematical models for surface roughness were obtained using RSM. For a check up of the validity of models used was the analysis of variance (ANOVA).

Hossain and Ahmad [19] decided to attempt with RSM and adaptive-neuro-fuzzy-inference system (ANFIS) in order to predict surface roughness in ball-end milling. After comparing ANFIS results with the RSM results the superiority of ANFIS results to the RSM results was showed.

Zuperl and Cus [20] developed a simplified model to provide functional relations between surface roughness, cutting chip size, cutting conditions and diameter of the ball-end mill. The ANFIS method was applied for predicting the cutting chip size in ball-end milling. In spite of being simple, the model has reliability and efficiency in predicting the R_a in-process by utilizing the chip size.

Quintana *at al*. [21] used artificial neural networks (ANN) for predicting of surface roughness in the function of spindle speed, feed per tooth, axial depth of cut, radial depth of cut and tool radius. The developed ANN enabled the prediction of surface roughness with a high degree of correlation (R^2 = 0.96296).

3. Materials and methods

3.1 Experimental setup and results

The experimental work explained in this paper referenced the work of Pejic V. [22], and was performed at the Department of Production Engineering, Faculty of Technical Sciences, at University of Novi Sad and at the company "ELMETAL" doo in Senta, Serbia. The experiments were conducted on HAAS VF-3YT vertical three-axis CNC milling machine and on hardened steel X210CR12 with 58 HRC. The cutting tools used were TiAlN-T3 coated two-flutes solid carbide ball-end milling cutters of diameter 6 mm (Emuge-Franken, type1877A). The dimension of a workpiece 300 mm × 58 mm × 20 mm was used in this study. Based on the tool manufacturer's recommendation, a cold air nozzle, which works on the principle of a vortex tube, was used for cooling the tool. Prior to performing the experiments, the workpiece was divided into 84 fields, with dimensions of 15.33 mm × 3 mm and a height of 2 mm, as shown in Fig. 1. Each field corresponded to one experimental point. This method enables machining in one clamp, and hence the same machining conditions at all experimental points. According to the data taken from the design of experiments (DoE) CNC programming code was set up in Edgecam 2015 for each and every experimental point, as seen in Table 2. The surface roughness value of the machined workpiece was measured using the MarSurf PS1 portable unit.

Applying the rotatable central composite design (RCCD), the Design of experiment (DOE) was obtained. Using different combinations of the input parameters levels performed was a total of 30 experiments. The machining parameters chosen to analyze their effect on surface roughness were spindle speed, feed per tooth, axial depth of cut and radial depth of cut. Values of cutting conditions have been determined for a 4-factor design of experiments according to tool producer recommendations and the workpiece material, Table 1.

