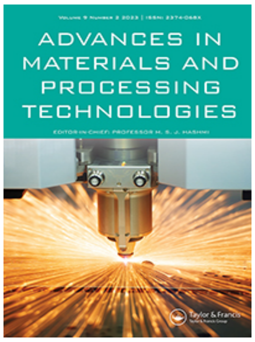

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ABSTRACT

This article has made an approach towards the multipass turning of AISI 4340 alloy steel with minimum quantity of coolant to determine the Optimal Turning Parameters for simultaneous maximisation of material removal rate and minimisation of surface roughness. Nine experimental runs were planned according to Taguchi's Design of Experiments and performed on Computer Numerically Controlled Lathe Machine with high carbon steel as a tool. The mathematical models developed for surface roughness and material removal rate at different levels of speed, DOC & feed rate are considered as objective functions. Less than 5% error was observed when experimental results were compared with Regression and ANN Models for both responses. A multi-objective genetic algorithm and a Grey relational analysis were used to determine the optimal turning parameters and the results were validated experimentally. The MOGA provides the best optimal parameters for the simultaneous achievement of SR minimisation and MRR maximisation. Results reveal that speed and feed rate have a significant effect on responses. The Pareto Front Plots extracted from MOGA provide the minimum Ra value, 2.32 µm and for the same point, maximum MRR is 6894.22 mm^3/min. However, the experimental method could not meet this Ra value, but the recorded minimum was 2.67 µm and the MRR was 6544.79 mm^3/min.

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KEYWORDS
AISI 4340 alloy steel; CNC multipass turning; surface roughness; material removal rate; GRA; MOGA; ANN; regression

1. Introduction

Now-a-days Industries adopting new Technologies in Machining process lead to many problems in the cutting process. Material cutting, also known as Machining, is a process to produce different components. The work of the cutting tool is to remove the chips from the raw material, which produces many difficulties in the cutting process. The CNC Turning Process also faces many difficulties, like the contact of metal chips, the inappropriate position of the tool or work piece, inappropriate feeds, speeds and coolant, which affect the productivity of the materials. The needs of customers are very high in terms of finishing and quality of the end product. Materials used in the machining

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process produce tool wear, heat, cutting forces, and complications in chip formation that produce poor surface quality. Hence, the study of roughness of material and rate of material removal is important in cutting process.

The AISI 4340 material is a steel of low alloy with high strength, and it is used in coating relatively softer substrates because of its hardenability characteristics. The material can be heat treated because it consists of Chromium, Nickel, and Molybdenum. Material having high toughness, strength, and hardenability in comparatively larger sections is achieved with a 'quench-and-temper' heat treatment. The material is becoming more important because of its applications. The material is used in aircraft landing gears, structural gears, power transmission gears, and sprockets. Hence, the study of this material is necessary to maintain the quality of the end product. In the machining industry, the roughness of the surface is the main influential characteristic of components and their cost. To improve the production rate, SR and MRR are the most influencing responses in Industries. The surface roughness should be less, and the MRR should be higher to improve the rate of production. Hence, the parametric study influences the optimisation technique to estimate the best optimal condition to achieve better surface roughness, depending on the materials used in machining.

[1] The RSM optimisation technique is used for the prediction of the best responses and the experimental investigation of AISI 4340 alloy steel in the turning process for the measurement of the relation between SR and the parameters estimated [2]. The turning of FDHT AISI 4340 Steel by selecting the depth of cut, feed rate, and speed is used as input factors to study the surface roughness as a response. The RSM optimisation technique is implemented for the prediction of the optimal setting [3]. The turning process with depth of cut, feed rate, and speed is used to predict surface roughness by comparing RSM, and GA methods of optimisation. GA is operated by the best-trained RE of the ANN approach [4]. AISI 4340 hardened steel is used in the turning process with tool nose radius, speed, hardness of w/p and feed rate as input factors for the study of cutting force, and the temperature of the chip–tool interface as responses. w/p hardness is the most effective parameter obtained by ANOVA, followed by the force of cutting and temperature of the interface, which are generated in hard turning [5]. Regression analysis of nickel alloy in the turning process to build the best model for further prediction of the relation between the I/O combinations. Feed rate, depth of cut, and speed are used as input factors, and SR, tool wear, machining time, and cutting force are responses [6]. TC_ANN and TP_ANN are used for the calculation of temperature. The tip steady-state temperature was calculated by ANN [7]. AZ91D magnesium alloy material is used in turning, and the results obtained were analysed by ANOVA and GRA [8]. Cobalt alloy (Stellite 6) material is used for turning operations with radius, cutting depth, speed, and feed rate as input factors and SR and MRR as responses. RSM and GRA techniques are used for the analysis of data to minimise SR [9]. The depth of cut, speed, feed/tooth, cutting time, and environment are used as factors for maximising MRR and minimising SR, wear of the flank, and force of cutting. The GRA technique is applied to the database for the prediction of the best model in the milling process [10]. Turning of mild steel with DOC, FR, and rake angle are used to measure the SR, MRR, and force of cutting. Response Surface Methodology, GRA, and ANOVA techniques were used for the optimisation process. The feed rate has the most significant effect on cutting force and surface roughness. Rake angle is the most effective factor over MRR [11]. The turning of

