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ORIGINAL ARTICLE

Optimal process parameters for minimizing the surface roughness in CNC lathe machining of Co28Cr6Mo medical alloy using differential evolution

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Abstract

This study is conducted to observe the optimal effect of rotational speed, feed rate, depth of cut, and tool tip radius on the surface roughness of a material. In the machining processes, surface roughness value should be made as low as possible and is determined by the value of the optimal process parameters. Currently, the application of differential evolution (DE) optimization technique in optimizing the process parameters for achieving minimum surface roughness, especially in CNC lathe machining of Co28Cr6Mo medical alloy, is still not given any consideration by the researcher. Therefore, in this study, a new approach of CNC lathe parameters optimization using DE algorithm is introduced. At first, a regression model is developed from the actual machining data provided by Asiltürk, Neşeli, and İnce [1]. The regression model of the surface roughness is formulated as a fitness function for DE algorithm. The results of this study have proven that the DE optimization technique is able to estimate the optimal process parameters that yield minimum surface roughness. The application of DE as a solution approach in process parameter optimization has significantly improve the surface roughness (*R*a) where the *R*a value is reduced by 81, 72, and 30% when compared to the experiments, regression modeling, and response surface methodology (RSM) respectively.

Keywords CNC lathe machining · Regression modeling · Differential evolution · Response surface roughness · Surface roughness · Optimization

1 Introduction

In the manufacturing industry, the surface texture of a product reflects the quality of the product as it affects the appearance, function, and reliability of the product itself. Customers have increasingly focused on product quality making surface roughness one of the most competitive dimensions nowadays as market competitiveness grows [2]. In CNC lathe machining operation, selecting suitable process parameters is an important task in achieving better cutting performance. The adopted process parameters are usually determined based on experiences or by the use of handbooks. However, the range of the process parameters given in these sources is actually the starting values and not the optimal values for the machining operation [3]. Thus, it is needed to develop an efficient optimization technique that can accurately predict the surface roughness of machining output and search for the best parameter setting. Theoretically, the relationship between *process parameters* and the desired response can be quantified using regression model. Regression modeling has existed for decades and it is the process in predicting optimal solutions with a minimum value of machining performance [4, 5].

Several techniques, such as the statistical regression and conventional optimization techniques have been implemented by researchers in developing the regression model and

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optimizing machining parameters. The conventional techniques include the Taguchi method, response surface methodology (RSM), and weighted principle component analysis (WPCA) [6–8]. Qureshi, Sorte, and Teli [9] stated that the quality of turned steel was commonly determined by the surface quality. The study was conducted to investigate the effects of process parameters in CNC lathe machining of AISI P20 steel with TiN-coated tungsten carbide insert. The process parameters investigated were spindle speed, feed rate, and depth of cut in achieving minimum surface roughness. In this study, the Taguchi method was applied to optimize the process parameters of the machining operation and analysis of variance (ANOVA) was employed to study the effects of the process parameters on surface roughness. They stressed that in order to minimize the surface roughness, it is necessary that a combination of high-level cutting speed, low-level feed rate, and middle-level depth of cut be employed. In another study by Kajal and Yadav [10], the calculations of surface roughness in CNC turning operation of EN354 alloy steel with CNMG 120408 GT cutting tool were made based on the cutting speed, feed rate, and depth of cut. In this study, the Taguchi method was employed in optimizing the process parameters of CNC turning by developing the regression model and analysis of variance (ANOVA) was then used in analyzing the end results. It was finally concluded that the cutting speed had the most significant effect on surface roughness followed by feed rate and depth of cut. Adem et al. [11] studied the effects of cryogenic treatment and drilling parameters on surface and hole quality in dry drilling using AISI 304 stainless steel. Two methods had been employed, i.e., Taguchi and RSM. Taguchi was used to achieve better surface roughness and minimize roundness error while RSM was used to find the most influential parameters affecting surface roughness and roundness error. Experimental results showed that cutting speed and feed rate were the most significant factors affecting surface roughness and roundness error. The regression model obtained from RSM was able to predict the optimal surface roughness and roundness error with the desired drilling parameters and heat treatments applied to the drilling machine. Even though conventional methods produced better results, the methods are of low efficiency and very time consuming apart from the repetitive desirable value achievement produced. A large sample data is needed in order to obtain the regression model from ANOVA. This method of optimization is not efficient when the practical search space is too large and is also not robust.

Realizing this, several efforts have been taken to minimize the surface roughness by applying a computational approach rather than doing the trial and error approach applied in real experiments. Several researchers have used the concept of non-conventional optimization techniques such as genetic algorithm (GA), symbiotic organisms search (SOS), simulated annealing (SA), firefly algorithm, particle swarm optimization (PSO), differential evolution (DE), and ant colony optimization (ACO) in process parameter optimization for achieving minimum surface roughness in various machining operations [12]. The capabilities of non-conventional optimization techniques are not only limited to minimizing the surface roughness but also have been employed in other manufacturing field such as multi-pass milling [13], optimizing the stiffener layout design of machine tool structures [14], electrical discharge machining (EDM) process parameter optimizing [15], production planning and scheduling [16], improving the quality of laser cutting process [17], and product quality produced from injection molding process [18].

A new algorithm known as differential evolution (DE) algorithm which is similar to the concept of GA was introduced by Storn and Price [19]. Considering the ability factors of DE for the machining optimization problem, work has been done to estimate the best combination of process parameters for the R_a performance in CNC lathe machining process. DE is one of the evolutionary algorithms (EAs) which is a population-based method that relies on mutation, recombination, and selection to evolve a collection of candidate solutions toward an optimal state [20]. Like most EAs, DE exploits the population via recombination. However, DE does not attempt to mimic natural searches, like those of ants, bees, the immune system, or those arising from social interaction, and only DE directly samples the population to drive mutation which is a beneficial strategy [21]. Consequently, DE owes it to a special kind of differential operator which is invoked to create new offspring from parent chromosomes instead of classical crossover of mutations [22]. A comparative study by Huanzhe, Kungi, and Xia [23] showed that the scheme of DE, i.e., “DE/best/1/exp” has excellent performance in solving unimodal function problems such as Quadric and Rosenbrock function when compared to artificial bee colony (ABC) and bee algorithms, and it can even get a better solution by crossover rate (CR) adjustment. In another study carried out by AbdulKader and Salam [24], DE was found to give better accuracy and converges to global minimum faster than that of particle swarm optimization (PSO) in training and testing feed-forward neural network for stock price prediction. Therefore, the study, in this aspect, has the potential in improving the surface roughness and optimizing the process parameters of the machining operations.