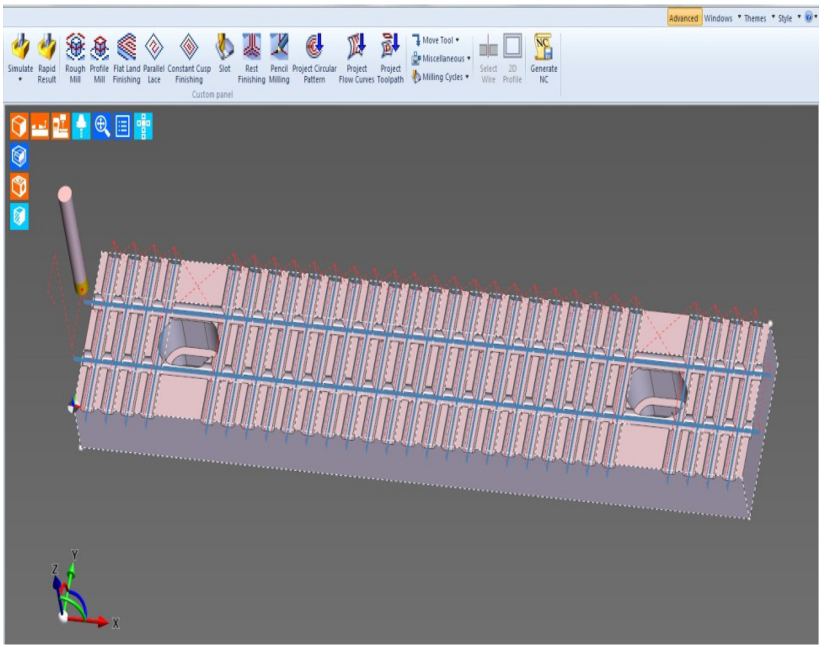

Fig. 1 Test part designed in Edgecam 2015

Table 1 Machining parameters and their levels

Parameters	Levels				
	-2	-1	0	1	1
Spindle speed, n (min^{-1})	3981	4777	5573	6369	7169
Feed per tooth, f_z (mm/tooth)	0.018	0.024	0.030	0.036	0.042
Axial depth of cut, a_p (mm)	0.04	0.08	0.12	0.16	0.20
Radial depth of cut, a_e (mm)	0.20	0.40	0.60	0.80	1.00

Spindle speed is calculated by the equation below:

$$n = \frac{v}{2 \cdot \pi \cdot \sqrt{a_p \cdot (d_1 - a_p)}} \tag{1}$$

where v is the cutting speed, a_p is the axial depth of cut and d_1 is a diameter of the tool.

Measured results of surface roughness are presented in Table 2.

Table 2 Experimental results for surface roughness R_a

Trial No.	Code					Parameters				Measured value
	x_0	x_1	x_2	x_3	x_4	n (min^{-1})	f_z (mm/z)	a_p (mm)	a_e (mm)	R_a (μm)
1	1	-1	-1	-1	-1	4777	0.024	0.08	0.40	0.745
2	1	1	-1	-1	-1	6369	0.024	0.08	0.40	0.305
3	1	-1	1	-1	-1	4777	0.036	0.08	0.40	0.643
4	1	1	1	-1	-1	6369	0.036	0.08	0.40	0.497
5	1	-1	-1	1	-1	4777	0.024	0.16	0.40	0.662
6	1	1	-1	1	-1	6369	0.024	0.16	0.40	0.569
7	1	-1	1	1	-1	4777	0.036	0.16	0.40	0.850
8	1	1	1	1	-1	6369	0.036	0.16	0.40	0.425
9	1	-1	-1	-1	1	4777	0.024	0.08	0.80	3.370
10	1	1	-1	-1	1	6369	0.024	0.08	0.80	3.040
11	1	-1	1	-1	1	4777	0.036	0.08	0.80	3.302
12	1	1	1	-1	1	6369	0.036	0.08	0.80	3.149
13	1	-1	-1	1	1	4777	0.024	0.16	0.80	3.261
14	1	1	-1	1	1	6369	0.024	0.16	0.80	3.116
15	1	-1	1	1	1	4777	0.036	0.16	0.80	3.379
16	1	1	1	1	1	6369	0.036	0.16	0.80	3.113
17	1	0	0	0	0	5573	0.030	0.12	0.60	1.677
18	1	0	0	0	0	5573	0.030	0.12	0.60	1.518
19	1	0	0	0	0	5573	0.030	0.12	0.60	1.571
20	1	0	0	0	0	5573	0.030	0.12	0.60	1.296
21	1	-2	0	0	0	3981	0.030	0.12	0.60	1.926
22	1	2	0	0	0	7166	0.030	0.12	0.60	1.159
23	1	0	-2	0	0	5573	0.018	0.12	0.60	1.334
24	1	0	2	0	0	5573	0.042	0.12	0.60	1.299
25	1	0	0	-2	0	5573	0.030	0.04	0.60	1.324
26	1	0	0	2	0	5573	0.030	0.20	0.60	1.285
27	1	0	0	0	-2	5573	0.030	0.12	0.20	0.245
28	1	0	0	0	2	5573	0.030	0.12	1.00	4.258
29	1	0	0	0	0	5573	0.030	0.12	0.60	1.470
30	1	0	0	0	0	5573	0.030	0.12	0.60	1.471

3.2 Response surface methodology (RSM) background

A collection of statistical and mathematical methods is named response surface methodology (RSM) and it can be used in modeling and optimization of different machining processes [23-25]. In the actual development of conventional predictive modeling this methodology is commonly present. The input variables are here referred to as independent variables, and they are subjected to the control of an engineer or a scientist, with the purpose of completing a test or an experiment.