SAE 1020 material is used to maximise the MRR. The Research predicts that the DOC is most effective on MRR [12]. AISI *P*-20 steel is turned with high-speed turning and optimised by a fuzzy approach and ANOVA [13]. Aluminium alloy 6063 materials is turned on a CNC with feed rate, speed, and DOC as factors to study SR. ANOVA is used for optimisation. The FR influences the operation more [14]. Speed and feed rate speed have a very high impact on SR and MRR in the turning of EN 19 steel material by considering depth of cut, feed rate, speed, and lubricants as factors [15]. Turning of AlSi7 Mg material with speed, feed rate, and depth of cut as input factors, with SR and MRR as responses, is optimised by Taguchi's GRA technique for prediction. If the feed rate increases, MRR will increase with a decrease in SR. Increased in speed, SR and MRR will be improved [16]. HCHCR material is turned on a CNC with dry conditions by selecting depth of cut, feed rate, and speed as input parameters to study MRR and SR. ANOVA is used for the prediction of the best fit [17]. Acrylonitrile butadiene styrene material is used as a working material in CNC turning operations for the study of MRR and surface roughness. The higher and lower values of SR were observed by varying FR and DOC by GRA [18]. Face turning operation is used for identification of machinability and best factors by RSM and Taguchi's method on EN 31 material by selecting speed, depth of cut, nose radius, and feed rate as factors for a measure of SR [19]. The Ti-6-Al 4-V material database is considered in the turning process, and the ANN RE is used for the GA technique to predict the best fit. This work integrates ANN and GA to minimise SR and increase the MRR [20]. The turning of Al-6063-O material with temperature, velocity, and FR as input factors to study the cutting conditions. The PSO soft computing technique is applied with ANN for developing relations between factors and responses [21]. Ti-6Al-4 V material is used in the turning process with TiCN-coated carbide tool material. Integration of RSM and ANN techniques is used for optimisation. ANN has fewer errors compared to RSM [22]. In the milling of Al7075-T6 material, speed, ADOC, and FR are used as input factors to measure cutting forces. The integration of GA and RSM is used for the optimisation of machining data. GA predicts the best model for cutting forces in milling [23]. ANOVA is applied to the machining data of the turning process to study flank wear and SR by utilising the SN ratio for the prediction of best fit [24]. 42CrMo4 steel is used in hard turning with high-pressure coolant, hardness of work piece, feed rate, and speed as input parameters to study the roughness and temperature of cutting by the combination of RSM and MOGA techniques [25]. Turning of AISI 4140 material with speed, feed, and DOC as input factors to study cutting forces and MRR. RSM and H-ABC applied for the prediction of best fit [26]. Hard turning of AISI 4340 steel with input factors such as insert type, feed, speed, and DOC for optimisation of MRR and SR using MOGA, MOSPSA, and MOEPCA techniques is used to predict the solution for the wiper insert case [27]. The turning of Inconel 718 material by considering speed, feed rate, and nano additives as inputs studied roughness, flank wear, and energy consumption by using a fuzzy inference system, ANN, and multi-objective genetic algorithm to obtain the outputs [28]. A multi-objective evolutionary algorithm is used to reduce and uncorrelated set of responses in outputs [29]. Drilling of aluminium alloy with feed rate, point angle, and speed as inputs, to reduce burr creation by flower pollination algorithm for finding optimal process parameters, and also used RA and ANN for validation of the work [30]. Turning of newly developed Magnesium Alloy by considering feed, depth of cut, and speeds as turning input factors to measure cutting force, and roughness by ANOVA [31]. Duplex Steel 2205 material by selecting FR, DOC, and speed for the measurement of roughness and flank wear by ANN and validated by experimental work in dry turning with a carbide-stripped insert [32]. Turning 42CrMo4 alloy steel material by coolant environment feed and speed as input parameters to measure roughness, temperature, cutting force, and MRR by the GRA-PCA method. Optimum settings were obtained at MQL with cutting oil [33]. A hard turning of AISI 4340 material is used for the study of the effect of the ceramic inserts on different roughnesses like mean depth, total and mean roughness, and tool wear by RSM [34]. The study of the formation of chips and their morphology along with the finishing of AISI 4340 material in turning with a yttria-stabilised zirconia-toughened alumina ceramic cutting tool by the RSM CCD approach [35] with different cooling conditions used in turning ASS material and the study of roughness, temperature of cutting, and force of cutting [36]. The study of product surface quality by MQL is studied by GRA to forecast the results. Also, the tribological properties of SiC nanofluids were analysed [37]. Analysed the roughness, chip formation, flank wear, and length of tool contact by machining Magnesium Alloy with dry and different cooling conditions [38]. Stainless steel (SUS304) and aluminium (Al6061) are used in machining by gathering input parameters using sensing technology to study surface roughness. The ANN is used for the prediction of best fit.

By going through the Literature Review, the different optimal solutions were obtained by various multi-objective optimisation methods in the turning process. It is difficult to determine the optimal solutions, hence the Optimisation Research is carried out in this Article, for the minimisation of the surface roughness and maximisation of the material removal rate at the same optimal condition. This work is an extension of Santhosh AJ [3], who worked on surface roughness using the ANN-GA method. The parameters used for the study are speed, depth of cut, and feed rate. Coded Model was generated using the RSM-FCC Design approach, and the Artificial Neural Network (ANN) approach is utilised in the Research to increase the regression coefficient to obtain the best fitness model for the Genetic Algorithm (GA). The error percentage was very low in the genetic algorithm when compared to the response surface methodology for AISI 4340 alloy steel.

This work encouraged extensive research to optimise surface roughness by introducing Material Removal Rate as an objective function in addition to the minimum quantity of coolant effects with the multipass Turning Process. In this Research, two multi-objective optimisation techniques were used: Grey Relational Analysis and a Multi Objective Genetic Algorithm to search for a feasible region of optimal solution. The models were developed by multiple regression modelling and are validated through models developed by artificial neural networks using MATLAB. The average percentage of error obtained by comparing the experimental results with regression and ANN models was less than 5% for both responses. The MOGA technique provides a simultaneous reduction of SR and an increase in MRR at the same optimal condition. Then, the results obtained by MOGA were validated experimentally through trials of the machining. The results of MOGA helped to identify the preferable conditions for an industrial application to achieve low SR, and high MRR. This study utilises soft computing techniques to model the responses of machining to attain optimal settings. The important goal of this work is to learn the approaches of soft computing techniques to develop accurate models of the cutting process.

The aim of this research is to provide deeper insight into multipass turning with a minimum quantity of coolant in AISI 4340 alloy steel to obtain reduced SR and increased MRR by using a new soft computing technique to provide optimal cutting conditions. Further research can be carried out using different parameters and responses, with a comparison of different soft computing techniques. The statistical parameters were tested for null and alternative hypotheses. Depending on the outcome, the input parameters optimal settings were predicted. The techniques applied in this work are expected to make remarkable contributions to the process application of various optimisations with a minimisation of cost and time approach.

2. Material and methods

The experimental work starts with the selection of the most influential responses of turning process. The surface roughness and material removal rate were selected for the study. Depth of cut, speed, and feed rate were selected as important input factors, along with the minimum quantity of coolant. The work is followed by a selection of levels of each factor for quantifying the effect on responses. The process of experimental investigation has been adapted in this work [2]. Then, the response obtained from the work is used to make a relation between factors and responses. The GRA optimisation technique is utilised for experimental results to obtain the effective performance characteristic of the machining process [7–9]. Then, the soft computing technique MOGA is applied to obtain the optimal settings of the machining process to minimise the SR and maximise the MRR by using regression equations [3,19,32]. The Artificial Neural Network (ANN) technique is used for the prediction of the best model. The regression model is validated by the ANN model. Then, the results obtained from MOGA were validated by experimental trials. [3.6.19].

2.1. Material properties

The material is designed with four digits, i.e. AISI 4340. The material consists of different kinds of compositions, like B, C, Cr, Ni, Mo, Si, Mn, and VA sets. This material can be heat-treated. The heat treatment will give it high strength and hardness. The chemical composition of AISI 4340 is shown in Table 1. The material selected for experimental investigation is AISI 4340 alloy steel and Table 2 describes the properties of selected material.

Table 1. Chemical composition of AISI 4340 alloy steel.

Elements	Fe	Ni	Cr	Mn	C	Mo	Si	S	P
(Wt%)	95–96	1.6–2.0	0.71–0.9	0.61–0.8	0.3–0.43	0.20–0.30	0.15–0.30	0.040	0.0350

Table 2. Mechanical properties of AISI 4340 alloy steel.