In a study by Marko et al. [25], where carbonized steel was subjected to CNC lathe machining operation, the result of which the cutting force, surface roughness, and maximal tool life values were calculated based on the input parameters of surface speed, feed rate, and cutting depth. Particle swarm optimization (PSO) was employed in order to determine the optimum process parameters for the minimum values of the responses with the use of Matlab software. It was finally determined that PSO gave better results when compared to the conventional optimization methods. Fuzzy logic artificial intelligence technique was used by Marani Barzani et al. [26] in order to study the effects of cutting speed, feed rate, and depth of cut on the surface roughness of Al–Si–Cu–Fe die casting alloy during CNC turning. ANOVA analysis was employed in optimizing the parameter conditions for the machining process. As a result, surface roughness increased with increasing feed rate and improved with rising cutting speed. In a study by Roque et al. [27], a modified couple stress theory was used to study the influence of a scale parameter of a Timoshenko functionally graded beam in free vibration. The beam was required to resonate at low frequencies for the micro device energy harvesting. In this study, differential evolution (DE) algorithm was applied in order to minimize the free vibration frequency of the beam. Three-parameter volume fraction laws of power law, sigmoid law, and exponential law were chosen in describing the volume fraction variation along the beams' thickness. The results showed that the scale parameter had no effect on the optimal material distribution across the beam thickness for the selected volume fraction law when linear analysis was considered. The results obtained were insensitive to the tested boundary conditions. Sreenivasa Rao and Venkaiah [28] had conducted an experiment on Nimonic-263 material by WEDM. They had studied the material removal rate and surface roughness as the performance measures with the input parameters of pulse-on time, pulse-off time, peak current, and servo voltage. The responses were identified with RSM from the developed mathematical model. In optimizing the WEDM process, a differential evolution (DE) technique was applied. The optimal values from the DE was evaluated and compared with the RSM technique. The results showed that DE algorithm was found to be more accurate than RSM. The most significant parameters in the WEDM process were pulse-on time and peak current.

Based on the literature reviews, it is clear that there is a deficiency of research in the medical material process parameter optimization. Furthermore, the differential evolution (DE) optimization technique has not been widely used in the optimization of the machining operations. Thus, the study of process parameter optimization of medical material in CNC lathe machining with the use of non-conventional optimization techniques can be taken as a new contribution in any domain of the machining fields. With the application of DE, it is expected to provide a better result of R_a compared to conventional method. Comparison of the results of minimum R_a based on experimental data, regression modeling, response surface roughness, and DE was made to find out which method would provide the best result. The percentage of variation in the values of R_a obtained by these four approaches is described.

2 Methodology

Factors such as machining parameters, cutting phenomena, work-piece properties, and cutting tool properties influence the surface roughness of a material. Optimization of rotational speed, feed rate, depth of cut, and tool tip radius for the surface roughness, R_a performance measure in CNC lathe machining by means of the differential evolution (DE) technique can be taken as a new contribution to the machining area.

In obtaining the optimal operating conditions to minimize machining surface roughness, R_a values in CNC lathe operation, the experimental study underwent four different phases. The four phases of process parameters optimization is illustrated in Fig.1.

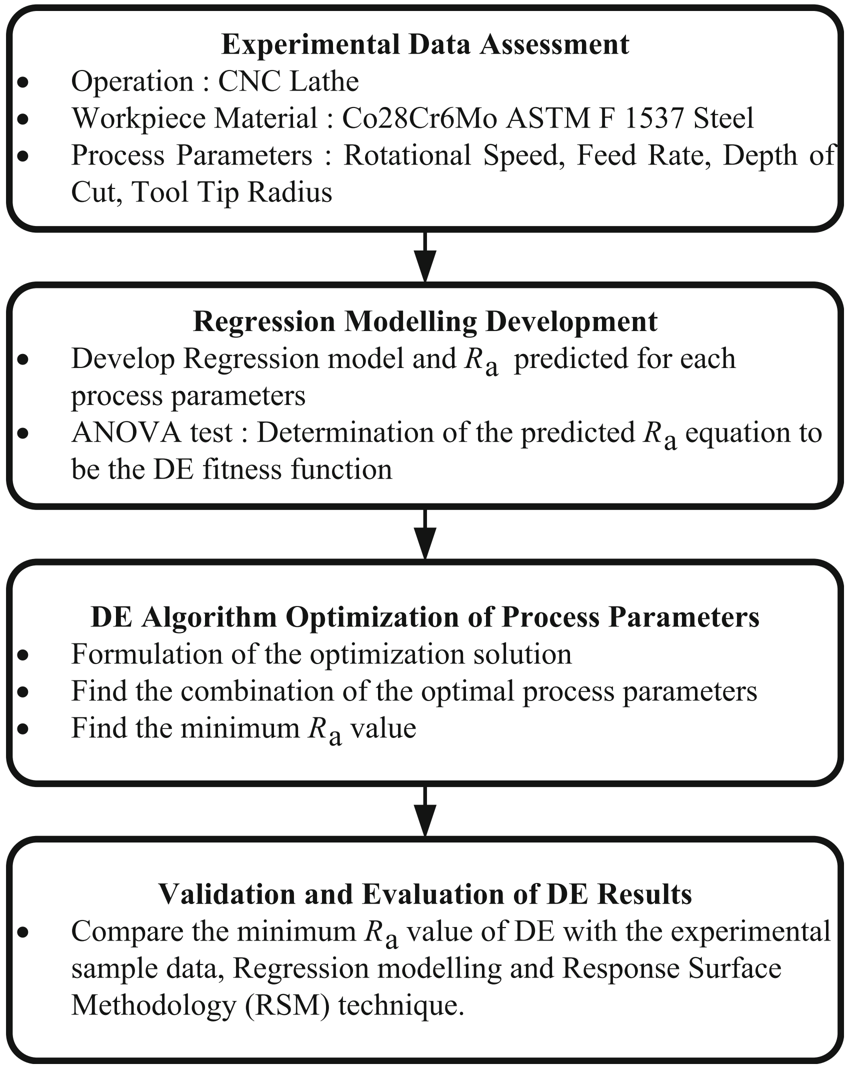
The explanation for each of the phases is given below:

i. The machining experimental data set were studied in order to examine the process parameters used (rotational speed, feed rate, depth of cut, and tool tip radius) which contribute to the surface roughness, R_a results. The CNC lathe machining of Co28Cr6Mo ASTM F 1537 steel were conducted under dry machining conditions using the experiment data set.
ii. The machining model was developed to describe the relationship between the process parameters (rotational speed, feed rate, depth of cut, and tool tip radius) and the response (surface roughness) by using the regression technique. The regression model was selected based on the ANOVA test for the fitness function (objective function) in the DE optimization module.
iii. The optimal values of the process parameters were determined to provide the minimum objective function by using DE technique. The objective function or fitness function of DE leads to the minimum (lower) value of surface roughness. The Matlab programming software was used to find the optimal solutions that would lead to the minimum value of surface roughness.
iv. DE optimization solution was evaluated by comparing the optimal process parameters that gave the minimum surface roughness values generated from DE with those obtained from the experiments, the regression model, and RSM.