Measurable output performance of the process is called response and it is a dependent variable being tested. RSM quantifies the relationship between the controllable input parameters and the obtained response, in other words, attempts to analyze the influence of independent parameters on a specific dependent response. For modeling and optimization of machining processes data are needed which are collected through experimental work. This methodology represents the empirical statistical technique, which is applied for the regression analysis of the data obtained through the experiment in order to obtain the equation which represents the response function (depending on the variable size being examined). This function can be graphically displayed as a response surface, whereby which this methodology has been named. A few advantages that Response surface methodology (RSM) offers when compared to the classical experimental or optimization methods where only one variable at a time technique is used are as follows [4]: implies a large amount of information from not so many experiments and a possibility to notice easily the interaction effect of the independent parameters on the response. To obtain information about the process useful was the empirical model as it linked the response to the independent variables and it could also be a practical tool for the optimization of machining processes.

According to RSM, the measurability of all the input process parameters is assumed and the corresponding equation expresses the process:

$$y = f(x_1, x_2, \dots, x_k) + \varepsilon \tag{2}$$

where y is the response, f is the unknown function of response, $x_1, x_2, \dots, x_k$ refer to the independent parameters or variables, k is the independent variables number and in the end ε is the statistical error that denotes other sources of variability not accounted for by f.

In RSM two models are commonly used. The first-degree model:

$$y = b_0 + \sum_{i=1}^{k} b_i \cdot x_i + \varepsilon \tag{3}$$

and the second-degree model:

$$y = b_0 + \sum_{i=1}^{k} b_i \cdot x_i + \sum_{i=1}^{k} b_{ii} \cdot x_i^2 + \sum_{j>1}^{k} b_{ij} \cdot x_i \cdot x_j + \varepsilon \tag{4}$$

where b_0 is coefficient of the free term, coefficients b_i are the linear terms, coefficients b_{ii} are quadratic terms and coefficients b_{ij} are interaction terms.

Value of coefficients b_i, b_{ii}, b_{ij} is determined using the method of least squares (MLS).

3.3 Genetic algorithm (GA) background

The GA is a search algorithm for optimization, based on a Darwinian theory of evolution and on the concept of "survival of the fittest". As in nature, the strong species remain intact, while the sleazy species is eliminated. The two most significant advantages of the GA approach are its simplicity of operation and computational efficiency. GA deals with chromosome populations. Actually, string representations of solutions to a particular problem are called chromosomes. Using the real analogy with biology, the chromosome is presented as the genotype, whereas the solution it describes is called the phenotype.

The simplest form of GA involves three types of operators: selection, crossover, and mutation. Fig. 2 illustrates the flowchart of GA for optimization [26]. For using this algorithm, a problem solution is defined in terms of the fitness function. A fitness function is used to evaluate each of the solutions in the population, represented by the chromosomes. Defining this function for the given problem is one of the most difficult tasks in creating a good genetic algorithm.

To allow the entire range of possible solutions (the search space) the original chromosome population is created randomly. Several hundreds or thousands of possible solutions is a typical content of the population size. The fitness function measures the quality of the represented solution and it depends on the nature of a problem. Selection is the process of choosing two or more parents from the population for crossing. The mixing of genetic material from two selected parent chromosomes to produce one or two child chromosomes is called the crossover operator. That crossover operation can be presented in many alternatives, and mutation is one of last GA operators. This is a background operator which produces spontaneous random changes in various chromosomes. The purpose of mutation in GA is preserving and introducing diversity. Population size, number of generations, crossover rate, and mutation rate are the dependable variables for the GA performance.

The GA can actually be stopped under some strict general criteria. Looking at the number of generations the stopping criteria are prescribed. In case the maximum number of the generations exceeds the number of generations, the GA process is terminated and optimised results are provided [17].