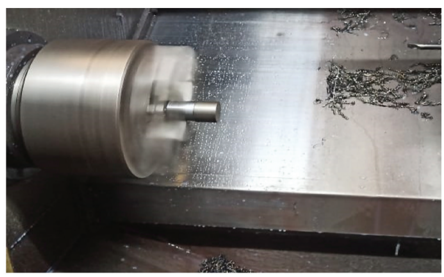
Properties	Metric
Tensile Strength (MPa)	745.0
Yield Strength (MPa)	470.0
Bulk Modulus (GPa)	140.0
Shear Modulus (GPa)	80.0
Modulus of Elasticity (GPa)	190.0–210.0
Poisson's Ratio (µ)	0.260–0.30
Elongation %	22
Area of Reduction %	50
Brinell Hardness (BH)	217

2.2. Experimental process

The experimental investigation was carried out by identifying machining input parameters and responses. Taguchi's statistical technique is planned for experimentation because of its accuracy in obtaining optimal settings. The experiment was conducted by selecting the L9 orthogonal array (OA). The MINITAB 19 statistical software is used to obtain L9 OA by selecting three levels and three parameters. The range and levels of each input parameter were selected by trial-and-error. The results recorded are optimised to reduce process credentials. The results are analysed by Taguchi's GRA and the soft computing technique MOGA. Then, the optimal settings obtained were compared with a confirmative test to validate experimental results. CNC lathe LL25T XL is used for turning operation shown in Figure 1(a) and work piece setup and processing with selected input process parameters over the machine shown in Figure 1(b).

The selected output response, i.e. surface roughness, was measured using the Mitutoyo Surf Test SJ-210 device, having a 360 µm (−200 µm to + 160 µm) range with standard

a. CNC lathe used for turning operation.



b. Work piece setup and processing.

c. Surface roughness measuring instrument.

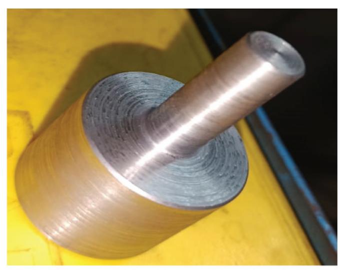
Figure 1. The experimental process and surface roughness measurement process.

measurement conditions, as shown in Figure 1(c). The memory can store only 10 readings. The surface measurement (Ra) was measured directly by placing the specimen below the stylus of the Mitutoyo device, as shown in Figure 1(c). The surface roughness is measured by moving the stylus perpendicular to the work piece and the same is recorded using the digital display that is associated with the device. To get accuracy in the result, three measurements are made at different places on the workpiece. The minimum value that the instrument can measure is 0.001 mm, with a maximum range of 16 mm.

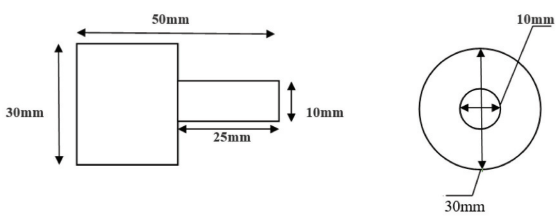
The material is tested for Brinell hardness, and the value of the test is 217 by using the TKB-3000 M machine. The load range of the machine is 250 kg to 3000 kg, in steps of 250 kg, with a maximum height of 380 mm and width of 80 mm. The test machine is fitted with a 10 mm diameter ball made of tungsten carbide, on which a high load will be transferred. The diameter of the ball indentation will be measured by a microscope, not the depth. The selection of load depends on the thickness of the workpiece being tested. Hard materials generate shallow indentations, while soft materials generate deeper indentations on the workpiece. In this test, 3000 kg (F) of load is applied to the ball of diameter (D) and held for a predetermined time. The indentation was made twice at different places, and the average diameter of both indentations will be considered as the diameter of the indentation (d). The hardness of the material was calculated using a formula.

The material is a mixture of different steels with Fe, C, Cr, Ni, Mo, Si, Mn, S, and P in different percentages. This material is consisting of less steel and can be heat treated. The material used in experiment had a dimension of 50 × 30 mm, as shown in Figure 2(a) As per Taguchi's design of experiments, the nine experiments have been conducted on a CNC lathe LL25T XL, a 2-axis lathe machine with a variable speed of 3500 rpm and

a. Work Piece used for experimental work



b. The Work Piece after turning process



c. The dimension of work piece after cutting of each experiment.

Figure 2. The work piece used for the experiment before and after, with dimensions.

Table 3. Combinations of cutting parameters.

Parameters	Units	Levels 1	2	3
SS	rpm	1000	1250	1450
DOC	millimetre	0.5	0.8	1
FR	millimetre/revolution	0.1	0.2	0.3

Table 4. Experimental results using L9 orthogonal array.

Sl. No	SS (rpm)	DOC (mm)	FR (mm/rev)	SR (μm)	MRR (mm^3/min)
1	1000	0.5	0.1	3.8	6544.8
2	1000	0.8	0.2	4.5	6283
3	1000	1	0.3	6.4	4487.86
4	1250	0.5	0.2	5.8	5817.59
5	1250	0.8	0.3	6.7	4759.85
6	1250	1	0.1	3.1	6829.35
7	1450	0.5	0.3	6.3	4908.59
8	1450	0.8	0.2	4.7	6041.35
9	1450	1	0.1	6.1	5066.94

a nominal power of 15 kw. Only 25 mm of length is turned, and the diameter reduced to 10 mm by Multipass Turning with minimum quantity of coolant as shown in Figure 2(b). The material is cut into equal size for experiment with same length. Dimension of work piece after cutting of each experiment shown in Figure 2(c). Table 3 represents combinations of cutting parameters. The process of experiment was carried out using L9 orthogonal array, i.e. Each run was done once over a workpiece. After Multiple Turning Operations, it is required to check the surface finishing of the worked material as it measures the quality. The L9 OA factors and responses are tabulated in Table 4.

Tool geometry is defined by its shape and angle, this geometry depends on the type of tool and the material of the tool. The tool used in the cutting process is a high-carbon steel tool. This tool contains high carbon, low-alloy element, tungsten, molybdenum, and chromium materials. It consists of more than 0.60% carbon and is more susceptible to corrosion and rust. It is an HSS Tool Bit, − 16 mm × 16 mm × 150 mm, S 500 Grade.

In unit time, how much amount of material can be removed is termed as MRR (mm^3/min) & is obtained by Equation 1, which has diameter before and after, along with time for all samples [15].

$$\text{Expression of MRR} = \frac{\pi}{4}\left(\mathrm{D_o^2} - \mathrm{D_i^2}\right)\frac{\mathrm{L}}{\mathrm{t}} \tag{1}$$

D_o = before turning diameter (mm), D_i = after turning diameter (mm), L = raw material length (mm)
t = time taken to complete multipass turning of combinations. (min) [15].

3. Models used for prediction

A large number of optimisation techniques are available for the prediction of models, which are listed in the literature. The models were selected depending on the experiment results and requirements. The selection depends on the factors, responses, datasets, and records. The selected technique may sometimes give the best model, sometimes it doesn't, because of experimental results or some other reason. Hence, selection plays a very important role in optimisation. In this research, Taguchi's traditional GRA is used for the analysis of experimental results [15,32]. Then, the regression equations are developed based on experimental results and parameters and validated by developing an ANN model [31]. These equations are used as objective functions in MOGA for the analysis of data using soft computing techniques to obtain accurate results [3,5].