3 Experimental details

The experimental study conducted by Asiltürk, Neşeli, and İnce [1] in measuring the surface roughness values in the CNC lathe machining was referred to in this study. A set of experiments were conducted on CNC lathe machine in determining the effects of machining parameters of rotational speed (n), feed rate (f), depth of cut (a), and tool tip radius (r) on the output response of surface roughness (R_a). The work-piece used was an annealed medical material, Co28Cr6Mo ASTM F 1537 steel having hardness of 40 HRC with dimensions of Ø50 × 500 mm. The whole experiment was conducted under dry machining conditions and a new cutting bit was used for every test. Three types of cutting bits produced by Taegutec Company were used in the work-piece longitudinal machining which was TNMG 160404 MT, TNMG 160408 MT, and TNMG 160412 MT form and cladded with TiCN by the PVD method and at the quality of TT 8020 while MTJNR-L 2525M16 was used as a tool holder.

Fig. 1 Process parameter optimization flow chart



According to the design of the experiment, the CNC lathe machining process parameters of Co28Cr6Mo ASTM F 1537 steel recommended by the manufacturer and three levels of the parameters selected is shown in Table 1. The combinations of experimental parameters used in the experimental study are presented in Table 2.

TC25-L type Sogotec CNC lathe machine and SJ-201 Mitutoyo device at 2.5-mm cut-off value were used to carry out the turning process and measure the surface roughness values of the machine work-piece as shown in Fig. 2 and Fig. 3 respectively. The average surface roughness values were recorded on three sections of the cylindrical surface along the work-piece at the end of every turning operation's feed rate. The surface roughness of the work-piece was measured by using SJ-201 Mitutoyo measuring device at 2.5-mm cut-off value.

Table 1 Machining parameters and their levels [1]

Symbol	Parameter	Unit	Level 1	Level 2	Level 3
n	Rotational speed	rpm	318	477	636
f	Feed rate	mm/rev	0.1	0.15	0.25
a	Depth of cut	mm	0.5	0.7	0.9
r	Tool tip radius	mm	0.4	0.8	1.2

4 Response surface methodology

RSM is the useful collection of mathematical modeling and statistical techniques for optimization and problem analysis of the cutting system's input process parameters which response to the dependent variables. The relationship of the input parameters and their respective responses can be predicted by using RSM. The desired response modeling of several process parameters can be found by using the design of experiments (DOE) and applying regression analysis.

RSM generally takes place in three stages. The first stage is the physical experiments carried out by forming an experimental parameter combination in obtaining the reactive values. Only a few and efficient experiments are needed

Table 2 Experimental parameters and recorded average surface roughness values [1]

Number of test	Parameter				Roughness
	n (rpm)	*f* (mm/rev)	*a* (mm)	*r* (mm)	$R_{a(exp)}$ (μm)
1	318	0.10	0.50	0.40	1.660
2	318	0.10	0.70	0.80	0.810
3	318	0.10	0.90	1.20	1.070
4	318	0.15	0.50	0.80	1.593
5	318	0.15	0.70	1.20	1.137
6	318	0.15	0.90	0.40	2.920
7	318	0.25	0.50	1.20	2.750
8	318	0.25	0.70	0.40	7.110
9	318	0.25	0.90	0.80	4.923
10	477	0.10	0.50	0.80	1.590
11	477	0.10	0.90	1.20	0.987
12	477	0.10	0.90	0.40	1.690
13	477	0.15	0.50	1.20	0.857
14	477	0.15	0.70	0.40	4.410
15	477	0.15	0.90	0.80	2.647
16	477	0.25	0.50	0.40	8.207
17	477	0.25	0.70	0.80	3.037
18	477	0.25	0.90	1.20	1.950
19	636	0.10	0.50	1.20	1.690
20	636	0.10	0.70	0.40	4.017
21	636	0.10	0.90	0.80	1.720
22	636	0.15	0.50	0.40	3.567
23	636	0.15	0.70	0.80	1.417
24	636	0.15	0.90	1.20	2.547
25	636	0.25	0.50	0.80	3.243
26	636	0.25	0.70	1.20	2.193
27	636	0.25	0.90	0.40	4.787
$R_{a(minimum)}$					0.810

compared to the number of experiments required by the conventional methods and therefore there would be a reduction in the costs involved. In addition, the mathematical model that has been developed enables the prediction of unknown intermediate reaction values in a short time based on the outcome of the analysis. The input process parameters obtained and their relationships are defined as a second-degree polynomial or exponential function in the second stage. For the final stage, surface graphics and ANOVA are used in predicting the optimum points of the input parameters. RSM quadratic model is

Fig. 2 TC25-L type Sogotec CNC lathe machine [1]

Fig. 3 SJ-201 Mitutoyo device [1]

formulated and expressed based on the relationship between the input process parameters and the reaction following a second-degree polynomial function of Eq. (1).

$$Y = \alpha_0 + \sum_{i=1}^{k} \alpha_i X_i + \sum_{i=1}^{k} \alpha_{ii} X_i^2 + \sum_j \sum_i^k \alpha_{ij} X_i X_j + e \quad (1)$$

Here, Y is the predicted response (R_a), α_0 is a constant where α_i, α_{ii}, and α_{ij} are the first- and second-degree input process parameters and the parameter interactions, respectively. X_i is the value of the i^{th} input process parameter while the residual e is the experimental error measurement of the observations.

5 Experimental design

The experimental design and results are discussed by referring to the previous experimental study conducted by Asiltürk, Neşeli, and İnce [1]. In order to get clear and accurate experimental observation conclusions, DO was used. Normally, to investigate a three-stage 13-factor (3^{13}) combination effects, the L_{27} orthogonal array is used. In this study, there was a total of 27 physical experiments executed in maintaining consistency by applying the Taguchi standard orthogonal experimental design with the use of three parameters and three-level array, L_{27} (3^{13}). The design arrangement suitable for this study, i.e., 3^4 with the corresponding reaction is given in Table 2. Three different cutting bits were used in machining to obtain the data shown. Referring to Table 2, the first column of the table shows the rotational speed (n), followed by feed rate (f), depth of cut (a), tool tip radius (r), and surface roughness values (R_a).