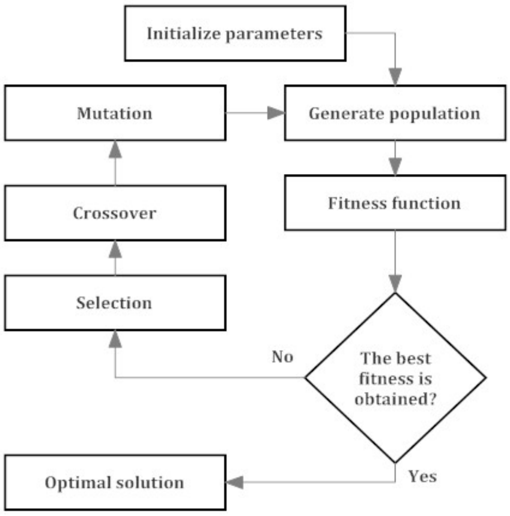

Fig. 2 The flow of GA for optimization

The pseudo code of the GA is presented in Fig. 3 [17]:

```
begin
        k = 0;
        initialize (k);
        evaluate P(t);
while (gen ≤ Max_gen)
        begin
        k = k + 1
        evaluate P(k –1)
        select P(k) from P(k – 1)
        crossover on P(k)
        mutation on P(k)
        evaluate P(t)
        end
end
```

Fig. 3 Pseudo code of the GA

3.4 Gray wolf optimizer (GWO) algorithm background

The leadership hierarchy and hunting mechanism of grey wolves in nature is imitated in the grey wolf optimizer (GWO) algorithm. In 2014 S. Mirjalilli *at al*. developed the algorithm [27]. Grey wolves mainly have a preference for living in a pack. To simulate the leadership hierarchy observed were four types of grey wolves such as alpha beta, delta, and omega. The alpha is actually the first level in the hierarchy and is referred to as the leader of the pack. In the hierarchy of grey wolves beta is the second, next level. The betas are subordinated to alphas but can be of assistance in decision-making or other pack activities. Omega is the lowest ranking of grey wolves. Even delta wolves are dominating over omega, but of course they have to submit to alphas and betas.

The main inspiration of this algorithm apart from their social leadership was the hunting technique of grey wolves. Alpha wolves always lead the way, but grey wolves hunt in groups and coordinate with each other very well. Multiple steps are taken when hunting a prey. That hunting can be divided into a few main stages: tracking, chasing, and approaching the prey; pursuing, encircling and harassing the prey until it stops moving; attack towards the prey [27]. Mathematical modeling hunting technique and social behavior of grey wolves is observed in this GWO algorithm. The prey is located by alpha, beta and delta through its body stance, uncoordinated movements or the smell of wounds and then the chasing starts. The dominant wolves are followed by omegas. The prey is first approached as near as possible, encircled and then harassed until it stops moving. The next step by the pack is jumping and attacking the prey. The flowchart of the GWO algorithm is shown in Fig. 4 [28].

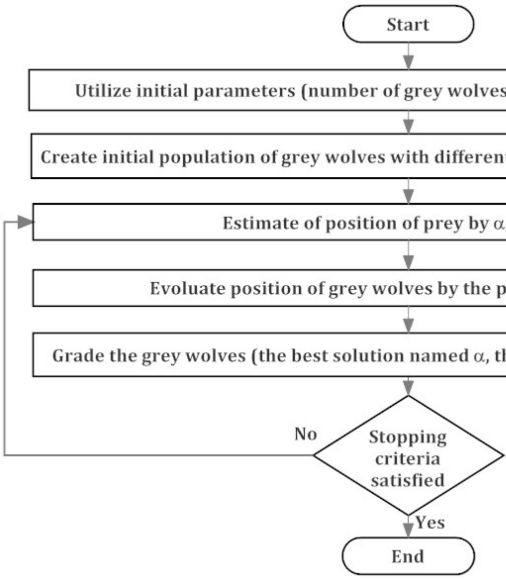

Fig. 4 Flowchart of the GWO algorithm

The most appropriate solution is α and this solution is followed by β and δ, respectively, and the rest of the solutions belong to the ω, in respect to the GWO. The first three fittest wolves that are closest to the prey are α, β, and δ who guide ω to search prey in promising search areas. Omega updates its location based on the location of alpha, beta, and delta in a 2D search space. In the GWO algorithm the search process is started by forming a random population of grey wolves (candidate solutions). The estimation of probable position of the prey is conducted by alpha, beta, and delta wolves using multiple iterations. The distance from the prey is updated by each candidate solution.