4. Optimization techniques

4.1. Multiple regression modelling

Multiple Regression is a simple bi-variate regression. This bi-variate regression provides a relationship between a single dependent and several independent variables for the prediction of the best fit for the model [20,23]. This regression provides an equation as the result in terms of model and coefficients (β) with the best relation between independent and dependent variables. The main objective is to predict the independent variable and determine the dependency of SR and MRR on multipass turning parameters. For turning the curved workpiece, second-order polynomial models will fit. Factors speed, depth of cut, and feed rate for all experiments selected by Taguchi's Orthogonal Array method [25,27,31]. Equations 4 and 6 are coding forms of the second-order regression model of the experimental database, with an R^2 value of 0.99 for both models. This clearly confirms that the residuals are very close to the straight line, and this reveals that errors are normal and specify that the models developed are significant. The significant level (0.05) confirms that the model is adequate and the null hypothesis is favourable [2].

$\boldsymbol{\beta}$ = coefficients
$\boldsymbol{\beta}_i$ regression coefficients
y_i= variable depends on I/P
f = function variable
x_i = variable Independent of factors
$\mathcal{E}_i$ = error
k represents I/P
$\boldsymbol{\beta}_0$ is constant coefficients
$\boldsymbol{\beta}_{ij}$ interrelation of x_i and x_j

The general equation of the multiple regression model

$$y_i = f(x_i, \boldsymbol{\beta}) + \varepsilon_i \tag{2}$$

y_i= variable depends on i/p, f = function variable, x_i = variable Independent of factors, β = coefficients, $\mathcal{E}_i$ = error [20,23].

The multiple regression model will be expressed as [20,23].

$$Y_i = \boldsymbol{\beta}_0 + \sum_{(i=0)}^{k} \boldsymbol{\beta} iXi + \boldsymbol{\beta}_2 X_{i2} + \sum_{i=0}^{k} \boldsymbol{\beta} iiX_{i2}^2 + \sum_{1 \le \mathbf{i} \le \mathbf{j}} \boldsymbol{\beta} ij\, X_i X_j + \varepsilon_i \tag{3}$$

where *k* represents i/p (3), β_0 is constant coefficients, β regression coefficients, x_i i/p variables, $\mathcal{E}_i$ residual, and β_{ij} interrelation of x_i and x_j [20,23].

$$\mathrm{Ra} = \beta_0 + \beta_S S + \beta_D D + \beta_F F + \beta_{SD} SD + \beta_{SF} SF + + \beta_{DF} DF \tag{4}$$

$$Ra = 4.236388 + 0.001153S - 15.5797D + 36.8376F + 15.43024FD - 0.0267SF + 0.008877SD \tag{5}$$

$$\mathrm{MRR} = \beta_0 + \beta_S S + \beta_D D + \beta_F F + \beta_D D^2 + \beta_{SF} SF + \beta_{FD} FD + \beta_{SD} SD \tag{6}$$

$$\mathrm{MRR} = 9798.326 - 5.8728S + 32615.11F - 2244.74D - 35.9108D^2 - 34229.5FD + 6.5366SD - 10.6677SF \tag{7}$$

Where,
Ra – average SR,
MRR = Material Removal Rate,
S – speed,
D – DOC,
F – feed rate,
β – linear constants.

4.2. Grey relational analysis

The ranks of each input combination are calculated by the GRA technique to predict the best i/p values for the experiment by using the experiment responses [15,17,36]. The process consists of six steps, in the first step, the SN ratios are calculated depending on the higher and lower, the better results. In the second step, the responses are brought between 0 and 1 by the normalisation process, on higher or lower the better. In the third step, the deviation sequence is calculated using normalisation values. In the fourth step, the coefficient of grey relations (GRC) is developed by previous responses. In the fifth step, the GR grades are developed by the GRC. In the sixth step, the Ranks will be given for all the Grades depending on the highest, first rank and continued. In the next step, the Grades are used for the development of the Response Table by using MINITAB19 software, and also speed, feed rate, and depth of cut vs. means are plotted.

4.3. Artificial neural network

In many engineering fields, the ANN is utilised for the prediction of best fits by many researchers. This performance is like the activity of the human brain [22,27,29] also called machine learning. This method helps to find the interrelationship among the factors in all industrial processes. ANN will produce a response model for the prediction of optimal settings. The process consists of inputs, hidden layers, and outputs in the network diagram. To develop the models, the MATLAB ANN tool is used. The L-M (Levenberg-Marquardt) algorithm is employed for training.

4.4. Multi Objective Genetic Algorithm (MOGA)

A multi-objective genetic algorithm is a soft computing optimisation technique that follows the genetic evolution of the species [3]. This technique selects inputs from the

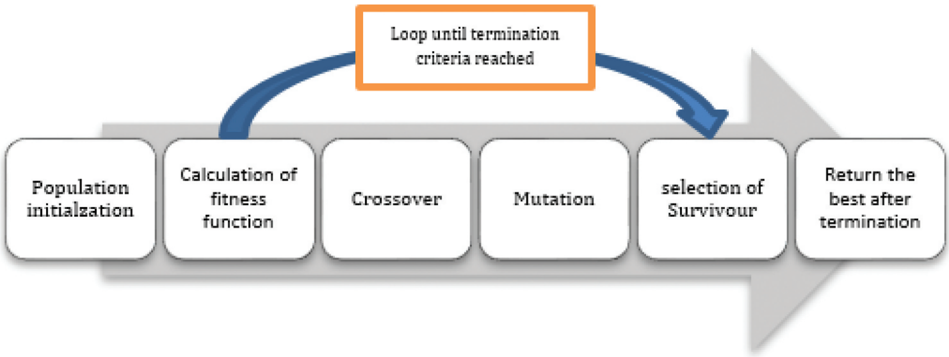


Figure 3. Flow chart of MOGA process.

range defined at the input. The MOGA provides a list of possible solutions. The solution in a genetic algorithm undergoes mutation and produces new children; like natural genetics, this process will be repeated for various generations. A fitness value is assigned to each individual depending on its objective function [19,27]. Until the process reaches stopping criteria, the individuals are given more chances to produce better individuals.

The Genetic Algorithm is now-a-days the best evolution-based algorithm for the prediction of the best fitness value through a set of iterations. A set of chromosomes can be defined as a population that is a subset of the current generation. The size of the population should not be large, as it will slow down the GA. The trial-and-error method is used for selecting population size. The function of fitness is defined as how best the fit is with the objective function. The fitness function will be an objective function, which may be one of the maximisation or minimisation. Offsprings are created by selecting parents who will mate and recombine for the coming generation. The size of the tournament is selected randomly from the population. The reputation of the process will be used to select the next parent. Crossover is biological and analogous. The generation of random variables is done by a mutation, which involves the generation of a random variable in each bit of order. The individuals who are to be kept for the next generation and who are not being selected by the survivor selection process. Then, the selected survivors are returned. The flow chart contains the process of multi- objective genetic algorithm. The Matlab steps for prediction of the best cutting factors as well as responses are shown in Figure 3.

5. Results and discussion

5.1. Traditional Taguchi's GRA

The grey relational analysis provides the relationship between input parameters and responses. With this method, complex problems can also be solved with effective results. The grade is an evaluation device that is obtained at the end of the process by ranking. Multi-Objective Optimisation can be done with this technique to obtain the best fit for a single grade [7–9]. The steps involved in predicting the Grade are as follows [10,15].