6 Regression modeling development for surface roughness

In the present study, a second-degree equation (quadratic model) for the output responses of surface roughness (R_a) in terms of input machining parameters of rotational speed (n), feed rate (f), depth of cut (a) and tool tip radius (r) in coded and actual factors were developed by using RSM. The experimental results obtained were used to model the surface roughness using RSM. The developed regression model was further used for optimizing the CNC lathe machining process. Due to the lower predictability of the first-order model to represent the present problem, the quadratic model was developed for the output response of surface roughness.

The second-degree equation which considers the two-factor interactions is given below as Eq. (2) [29]:

$$\begin{aligned} Y = {} & \beta_0 + \beta_1 n + \beta_2 f + \beta_3 a + \beta_4 r + \beta_{11} n^2 + \beta_{22} f^2 \\ & + \beta_{33} a^2 + \beta_{44} r^2 + \beta_{12} nf + \beta_{13} na + \beta_{14} nr + \beta_{23} fa \\ & + \beta_{24} fr + \beta_{34} ar \end{aligned} \quad (2)$$

where Y is the predicted surface roughness and β is the constant.

The statistical analysis software, Design-Expert, was used in analyzing the experimental data obtained from the previous study and in determining the regression coefficients of the developed model. Analysis of variance (ANOVA) was employed in testing the significance of the machining parameters in CNC lathe machining. The predicted model was established in terms of actual factors and used to show the reaction formed by using the codes of the input parameters. The coefficient of determination (R^2) was computed in order to check the fitness of the regression model to the experimental data.

The regression equation and coefficient of the quadratic model was obtained from the experimental data for the response characteristics as a function of the four input process parameters which are rotational speed, feed rate, depth of cut, and tool tip radius by using Design-Expert software. The regression equation was obtained together with the coefficient of determination (R^2). R^2 is defined as a measure of the goodness of fit. In other words, the more R^2 approaches unity, the better the response model fits the actual data. Equation (3) states the prediction model for the surface roughness measurement.

$$\begin{aligned} R_a = {} & -3.574 + 0.013n + 66.380f \\ & + 2.891a - 9.710r - 1.828e^{-6} n^2 \\ & + 34.213f^2 - 3.180a^2 \\ & + 3.891r^2 - 0.066fn - 2.142e^{-3} an \\ & + 1.546e^{-3} nr - 12.941af - 25.641fr + 5.353ar \end{aligned} \quad (3)$$

Based on Design-Expert software, the coefficient of determination (R^2) of the surface roughness quadratic model was found to be 0.9200. This shows that this model is able to explain the variation in R_a to the extent of 92%. It can be said

Table 3 R_a experimental and predicted values of regression modeling

Number of Test	Parameter				Roughness	
	n (rpm)	f (mm/rev)	a (mm)	r (mm)	$R_{a(exp)}$ (μm)	$R_{a(predicted)}$ (μm)
1	318	0.10	0.50	0.40	1.660	2.036
2	318	0.10	0.70	0.80	0.810	0.538
3	318	0.10	0.90	1.20	1.070	0.887
4	318	0.15	0.50	0.80	1.593	1.609
5	318	0.15	0.70	1.20	1.137	1.142
6	318	0.15	0.90	0.40	2.920	3.080
7	318	0.25	0.50	1.20	2.750	2.750
8	318	0.25	0.70	0.40	7.110	7.591
9	318	0.25	0.90	0.80	4.923	4.340
10	477	0.10	0.50	0.80	1.590	1.142
11	477	0.10	0.90	1.20	0.987	1.730
12	477	0.10	0.90	0.40	1.690	2.125
13	477	0.15	0.50	1.20	0.857	1.021
14	477	0.15	0.70	0.40	4.410	3.805
15	477	0.15	0.90	0.80	2.647	1.869
16	477	0.25	0.50	0.40	8.207	7.340
17	477	0.25	0.70	0.80	3.037	3.945
18	477	0.25	0.90	1.20	1.950	2.397
19	636	0.10	0.50	1.20	1.690	1.598
20	636	0.10	0.70	0.40	4.017	3.221
21	636	0.10	0.90	0.80	1.720	1.957
22	636	0.15	0.50	0.40	3.567	4.320
23	636	0.15	0.70	0.80	1.417	2.240
24	636	0.15	0.90	1.20	2.547	2.007
25	636	0.25	0.50	0.80	3.243	3.339
26	636	0.25	0.70	1.20	2.193	1.648
27	636	0.25	0.90	0.40	4.787	4.849
$R_{a(minimum)}$					0.810	0.538

that the model is adequate in representing the machining process based on the high value of R^2.

After that, Eq. (3) is applied in predicting the surface roughness values and the results are summarized in Table 3. The minimum predicted surface roughness values was then compared with the minimum experimental surface roughness values together with their corresponding value of process parameters.

Referring to Table 3, the lowest predicted value of experimental surface roughness, $R_{a(exp)}$ and predicted surface roughness, $R_{a(predicted)}$ is 0.810 and 0.538 μm respectively in this study of medical material in CNC lathe machining operation. It was found that in achieving the lowest value of both $R_{a(exp)}$ and $R_{a(predicted)}$, the combination of the process parameters are rotational speed, n of 318 rpm; feed rate, f of 0.1 mm/rev; depth of cut, a of 0.7 mm; and tool tip radius, r of 0.8 mm. Thus, the predicted results are better than the experimental results in terms of surface roughness.

7 Differential evolution optimization

Differential evolution (DE) algorithm is a simple and fast and population-based stochastic function that was first developed by Rainer Storn and Kenneth Price [19]. DE is a non-conventional optimization technique and also one of the best genetic-type algorithms for complex nonlinear problems and has been successfully used in several areas [30]. There are few advantages when using the DE optimization method which are its simple structure, ease of use, speed, and robustness.