With the goal to stimulate the main phases of grey wolf hunting proposed are more vector equations [27], which indicate the position of the prey and grey wolfs during encircling prey, hunting and attacking prey. The pseudo code of the GWO algorithm is presented in Fig. 5 [27] where t indicates the current iteration, a is a component which linearly decreased from 2 to 0 over the course of iterations, A and C are coefficient vectors, $X_{\alpha,\beta,\delta}$ are the position vectors of grey wolfs.

```
Initialize the grey wolf population Xi (i = 1,2,...,n)
Initialize a, A and C
Calculate the fitness of each search agent
Xα = the best search agent
Xβ = the second best search agent
Xδ = the third best search agent
while (t < Max number of iterations)
      for each search agent
                  Update the position of the current search agent
      end for
Update a, A and C
Calculate the fitness of all search agent
Update Xα, Xβ and Xδ
t = t + 1
end while
return Xα
```

Fig. 5 Pseudo code of the GWO algorithm

4. Results and discussion

4.1 Modeling surface roughness by RSM

Applying Design Expert software created was RSM model with the intention to model and analyze surface roughness. Setting up a relationship between surface roughness and the process parameters such as spindle speed, feed per tooth, axial depth of cut and radial depth of cut a for the ball-end milling of hardened steel is the most important objective of the surface roughness model. The mathematical model for surface roughness as a function of machining parameters was developed by using a reduced second-order polynomial response surface mathematical equation. Analysis of variance (ANOVA) for response surface reduced quadratic model is the basis for this kind of equation, as shown in Table 3.

The developed mathematical model to predict surface roughness R_a is:

$$R_{a(RSM)} = 0.95 - 1.85 \cdot 10^{-4} \cdot n + 1.53 \cdot f_z + 0.26 \cdot a_p - 0.85 \cdot a_e + 5.76 \cdot a_e^2 \tag{5}$$

Table 3 Choice of model type based on ANOVA

Response	R_a						
ANOVA for response surface							
Analysis of variance table (Partial sum of squares – Type III)							
Source	Sum of squares	df	Mean square	F Value	p-value Prob > F		PC (%)
Model	37.24	5	7.45	140.10	< 0.0001	significant	
A-n	0.52	1	0.52	9.78	0.0046		1.35
B-f_z	2.017E-03	1	2.017E-03	0.038	0.8472		0.01
C-a_p	2.521E-03	1	2.521E-03	0.047	0.8294		0.01
D-a_e	35.19	1	35.19	661.90	< 0.0001		91.36
D^2	1.53	1	1.53	28.72	< 0.0001		3.96
Residual	1.28	24	0.053				3.31
Lack of fit	1.20	19	0.063	3.93	0.0677	not significant	3.10
Pure error	0.080	5	0.016				0.21
Corrected total	38.51	29					100
	R^2 = 0.9669; Adj R^2 = 0.9599						

With the aim to justify the validity of the model the ANOVA was conducted. The p-value is lower than 0.05 which proves that the model is considered adequate at the 95 % confidence level. The validity of the model is confirmed, by the determination coefficient $R^2 = 0.9669$. If R^2 convergences unity the response model gives better results and there exists less difference between predicted and measured data. The variability measure of the observed output is the adjusted correlation coefficient (Adj $R^2 = 0.96$). The approximate value of the Adj R^2 with R^2 determines the fitness of the model The p-value is separately calculated for all the parameters of the proposed model and it can be concluded the radial depth of cut a_e ($p < 0.0001$) is the most significant parameter on surface roughness.

4.2 Modeling surface roughness by GA

The RSM was used to develop basically the reduced second-order polynomial response surface mathematical model for prediction of surface roughness in ball-end milling and GA was used for fine-tuning of the constants in Eq. 5, which obtained from RSM. The fine-tuning of the constants in GA is performed in order to find the minimum value of the fitness function.

The fitness function is defined as:

$$\Delta = \frac{1}{n} \sum_{i=1}^{n} \frac{|E_i - G_i|}{E_i} \cdot 100\% \tag{6}$$

where n is the size of sample data, E_i the measured R_a and G_i the predicted R_a calculated by GA.