S1: The SN Ratios are calculated depending on the higher and lower, the better [25,30]

$$1.Higher - the - better\,for\,MRR\,S/N\,Ratio = -10\,log\,10(1/R)\sum\nolimits_{i=1}^{R}\frac{1}{x^2{}_{ij}} \quad (8)$$

$$2.Lower - the - better\,for\,SR\,S/N\,Ratio = -10\,log\,10(1/R)\sum\nolimits_{i=1}^{R}x^2{}_{ij} \quad (9)$$

Where R = revisions x_{ij}= observations, j = 1, 2, 3, 4 . . . . S; i = 1, 2, 3, 4 . . . . R.

S2: The outcomes of the experiment are normalised between 0 and 1, called data pre-processing. For surface roughness, the lower the better, and for material removal rate, the higher the better, formulas are used [7–9].

Lower -the-better is:

$$\mathbf{V_{rs}} = \frac{\mathbf{Maximum(A_{rs}) - A_{rs}}}{\mathbf{Maximum(A_{rs}) - Minimum(A_{rs})}} \quad (10)$$

Higher -the-better expressed as:

$$\mathbf{V_{rs}} = \frac{\mathbf{A_{rs} - Minimum(A_{rs})}}{\mathbf{Maximum(A_{rs}) - Minimum(A_{rs})}} \quad (11)$$

Observed value is$\mathbf{A_{rs}}$, minimum ($\mathbf{A_{rs}}$) is the smallest of $\mathbf{A_{rs}}$ & maximum ($\mathbf{A_{rs}}$) is the highest of$\mathbf{A_{rs}}$, r is the outcome variables and s is called trials. Basically, bigger than the normalised values.

S3: The deviation sequence is calculated by using the normalisation values.

The output investigation of the experiment is r, after preprocessing of data, ds_{rs} value is equal to or close to one out of all responses. The response s is considered as best for outstanding performance of r. The sequence of reference is ds_0 and is given by (ds_1, ds_2 . . . . ds_s, . . . , ds_n) = (1,1 . . . .1 . . . 1), ds_{0s} is defined as s^{th} reference value and then it will search for its best reference sequence. Table 5 shows GRA steps and deviation sequences. Later, GRC is used for calculating how close d_{rs} is to d_{os}. If GRC is a higher value, then the ds_{rs} and ds_{os} are very close.

S4: The coefficient of grey relations is developed by previous responses.

$$(d_{0s}, d_{rs}) = \frac{\Delta_{min} + \xi\Delta_{max}}{\Delta_{rs} + \xi\Delta_{max}} \quad (12)$$

For r = 1, 2, 3, 4 . . . . . . m and s = 1, 2, 3, 4 . . . .n (ds_{os}, ds_{rs}) is the GRC between d_{os} and ds_{rs}
$\blacktriangle_{rs}$= | ds_{os} - ds_{rs} |

Table 5. Normalised results for the optimum machining condition.

	S/N Ratio		Normalization		Delta Oj		GR Coefficient			
Sl No	SR (µm)	MRR (mm³/min)	SR (µm)	MRR (mm³/min)	SR (µm)	MRR (mm³/min)	SR (µm)	MRR (mm³/min)	Grade	Rank
1.	**−11.596**	**76.32**	**0.977**	**0.899**	**0.023**	**0.101**	**0.956**	**0.831**	**0.894**	**1**
2.	−8.293	75.96	0.484	0.801	0.516	0.199	0.492	0.716	0.604	7
3.	−11.352	73.04	0.941	0.000	0.059	1.000	0.894	0.333	0.614	6
4.	−10.497	75.29	0.813	0.618	0.187	0.382	0.728	0.567	0.647	4
5.	−11.750	73.55	1.000	0.140	0.000	0.860	1.000	0.368	0.684	2
6.	−5.056	76.69	0.000	1.000	1.000	0.000	0.333	1.000	0.667	3
7.	−11.216	73.82	0.920	0.213	0.080	0.787	0.862	0.389	0.625	5
8.	−8.671	75.62	0.540	0.708	0.460	0.292	0.521	0.631	0.576	9
9.	−10.792	74.09	0.857	0.289	0.143	0.711	0.777	0.413	0.595	8

Table 6. Response of means.

Level	SS in rpm	DOC in mm	FR in mm/rev
1	**0.7037**	**0.7221**	**0.7121**
2	0.6659	0.6212	0.6154
3	0.5989	0.6251	0.6409
Error	0.1048	0.1009	0.0967
Rank	1	2	3

$\blacktriangle_{min}$ = minimum {P_{rs}, r = 1,2,3,4 . . . .m & s = 1,2,3,4 . . . . n}, $\blacktriangle_{max}$ = maximum {P_{rs}, r = 1,2,3,4 . . . .m & s = 1,2,3,4 . . . . n} $\xi \epsilon$ (0, 1] called as distinguish factor. ξValue assumed as 0.5 (0.1to1). If the value of fjfj is least, then the distinguishing ability is more [10,15,37].

S5: The GRA grades are developed by GRC values [15,37]

$$\gamma\ (\mathrm{d_{os}}, \mathrm{d_{rs}}) = \sum\nolimits_{s=1}^{n} w_s\delta\ (\mathrm{d_{os}},\mathrm{d_{rs}}) \tag{13}$$

For r = 1, 2 . . . m Where $\sum\nolimits_{s=1}^{n} w_s = 1$

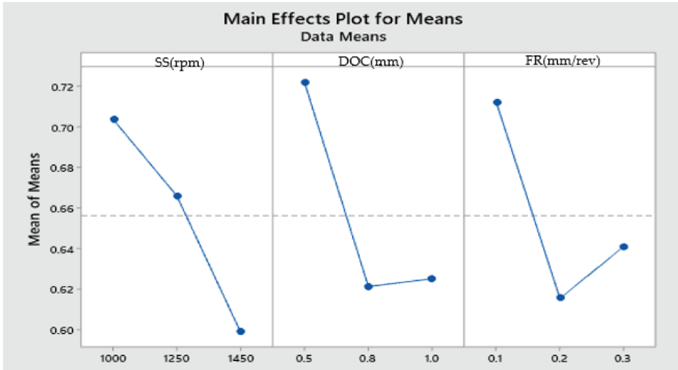
w_s is the weight of response s, and the GRG indicates the similarity between the sequence of references and comparability. If the value of the grade is higher than all, then it is considered the best experiment because it is similar to the reference.

S6: The Ranks are given for all combinations, depending on the highest being the First Rank and continued after calculating the grade, the ranking for grades is allocated depending on the highest being first and the lowest being last. Experiment number 1, highlighted, is the closest combination of controllable parameters of speed of 1000 rpm, DOC of 0.5 mm, and feed rate of 0.1 mm/rev with 3.8 µm surface roughness, and 6544.8 mm^3/min material removal rate.