Based on Fig. 4, there are three important operations used by DE which are mutation, crossover, and selection. The randomly generated initial population is evolved to final individual solution by using the three operators of DE. The trial vectors generated by mutation, crossover, and selection are then used in determining whether the target vector or the trial vector can survive to the next

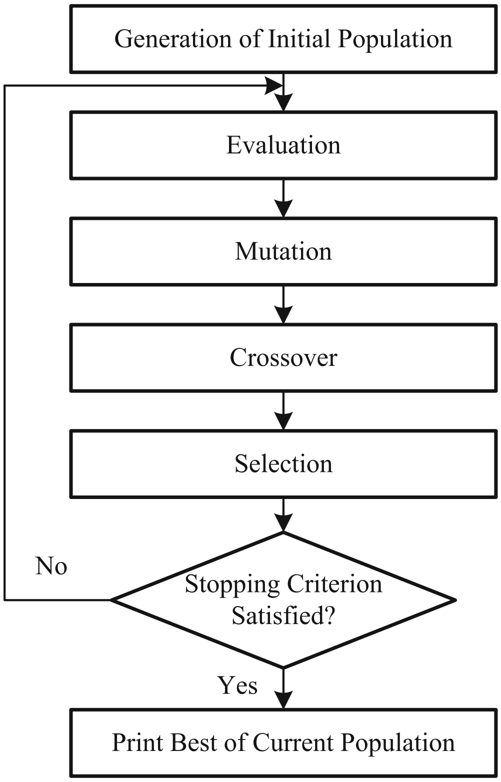


Fig. 4 Differential evolution algorithm flow chart

generation. The procedure of DE is explained as follows:

i. Step 1: Initialization

An initial population of new solutions called vectors is first generated at the beginning of the DE optimization procedure. The initial population is generated randomly within the feasible variable ranges at current generation, t, with j as the dimensions. The initial population for each control variable is generated by using the Eq. (4). The value of i^{th} particle's j^{th} variable is given by:

$$x_{i,j} = x_j^{min} + rand(0,1)\left(x_j^{max} - x_j^{min}\right) \quad (4)$$

where x_j^{max} and x_j^{min} are the upper and lower bounds of j^{th} variable respectively.

ii. Step 2: Mutation

A trial vector $v_i(t)$ is produced by the mutation operator corresponding to each individual of the current population by weighted differential target vector mutation and three different members x_{r1}, x_{r2} and x_{r3}, which do not coincide with the current member, x_i, are then chosen randomly. Thus, the j^{th} component of $v_i(t)$ can be stated as:

$$v_{i,j}(t+1) = x_{r1j}(t) + F\left(x_{r2j}(t) - x_{r3j}(t)\right) \quad (5)$$

This equation creates the trial vector $v_i(t)$ and the typical value of differentiation constant, F is in the range of 0.4 to 1.0.

iii. Step 3: Crossover

Crossover operator merges the trial vector, $v_i(t)$ and the parent vector, $x_i(t)$ in order to produce more descendants to increase the diversity of the population. The crossover performs on all the variables on the randomly picked number which is between 0 and 1 and within the crossover rate (CR) value.

$$u_{i,j}(t) = \begin{cases} v_{i,j}(t) \text{ if } rand\ (0,1) < CR \\ x_{i,j}(t) \text{ else} \end{cases} \quad (6)$$

where $u_{i,j}(t)$ represents the descendant that will be compared with the parent vector, $x_{i,j}(t)$.

iv. Step 4: Selection

The selection operator determines which individuals will survive in the next generation, at time $t = t + 1$. If the vector, $u_i(t)$, yields better fitness value, it will replace its parent in the next generation; otherwise, the parent remains in the population. The population will either get better in terms of the fitness function or remains constant but never deteriorates. The selection process can be expressed as:

$$x_i(t+1) = \begin{cases} u_i(t) \text{ if } f(u_i(t)) \leq f(x_i(t)) \\ x_i(t) \text{ if } f(x_i(t)) < f(u_i(t)) \end{cases} \quad (7)$$

where function f () is the function to be minimized.

After the installation of the new population, the mutation, crossover, and selection procedure will be repeated until the maximum number of generations is reached.

7.1 Problem formulation and optimization solution

In this study, the target of the optimization process is to determine the optimal set values of process parameters that contribute to the minimum surface roughness, R_a value. To optimize the surface roughness, it is important to determine the machining problem which consists of rotational speed (n), feed rate (f), depth of cut (a) and tool tip radius (r). The options selected for the problem formulation are tabulated in Table 4.

Table 4 Problem formulation options

Option	Justification
Number of variables	4
Population type	Double vector
Population size	40

Table 5 Machining parameters and their range

Symbol	Parameter	Unit	Lower boundary	Upper boundary
n	Rotational speed	rpm	318	636
f	Feed rate	mm/rev	0.10	0.25
a	Depth of cut	mm	0.50	0.90
r	Tool tip radius	mm	0.40	1.20

The main fitness function for this problem is surface roughness. The surface roughness regression model proposed by Eq. (8) below was selected as the fitness function to formulate the optimization problem for CNC lathe machining:

$$Y = \beta_0 + \beta_1 n + \beta_2 f + \beta_3 a + \beta_4 r + \beta_{11} n^2 + \beta_{22} f^2 + \beta_{33} a^2 + \beta_{44} r^2 + \beta_{12} nf + \beta_{13} na + \beta_{14} nr + \beta_{23} fa + \beta_{24} fr + \beta_{34} ar \tag{8}$$

The minimization of the fitness function value of Eq. (8) is subjected to the boundaries of the machining parameters. The range of experimental process parameter values given in Table 1 was selected in presenting the limitations of the optimization solution and is tabulated in Table 5.

Once the optimization problem was formulated, it was then solved using differential evolution algorithm (DE) by developing and running the program with Matlab programming software. In order to get the best optimal results, there are some criteria that need to be set properly which includes the initial population size, the differentiation constant, the crossover rate and the selection function type. In this study, the best combination of the process parameter set values will lead to the minimum surface roughness. The recommended parameter setting for these criteria from the previous researchers was first followed in obtaining the most optimal result that is to be expected from this study. After that, a few combinations for the parameter settings were tested by using Matlab programming software to obtain the best optimal result for the surface roughness.

In this study, there are differences between the symbols used in the RSM regression modeling and the equations of DE. Each symbol in the DE algorithm is related with the symbols in the RSM regression modeling in order to optimize the CNC lathe machining operation process parameters in obtaining the minimum surface roughness value. Table 6 summarizes the relationship between the symbols in regression modeling and in DE algorithm with their respective ranges.

In a nutshell, the parameter settings of the initial population size, differentiation constant, the crossover rate and the number of generation was first decided within the range of number in the DE optimization algorithm of this research study. DE optimization algorithm for this study was done with the generation of new solutions' population of 40 vectors in the first step. After that, each vector with 4 dimensions which are the process parameters in the population was evaluated for the fitness value, R_a and then took turns to be a target vector. A trial vector was formed by combining three randomly selected vectors from the 40 vectors excluding the target vector by using Eq. (5) with the differentiation constant, F within the range of 0.4 to 1.0. The selection between the target vector and the trial vector was done in order to keep only one winning vector with better fitness value which is the lower R_a value for the survival into the next round. The mutation, crossover and the selection processes were repeated once the new generation was installed until the stopping criterion of number of generations was satisfied. The simulation of the DE optimization algorithm was repeated by changing the combination of the parameter settings until the best fitness value which was the minimum R_a value is obtained.