The lower the values of Eq. 6, the better agreement of the model is to the experimental data. For implementing GA GATool was used in MATLAB. The GA predictive model is developed using 25 datasets selected based on experimental results, without 6 datasets on the average level (center points), Table 2. Six datasets on the average level were used as one average value. The best result was obtained with population size of 1500. The developed mathematical model to predict surface roughness R_a using GA is:

$$R_{a(GA)} = 1.48 - 1.85 \cdot 10^{-4} \cdot n + 4.75 \cdot f_z + 0.79 \cdot a_p - 3.94 \cdot a_e + 8.8 \cdot a_e^2 \tag{7}$$

4.3 Modeling surface roughness by GWO algorithm

The fitness/objective function in GWO algorithm is calculated identically as in GA, using Eq. 6 and same datasets of experimental results. Solving of the optimization problem is finding the minimum value of fitness function. For implementing GWO was used GWO toolbox in MATLAB, developed by S. Mirjalilli *at al.* [27]. This toolbox is very simple and can be used without high programming skills because its user-friendly graphical interface. In the toolbox the parameters of the GWO algorithm parameters can easily be calculated. Cost Function is the objective function default name for this toolbox.

The developed mathematical model to predict surface roughness R_a using GWO algorithm is:

$$R_{a(GWO)} = 1.47 - 1.81 \cdot 10^{-4} \cdot n + 4.30 \cdot f_z + 0.86 \cdot a_p - 4.0 \cdot a_e + 8.88 \cdot a_e^2 \tag{8}$$

4.4 Comparison of RSM, GA and GWO model performance

Predicted values for surface roughness as obtained in the RSM, GA and GWO are compared with the experimental values. In Table 4 presented are the compared values of the predictive performance for all the three models (RSM model, GA model, and GWO model) with the measured value. The prediction accuracy PA of each datasets was calculated using Eq. 9 [29]. The model accuracy of the developed RSM, GA and GWO models to predict the surface roughness, was evaluated using Eq. 10.

$$PA = \left[1 - \frac{|Expt\_value_i - Model\_pred_i|}{Expt\_value_i}\right] \cdot 100 \tag{9}$$

$$MA = \frac{1}{n} \sum_{i=1}^{n} PA_i \tag{10}$$

The model accuracy of the RSM, GA and GWO models are 86.79 %, 91.78 %, and 91.80 %, respectively. It can be concluded that the model accuracy of the GWO and GA models almost the same although they have been developed using the various approaches to predict surface roughness in ball-end milling process and different pseudo codes. Both models showed good agreement with the experimental data, but GWO model was more accurate than the GA model. It should be noted that the GWO algorithm is easier for application than the GA and the time required to calculate the minimum value of the fitness function is shorter than when using the GA.

Confirmation for the models developed has also been conducted using ten additional experiments, which were randomly selected from the set of experiments performed as according to Taguchi orthogonal array L_{25} (5^6). Those confirmation tests have also proved good accuracy of all the models obtained, having in mind the model based on GWO enabled the best predictability of surface roughness for the given case. In Table 5 presented are the values of the input parameters as well as the results of the roughness measured for all the ten additional measurements.