Table 6 provides the means of each input parameter along with levels and also provides the error of speed, depth of cut, and feed rate. From the table, it can be concluded that speed has a significant effect based on Rank over output responses. Feed rate shows the least significant effect on output response. Figure 4 shows a graph indicating a relationship between input parameters and output responses. Figure 4 shows that when speed is at its lowest, the mean is at its highest point, as speed increases the mean decreases. However, the depth of cut shows that as the level is at its lowest, the mean increases. Later, it deviates from higher to lower at increasing levels of depth of cut. From the figure, the feed rate also follows the same path as that of the depth of cut. In the plot, the speed is 1000 rpm at the highest mean of means; similarly, the depth of cut is 0.5 mm, and the feed rate is 0.1 mm/rev. In these predicted input parameters, surface roughness is the lowest. For these inputs, the responses already exist in Table 4 with a 3.8 µm surface roughness and a 6544.8 mm^3/min material removal rate [7].

5.2. *Artificial neural network*

Figure 5 shows the network diagram for training, which contains 3 input layers, 15 hidden layers, and 2 output layers. It consists of input parameters, responses, and a hidden layer. After adding input data for the MATLAB ANN tool, this will be generated depending on the required data. Initially, the model is used to compute the mean square



Cutting conditions: Speed in rpm, DOC in mm, and FR in mm/rev

Figure 4. Relationship between output responses and means.

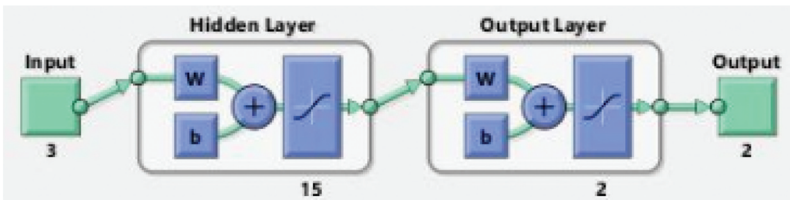


Figure 5. General structure of ANN.

of the error [3]. The input and target data are set in the worksheet for importing into MATLAB. The network is created by selecting the feedforward type of network, then the TRAINLM (Levenberg–Marquardt) function is used for training, LEARN GDM (gradient descent with momentum) as an adoption learning function, and the performance function as MSE. Two layers with fifteen neurons were used with TRANSIG as a transfer function for training [19,38]. The measure of surface roughness and material removal rate is obtained by loss propagation, and the results obtained show little variation from the observed values in the study with the least residual error. Predicted values are shown in Table 7. ANN is one of the best techniques for predicting the best fit with better accuracy in results. Some of the samples may be varied because of fewer experiments. For Training of ANN min_grad = 1e-05, max_fail = 100, time = Infinite, goal = 0, and Epochs = 1000 is applied.

Procedure for creation of an ANN model in MATLAB R2014a software. The parameter and response data are used as input and target data, respectively, for ANN. The neural network is created depending on the number of inputs and the target. The training, validation, and testing data are selected in terms of percentage for training. The number of hidden layers is selected until we train good outputs. The Levenberg–Marquardt function is used for training. Then, the whole process is trained. For Training ANN min_grad = 1e-05, max_fail = 100, time = Infinite, goal = 0, and epochs = 1000 is applied. Then, the regression graph is plotted. The R^2 value is

Table 7. Result extracted from MOGA.

Sl No	Speed (rpm)	DOC (mm)	FR (mm/rev)	SR (µm)	MRR (mm^3/min)
1	**1146.52**	**1.000**	**0.1000**	**2.3219**	**6894.2227**
2	1354.07	1.000	0.3000	7.0723	3598.7375
3	1170.43	1.000	0.1140	2.7927	6686.8363
4	1244.40	1.000	0.2975	6.8032	3914.6575
5	1179.96	1.000	0.2710	6.1197	4452.6663
6	1185.25	0.999	0.2523	5.7490	4708.5125
7	1309.22	1.000	0.2986	6.9574	3736.0679
8	1257.66	1.000	0.2471	5.8885	4640.2241
9	1161.05	1.000	0.1240	2.9401	6551.9562
10	1155.41	1.000	0.1419	3.2846	6306.7848
11	**1146.52**	**1.000**	**0.1000**	**2.3219**	**6894.2227**
12	1172.24	0.999	0.1536	3.6360	6127.5141
13	1153.55	1.000	0.1525	3.5013	6160.3166
14	1291.55	1.000	0.2478	6.0178	4561.0836
15	1271.54	0.999	0.2763	6.4713	4170.1649
16	1225.28	1.000	0.2989	6.7901	3943.1736
17	1157.93	1.000	0.1741	3.9888	5854.3795
18	1161.72	0.999	0.1362	3.2057	6380.0164
19	1237.20	1.000	0.2205	5.3072	5073.6039
20	1180.92	1.000	0.1983	4.6135	5483.5705
21	1354.07	1.000	0.3000	7.0723	3598.7375
22	1160.32	0.999	0.1977	4.5057	5521.9499
23	1180.80	0.999	0.1842	4.3234	5684.9092
24	1172.54	1.000	0.2842	6.3742	4282.4895
25	1197.12	1.000	0.2453	5.6454	4783.2008

Objective 1 —- Ra minimise (S DOC FR), objective 2 —-MRR maximise (S DOC FR), 1000 ≤ S ≤ 1450. ≤ DOC ≤ 1; 0.1 ≤ FR ≤ 0.3;

Table 8. Shows confirmation test for developed vs observed models.

			ANN				RA			
	Observed		Predicted		Error in %		Predicted		Error in %	
Runs	SR (µm)	MRR (mm^3/min)	SR (µm)	MRR (mm^3/min)	SR (µm)	MRR (mm^3/min)	SR (µm)	MRR (mm^3/min)	SR (µm)	MRR (mm^3/min)
1	3.8	6544.8	3.5	6544.8	7.89	0	3.8	6545.69	0	0.013
3	6.4	4487.86	6.7	4487.86	4.68	0	6.4	4496.81	0	0.19
4	5.8	5817.59	5.8	5817.59	0	0	5.7	5844.43	1.72	0.46
7	6.3	4908.59	6.7	4908.59	6.34	0	6.3	4900.03	0	0.17
8	4.7	6041.35	4.7	6041.35	0	0	4.8	6022.71	2.12	0.31

observed, if it is close to 1 then the training is stopped. Then, the output generated is recorded.

Figure 6 shows a best-trained fitness model for responses and depicts the observed and predicted values of the ANN model. With repeated training, the value of R^2 is 0.99 with high accuracy results, hence having better agreement with the observed values. The graph clearly indicates that the value of R^2 is very close to 1, which means that the results obtained from ANN are the best fit for the turning process. This clearly confirms that the residuals of the plot in Figure 6 are very close to the straight line. This reveals that the errors are normally dispersed and specifies that the models developed are significant. The residual curve generated from ANN is obtained from 1 to 9 experimental cutting conditions, and the responses are recorded [3,27,29].