7.2 DE objective function and optimization execution

The execution process of DE optimization technique in optimizing the process parameters that affect the surface roughness, R_a value of Co28Cr6Mo medical material CNC lathe machining was divided into four main phases which are the initialization,

Table 6 Relationship between the symbols of regression modeling and DE algorithm with their range

Setting	Regression modeling	DE	Range
Fitness function (objective function)	R_a	f	–
Number of process parameters	4 × 1 matrix	D	4
Minimum surface roughness	$R_{a(minimum)}$	f_{best}	–
Rotational speed	n	X_1	318–636 rpm
Feed rate	f	X_2	0.10–0.25 mm/rev
Depth of cut	a	X_3	0.50–0.90 mm
Tool tip radius	r	X_4	0.40–1.20 mm

Table 7 Optimal solution of DE parameter settings combination

Parameter	Setting value
Population size, *NP*	40
Differentiation constant, *F*	0.4
Crossover rate, *CR*	0.9
Number of generation, *GEN*	100

mutation, crossover, and selection process. The DE program was developed and run by using Matlab programming software and the input process parameters levels were fed to the DE program in order to optimize the process parameters of the machining process within the constraints given.

The regression equation was obtained from the experimental data of the response characteristics as a function of the four input process parameters which are the rotational speed, feed rate, depth of cut and tool tip radius by using Design-Expert software. Equation (9) states the objective function that is used for the process parameter optimization and surface roughness minimization in Matlab programming software.

$$\begin{aligned} R_a = & -3.574 + 0.013X_1 + 66.380X_2 \\ & + 2.891X_3 - 9.710X_4 - 1.828e^{-6}(X_1)^2 \\ & + 34.213(X_2)^2 - 3.180(X_3)^2 \\ & + 3.891(X_4)^2 - 0..66X_1X_2 - 2.142e^{-3}X_1X_3 \\ & + 1.546e^{-3}X_1X_4 - 12.941X_2X_3 - 25.641X_2X_4 \\ & + 5.353X_3X_4 \end{aligned} \quad (9)$$

where X_1 is the rotational speed (n) in rpm, X_2 is the feed rate (f) in mm/rev, X_3 is the depth of cut (a) in mm and X_4 is the tool tip radius (r) in mm.

In order to obtain the optimal process parameters and the minimum surface roughness, R_a value, there is a range of technical specifications of the machining process parameters that need to be considered. The process parameters in this study were referred to the boundary values for the lower and upper parameters which were based on the previous experiment aforementioned. The boundary values of the process parameters influenced the DE results and the number of iteration to be processed. The lower and upper boundary value used for Co28Cr6Mo medical material CNC lathe machining in the experiments are as follows:

$$318\ rpm \le X_1 \le 636\ rpm \quad (10a)$$

$$0.1\ \ mm/rev \le X_2 \le 0.25\ mm/rev \quad (10b)$$

$$0.5\ mm \le X_3 \le 0.9\ mm \quad (10c)$$

$$0.4\ \ mm \le X_4 \le 1.2\ mm \quad (10d)$$

7.3 Surface roughness optimization

In this study, several combinations of initial population size (*NP*), the differentiation constant (*F*), the crossover rate (*CR*) and the number of generation (*GEN*) have been tested by using Matlab programming software in order to achieve the optimal results of the surface roughness, R_a value as the minimum R_a value of CNC lathe machining is achieved with the best combination of the four process parameter values.

Population sizes of 10, 20, 40, 60 and 80 have been tested in this program and for each population size, the algorithm has been executed 10 times. Based on the experiments, the minimum and constant R_a value of 0.1502 μm was obtained by using the population size of 40, which is 10 times the value of the process parameters. When the population size was increased to 60 and 80, there was no changes to the values of R_a achieved which was 0.1502 μm.

In addition, it was found that the number of generation of 100 produced the minimum and constant result of R_a value. If the number of iteration was increased, the DE results did not produce any significant differences. Meanwhile, for the differentiation constant, *F* used in the DE algorithm during the mutation stage, the lower the value of *F*, which was within the range of 0.4 to 1.0, the more constant and minimal the results became. It can be seen that there was not much changes in the minimum R_a value for the fitness function even though the crossover rate was varied between the values of 0.1 to 0.9 based on the experiments. As a result, the best combination of the settings applied that lead to the minimum R_a value is given in Table 7 after several trials of parameter setting conducted.

The DE result was generated by using the objective function in Eq. (9) and the boundary of the process parameters formulated by Eq. 10a–d. Table 8 shows the minimum values of R_a

Table 8 Output values of DE with respect to input process parameters

Condition		Unit	Result
Optimal process parameter	Rotational speed, *n*	rpm	331.9852
	Feed rate, *f*	mm/rev	0.1073
	Depth of cut, *a*	mm	0.5555
	Tool tip radius, *r*	mm	1.0851
Minimum fitness function	Surface roughness, $R_{a(min)}$	μm	0.1502