Table 4 Comparison of RSM, GA, and GWO predictive models

Trial No.	Measured value R_a (μm)	RSM		GA		GWO		
		Predicted value R_a (μm)	Prediction accuracy (%)	Predicted value R_a (μm)	Prediction accuracy (%)	Predicted value R_a (μm)	Prediction accuracy (%)	
1	0.745	0.705	94.63	0.600	80.56	0.593	79.66	Training data
2	0.305	0.411	65.25	0.306	99.79	0.305	99.96	
3	0.643	0.724	87.40	0.657	97.80	0.645	99.68	
4	0.497	0.429	86.32	0.363	72.97	0.356	71.73	
5	0.662	0.726	90.33	0.663	99.82	0.662	99.99	
6	0.569	0.432	75.92	0.369	64.79	0.373	65.64	
7	0.850	0.745	87.65	0.720	84.73	0.714	83.96	
8	0.425	0.450	94.12	0.426	99.85	0.425	99.98	
9	3.370	3.130	92.88	3.246	96.31	3.254	96.55	
10	3.040	2.836	93.29	2.951	97.08	2.965	97.53	
11	3.302	3.149	95.37	3.303	99.98	3.305	99.90	
12	3.149	2.854	90.63	3.008	95.53	3.017	95.80	
13	3.261	3.151	96.63	3.309	98.54	3.322	98.12	
14	3.116	2.856	91.66	3.014	96.73	3.034	97.35	
15	3.379	3.169	93.79	3.366	99.61	3.374	99.85	
16	3.113	2.875	92.35	3.071	98.66	3.085	99.11	
17	1.677	1.560	93.02	1.484	88.48	1.484	88.50	
18	1.518	1.560	97.23	1.484	97.75	1.484	97.77	
19	1.571	1.560	99.30	1.484	94.45	1.484	94.47	
20	1.296	1.560	79.63	1.484	85.51	1.484	85.49	
21	1.926	1.854	96.26	1.778	92.33	1.773	92.04	
22	1.159	1.265	90.85	1.189	97.40	1.195	96.87	
23	1.334	1.541	84.48	1.427	93.04	1.432	92.62	
24	1.299	1.578	78.52	1.541	81.38	1.536	81.78	
25	1.324	1.539	83.76	1.421	92.69	1.415	93.09	
26	1.285	1.580	77.04	1.547	79.62	1.553	79.17	
27	0.245	0.056	22.86	0.246	99.75	0.245	99.99	
28	4.258	4.906	84.78	5.537	69.97	5.565	69.30	
29	1.470	1.560	93.88	1.484	99.06	1.484	99.04	
30	1.471	1.560	93.95	1.484	99.13	1.484	99.11	
Model accuracy			**86.79**		**91.78**		**91.80**	
1	1.587	1.854	83.16	1.778	87.94	1.773	88.30	Testing data
2	1.402	1.678	80.30	1.543	89.97	1.542	89.98	
3	3.235	3.141	97.08	3.277	98.70	3.288	98.37	
4	5.259	5.064	96.29	5.715	91.32	5.744	90.78	
5	0.523	0.598	85.57	0.576	89.88	0.578	89.51	
6	1.328	1.548	83.43	1.449	90.86	1.441	91.47	
7	3.640	3.010	82.70	3.184	87.47	3.187	87.55	
8	1.602	1.424	88.89	1.371	85.59	1383	86.30	
9	4.851	4.758	98.07	5.386	88.96	5.412	88.43	
10	3.405	2.710	79.60	2.870	84.28	2.898	85.10	
Model accuracy			**87.51**		**89.50**		**89.58**	

Table 5 Experimental results of confirmation tests

Trial No.	Parameters				Measured value
	n (min^{-1})	f_z (mm/z)	a_p (mm)	a_e (mm)	R_a (μm)
1	3981	0.030	0.12	0.60	1.587
2	4777	0.018	0.08	0.60	1.402
3	4777	0.024	0.12	0.80	3.235
4	4777	0.030	0.16	1.00	5.259
5	5573	0.030	0.20	0.40	0.523
6	5573	0.036	0.04	0.60	1.328
7	5573	0.042	0.08	0.80	3.640
8	6369	0.024	0.20	0.60	1.602
9	6369	0.036	0.08	1.00	4.851
10	7166	0.018	0.20	0.80	3.405

5. Conclusion

This paper presents the predictive models for surface roughness R_a during ball-end milling process which were developed using RSM, GA and GWO algorithm. In the first step of the research basic mathematical model was developed by the use of RSM. The developed model is adequate. The validity of the model was confirmed using ANOVA. This reduced quadratic model was used in next steps as basic shape for a build-up of predictive models using GA and GWO algorithm. In the second step, the predictive models were developed applying GA and GWO algorithm. The fitness function was same for both algorithms and was calculated identically, using Eq. 6. For implementing GA and GWO algorithm were used toolboxes in MATLAB. The predictive capability developed models were compared. Experimental results were compared with predicted values for all three the models. The predictive model developed using GWO algorithm providing the best prediction accuracy. The model accuracy for surface roughness was 91.8 % and 89.58 % for training and testing data, respectively. On comparison RSM, GA and GWO models were found that nature-inspired algorithms show the good ability for prediction of surface roughness in ball-end milling process. Results have confirmed that new swarm intelligence-based algorithm, called GWO as useful for modeling machining processes.

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