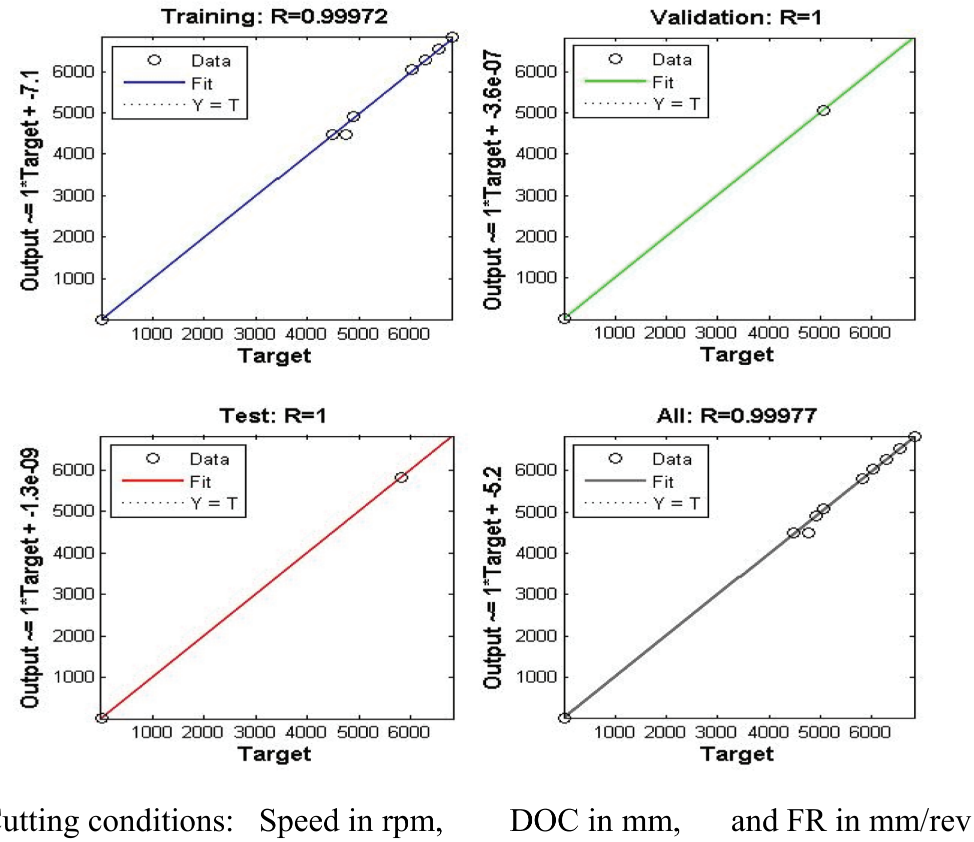


Figure 6. Results of ANN model for *R* value obtained from L (1–9) cutting condition.

5.3. Genetic algorithm approach

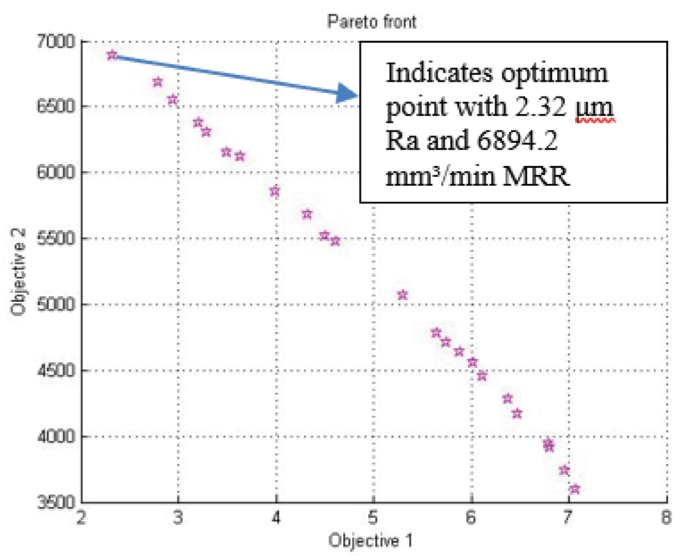
Equation 5 is used as an objective function for SR, and equation 7 is used as an objective function for MRR. The ranges are to be set in the MATLAB optimisation of the MOGA tool. The ranges selected for parameters in this work are speed in the range of 1000 rpm to 1450 rpm, DOC in the range between 0.5 mm and 1.0 mm, and feed rate in the range of between 0.1 mm/rev and 0.3 mm/rev. The regression equations developed are used as OF in the MOGA to search for the best responses to minimise SR values and maximise MRR at the same point [3].

The Population type used for MOGA is a double vector: population size is 50 with Feasible population, in the function selection, the size of the tournament is 2, in reproduction crossover is 0.8, in the function of mutation the constraint is dependent on adaptive feasible, in function crossover the intermediate is taken as 1.0, in migration, the fraction is selected as 1, with Interval of 10, in settings of the multi-objective the function of distance measure is considered a crowding of distance, with population fraction for Pareto, is 0.5, and in Stopping criteria with generation 2000, stall generation 100, functional tolerance is 1×10^{-5}, and constraint tolerance is 1×10^{-3} are used to obtain the best fit.

Table 7 shows GA results obtained from MATLAB. Figure 7 shows the Pareto front graph generated from the MATLAB MOGA tool by providing the cutting condition along with the process requirement at the input level to plot the graph. For simultaneous operation, the least SR and most MRR are obtained at 1146.52 rpm speed, 1 mm DOC and a 0.1 mm/rev feed rate. The Fig. indicates the graph of SR (objective 1) vs. MRR (objective 2). The aim is to minimise SR and maximise MRR. From Fig. SR of 2.32 µm the least value at the same point, the MRR is 6894.22 mm^3/min which is the highest; hence, it is validated [19,22]. As compared to the previously published results [3], the value of surface roughness was 1.25 µm at feed rate: 0.4321 mm/rev, speed: 1192.3 rpm, and DOC: 0.5738 mm. Only the study of surface roughness was observed when compared with this research. This research involved the simultaneous reduction of SR and improvement of MRR at the same point of the Pareto front graph generated by MOGA. The optimal settings extracted by the Pareto graph are 1146.52 rpm speed, 1 mm DOC, and 0.1 mm/rev feed rate. SR of 2.32 µm the lowest value at the same point, the MRR is 6894.22 mm^3/min which is the highest. For selected cutting parameters at a single point of the Pareto graph, the least value of SR and a higher value of MRR are observed. The Pareto front obtained in this study is to minimise objective 1 and maximise objective 2.

By comparing the tables of DOE and MOGA, that is, Tables 4 and 7, the range of parametric values of speed in MOGA is 1146.52–1197.12 rpm, whereas in DOE 1000–1450 rpm, hence, from MOGA the reduced range is obtained. On the other hand, the DOC stuck at 1 mm, and the FR ranged from 0.1 to 0.3 mm/rev in MOGA as compared to the range of experimental input values of DOC of 0.5 mm to 1 mm and FR of 0.1 mm/rev to 0.3 mm/rev [24,26–28].

The best outcomes obtained are speed: 1146.52 rpm, DOC: 1.0 mm, and FR: 0.1 millimetre per rev with 25 outputs in the single-rank histogram as shown in Figure 8.



Cutting conditions: Speed in rpm, DOC in mm, and FR in mm/rev

Figure 7. GA Pareto front graph of Ra vs MRR obtained from 1–9 cutting condition.