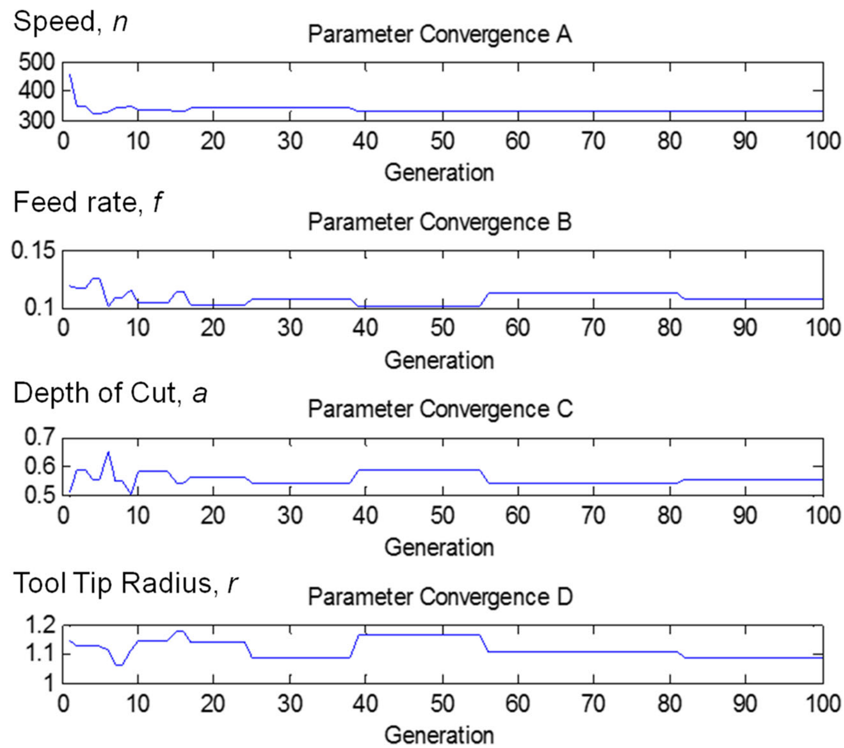


Fig. 5 Performance of each machining parameters

with respect to the input process parameters of Co28Cr6Mo medical material CNC lathe machining in DE. Figure 5 and Fig. 6 show the performances of each process parameter and the plot function diagram of the DE algorithm respectively. Thus, based on the DE optimization results, it can be concluded that there is a possibility to select a combination of rotational speed, feed rate, depth of cut and tool tip radius which would lead to the best surface finish.

Based on Table 8, it can be observed that the minimum surface roughness, R_a value is 0.1502 µm. The set values of process parameters that lead to the minimum surface roughness value are rotational speed of 331.9852 rpm, feed rate of 0.1073 mm/rev, depth of cut of 0.5555 mm, and tool tip radius of 1.0851 mm. The convergence profile in Fig. 6 indicates that the minimum surface roughness value is 0.15015 µm. Besides that, the optimal solution obtained for the minimum surface

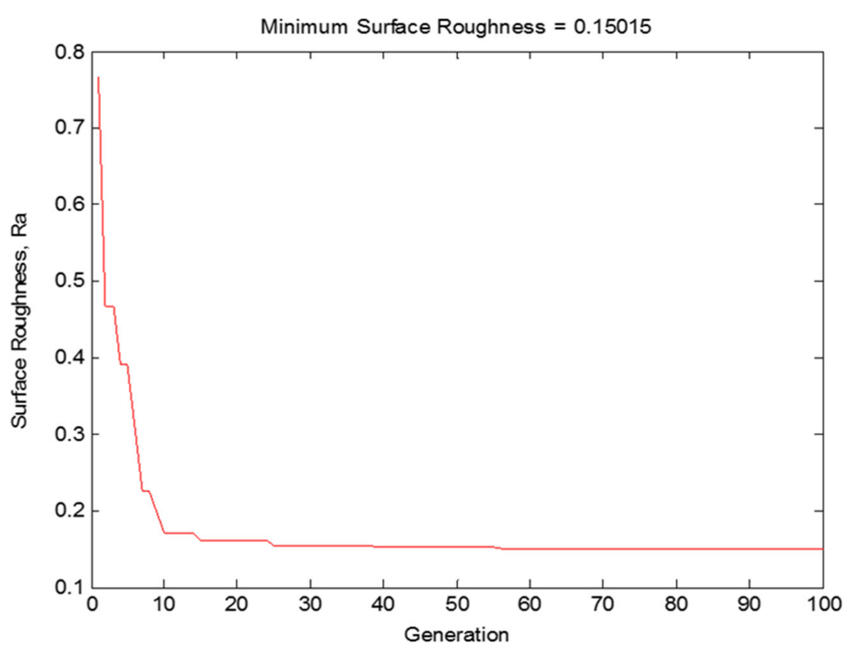


Fig. 6 DE convergence profile

Table 9 Summary of the DE results

Variables	Consideration factors	Issue 1: best fitness, $R_{a(min)}$ (μm)	Issue 2: mean fitness, $R_{a(mean)}$ (μm)	Issue 3: optimal process parameter of DE	Remarks
R_a	Experimental result	0.81	2.76	–	DE optimization technique gives better minimum and mean R_a value compared to experimental and regression modeling
	Regression modeling	0.538	2.76		
	DE result	0.15	0.2		
Rotational speed, *n*	Required range 318–636 rpm	–	–	331.9852	Optimal solution set of the process parameters from DE optimization technique are within the constraints of the required values
Feed rate, *f*	Required range 0.1–0.25 mm/rev			0.1073	
Depth of cut, *a*	Required range 0.5–0.9 mm			0.5555	
Tool tip radius, *r*	Required range 0.4–1.2 mm			1.0851	

roughness is at the 56th generation (iteration) of the DE algorithm as indicated on Fig. 6.

7.4 Evaluation and validation of the DE result

After the minimum surface roughness value was estimated based on the DE optimization algorithm, the results was validated and evaluated. The minimum surface roughness value estimated by DE optimization is expected to be of a lower amount than the surface roughness values obtained experimentally, by regression modeling and by Response Surface Methodology (RSM). The optimal process parameters which lead to the best fitness function in CNC lathe machining operations which was achieved at the last iteration of DE is expected to be in the same boundaries of values as those with the experimental process parameters which are given in the Table 5. Those values will give the minimum surface roughness value.

In order to evaluate the DE result, there are three main issues that need to be concerned with in this research study. The first issue is the surface roughness, R_a value obtained from the DE optimization which is expected to be lower than the minimum R_a value of the experimental and regression modeling. Besides that, the mean R_a value from DE optimization is expected to be lower than that of the experimental and regression modeling and the values of optimal process parameters which lead to the minimum R_a of the machining process is expected to be in the same range as the experimental design.

In the real CNC lathe machining experiment, the minimum R_a value is 0.810 μm whereas for the regression modeling, the minimum R_a value is 0.538 μm as indicated in Table 3. Based on Table 8, the best-predicted R_a value obtained from the DE optimization is 0.150 μm. Hence, it can be assumed that the DE optimization has given the minimum result of R_a value compared to the experimental and regression modeling.

Besides that, the mean R_a value obtained from the experiments, regression modeling and DE technique are 2.760, 2.760, and 0.200 μm respectively. Hence, the DE optimization technique has given the minimum predicted mean R_a value compared to the experimental and regression modeling. Moreover, the optimal values of the process parameters predicted by using the DE optimization technique can be applied in the real machining experiment in order to obtain the minimum surface roughness of 0.150 μm as the values obtained are within the constraints of the actual settings of the cutting conditions in the CNC lathe machining operation.

The best results of the process parameters of Co28Cr6Mo medical material CNC lathe machining which lead to the minimum R_a value using DE optimization technique are rotational speed of 331.9852 rpm, feed rate of 0.1073 mm/rev, depth of cut of 0.5555 mm, and tool tip radius of 1.0851 mm. Theoretically, the optimal values of the process parameters will be transferred into the regression model of Eq. (9), which is the objective function of the DE optimization technique, in order to validate the result obtained by the DE algorithm. The values of the optimal solution set of the rotational speed, X_1; feed rate,

Table 10 Process parameters scaling classifications for optimal result comparison

Process parameters	Unit	Process parameters scaling classifications				
		Lowest	Lower	Medium	Higher	Highest
Rotational speed, *n*	rpm	318	400	477	560	636
Feed rate, *f*	mm/rev	0.1	0.12	0.15	0.2	0.25
Depth of cut, *a*	mm	0.5	0.6	0.7	0.8	0.9
Tool tip radius, *r*	mm	0.4	0.6	0.8	1	1.2

Table 11 DE and RSM optimal process parameters result comparison

Technique	Rotational speed, n (rpm)		Feed rate, f (mm/rev)		Depth of cut, a (mm)		Tool tip radius, r (mm)		Best fitness, $R_{a(min)}$ (μm)
	Optimal	Level	Optimal	Level	Optimal	Level	Optimal	Level	
DE	331.99	Lowest	0.11	Lowest	0.56	Lowest	1.09	Higher	0.15
RSM	341.31	Lowest	0.1	Lowest	0.59	Lower	1.2	Highest	0.215

X_2; depth of cut, X_3; and tool tip radius, X_4 were substituted into the Eq. (9) and the solution is obtained as follows:

$$\begin{aligned} R_a = & -3.574 + 0.013(331.9852) + 66.380(0.1073) \\ & + 2.891(0.5555) - 9.710(1.0851) - 1.828e^{-6}(331.9852)^2 \\ & + 34.213(0.1073)^2 - 3.180(0.5555)^2 + 3.891(1.0851)^2 \\ & - 0.066(331.9852)(0.1073) \\ & - 2.142e^{-3}(331.9852)(0.5555) + 1.546e^{-3}(331.9852)(1.0851) \\ & - 12.941(0.1073)(0.5555) \\ & - 25.641(0.1073)(1.0851) + 5.353(0.5555)(1.0851) \\ R_a = & \ 0.1497 \end{aligned} \tag{11}$$

The predicted R_a value obtained by the DE is 0.1497 μm as shown in Eq. (11) when the optimal values of the process parameters obtained from DE are transferred into the Eq. (9). The minimum R_a value of the DE technique is 0.1502 μm based on Table 9 and this result is close to the results of the transformation process. Thus, it can be said that the R_a value of 0.1502 μm might be obtained in the real Co28Cr6Mo medical material CNC lathe machining process when the optimal solution set of process parameters predicted by DE technique is used.

8 Discussion

The most important element in any machining process of the work-piece is the determination of the optimal machining parameters. In this research study, DE optimization technique is employed in order to predict the optimal solutions of process parameters which lead to the minimum surface roughness value of the machining process. Based on the literature review, it was found that there is no study taken so far by the researchers in applying DE algorithm for Co28Cr6Mo medical material CNC lathe machining surface roughness optimization problems. Thus, the study of DE in medical material can be taken as a new contribution in any domain of machining area.

The experimental study conducted by Asiltürk, Neşeli, and İnce [1] in measuring the surface roughness values in the CNC lathe machining was referred to in this study. The statistical analysis such as ANOVA was done before the DE optimization technique was performed. Analysis using ANOVA was performed to find the optimum level and percentage of contribution of each process parameter on the surface roughness. A regression model was developed using the Design-Expert software and the analysis of the model was conducted. The objective function which was used in the DE optimization solution is the regression model developed by using the Design-Expert software. The results of the DE technique from Matlab programming software were discussed in the evaluation and validation of the DE results and summarized in Table 9. The process parameters scaling classification of the lowest, lower, medium, higher and highest scale for comparing the optimal results is shown in Table 10.

9 Conclusion

Based on Table 9 until Table 11, it can be concluded that the DE optimization technique can be considered an effective technique in obtaining a better result of minimum surface roughness value and mean surface roughness value of CNC lathe machining process compared to the experimental and response surface methodology, RSM. The optimal solution set of the process parameters recommended by the DE optimization technique which lead to the minimum R_a value is also within the constraints of the cutting conditions applied in the real CNC lathe machining experiment.

Moreover, based on the best fitness value from Table 11, the DE optimization technique outperforms the RSM technique by 0.065 μm. The minimum R_a value obtained from RSM is 0.215 μm with the lowest range of rotational speed, the lowest feed rate, the smaller depth of cut, and the highest range of tool tip radius of the scaling of the machining parameters with the consideration of the conditions given in Table 10. However, the DE optimization technique predicts a lower value of R_a of 0.150 μm compared to the RSM optimization technique with the lowest rotational speed, the lowest feed rate, the smallest depth of cut, and the larger tool tip radius of the scaling.

As mentioned before, the objective of the DE optimization process in this research study is to determine the optimal solution set of the process parameters of the CNC lathe machining which would lead to the finest surface roughness of the Co28Cr6Mo medical material. In a nutshell, it has been found that the DE optimization technique reduces the surface roughness value of the Co28Cr6Mo medical material in the CNC lathe machining by 81, 72, and 30% respectively when comparing with the minimum surface roughness value of the experimental data (0.810 μm), the regression modeling (0.538 μm), and the RSM desirability analysis (0.215 μm). The performance of DE is superior when compared to the experimental, regression modeling, RSM, in terms of CNC lathe machining parameter optimization.

In a nutshell, this study provides a new idea on the implementation of modern approach for solving CNC lathe machining optimization parameters. This new optimization strategy is presented with systematic guidelines to improve the quality of the machining output. Regardless of its purpose for CNC lathe machining of Co28Cr6Mo medical material, DE algorithms can be adopted for broader range of parameter optimization, which means the factor of material could be eliminated in order to gain an optimization algorithm for any kind of materials. Furthermore, DE algorithm has unique capability to enhance the prediction of surface where it does not need to calculate the gradient descent that required by conventional method such as RSM which tend to trap at local minima; hence, it can be applied to various kinds of objective functions in machining process. The contributions of the study are highlighted as follows:

1. Details implementation of DE algorithm and formulation for process parameters optimization.
2. Provide new optimization approaches for CNC lathe machining using DE algorithm and comparative study with conventional method (RSM).

This study can be further work on any manufacturing process optimization as users know how to formulate their objective function and the range of process parameters. Finally, investigating the performance of DE algorithm of other manufacturing fields would be interesting for future research.

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