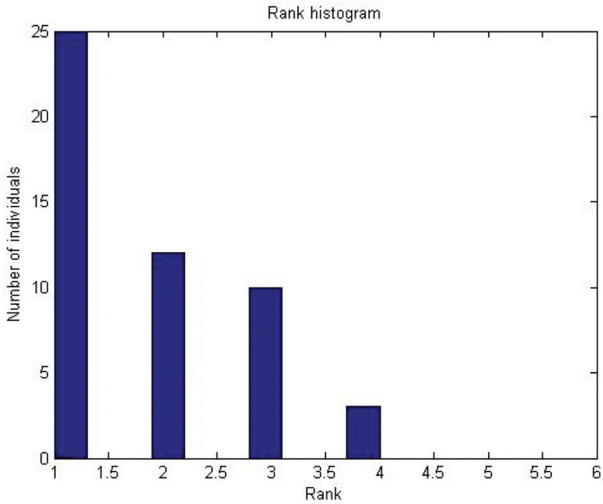
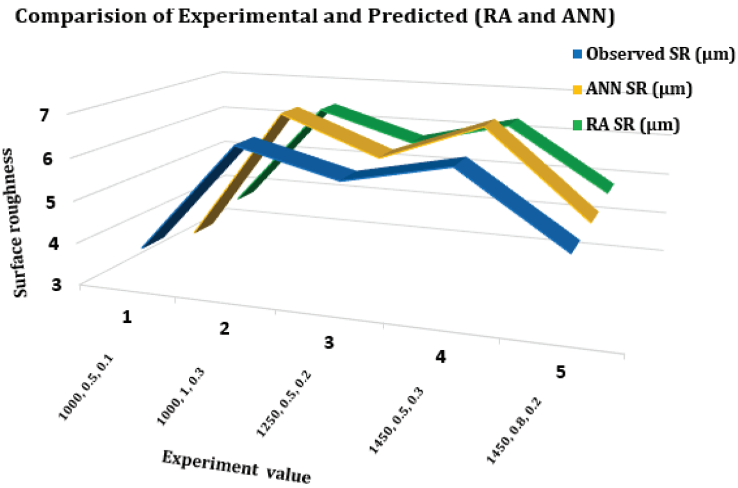


Figure 8. Histogram with number of individuals extracted from MOGA for parametric constraints.

Figure 8 also shows a graph, of rank vs. number of individuals, from this graph, the highest number of individuals shows Rank 1 which is selected for results. These desirable values of MOGA are implemented in experimentation for confirmation tests by considering speed: 1146.5 rpm, DOC: 1.0 mm, feed rate: 0.1 mm/rev. The minimum obtained value is 2.67 µm and 6544.79 mm^3/min, which is very close to the results obtained from GA.

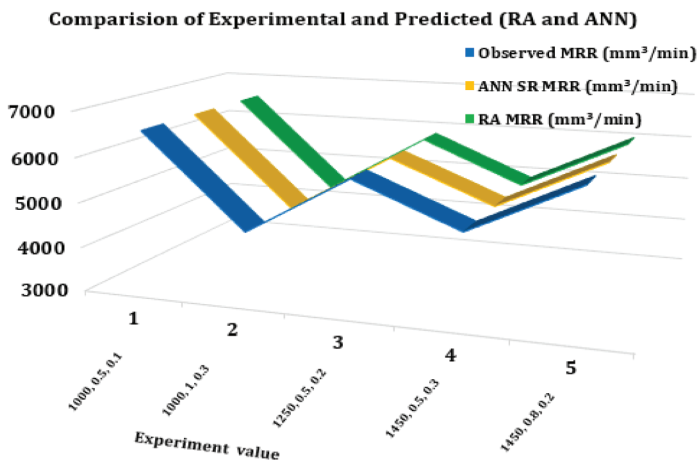
5.4. Confirmation test

The responses considered in this work are best described by second-order Polynomial Models. From investigations of surface roughness and material removal rate after the Multipass Turning Process, it was found that the regression model and ANN model followed the experimental results and the residual error of both models is close to a straight line [1]. The Regression Model is validated by the ANN model and holds well. The models developed by RA and ANN are considered significant and in line with the validation results. Table 8 Shows confirmation test for developed vs observed models. Lower feed rate shows the confirmation test for developed vs. observed models. The average errors obtained by both models are less than 5%. The value of R^2 in the regression model was higher than the confidence level (95%); hence, the prediction model is acceptable. The errors of the regression models for both responses are less than 5% hence these regression equations are used as objective functions in MOGA for prediction of optimum parameters and responses. The 3D line graph in Figures 9 and 10 shows comparisons of SR and MRR vs experimental results. This clearly indicates that the models developed by regression and ANN follow the experimental values. The blue colour line in both shows the experimental results of SR and MRR, respectively. The yellow colour indicates ANN responses and green colour indicates RA responses, which follows the blue colour lines. Hence, the models are significant.



Cutting conditions: Speed in rpm, DOC in mm, and FR in mm/rev

Figure 9. Comparison of experimental and predicted values of surface roughness.



Cutting conditions: Speed in rpm, DOC in mm, and FR in mm/rev

Figure 10. Comparison of experimental and predicted values of material removal rate.

6. Conclusion

In the present research work, the author aims to obtain the optimum cutting condition by considering the restrictions of the parametric range planned for the experiment. The Multipass Turning of AISI 4340 alloy steel is machined on a CNC lathe. Parameters such as speed, depth of cut and feed rate with MQC are used for the minimisation of SR and maximisation of MRR by optimisation processes. To reduce the material and number of experiments a design of experiments is utilised. By using Taguchi's L9 array, an experimental database is obtained for different combinations. The main aim of optimisation is to reduce cost and errors in less time.

In the present investigation, the author applied traditional GRA to predict the optimal setting. The regression analysis is applied to obtain the model and ANN is used to validate the model developed by the Regression Equation. The confirmation test has been made for ANN and Regression Models. These Regression Equations are used as objective functions in MOGA for optimisation of parameters. The objective of employing MOGA is to minimise the SR and maximise the MRR at the same time. The main aim is to detect which optimisation practice delivers the best outcomes for SR and MRR. From the present research, the following conclusions can be drawn:

- The traditional GRA technique is used for the prediction of the best response from the database, as the author has obtained the optimal combination of SS1DOC1FR1 (speed 1000 rpm, DOC of 0.5 mm, Fr of 0.1 mm/rev) at controllable parameters with SR and MRR as 3.8 μm and 6544.8 mm^3/min respectively. Showing all parameters is its lowest range effects, which is best for surface roughness. Minimum surface roughness is attainable at a lower feed rate, speed and depth of cut by GRA. The percentage error in comparison of experimental and predicted results is nil.
- The value of R^2 in the regression model was higher than the confidence level (95%) hence, the prediction model is acceptable. The confirmation test was also made for the regression model by the soft computing technique ANN. The percentage error of the regression and ANN model is less than 5% for surface roughness and material removal rate. This is also satisfactory in describing the performance indicator.
- The results obtained from MOGA are 2.32 μm surface roughness and material removal rate of 6894.22 mm^3/min with speed 1146 rpm, DOC: 1.0 mm, feed rate: 0.1 mm/rev as input parameters. However, the conventional method could not meet this Ra value but the experimental results recorded at the same input parameters were 2.67 μm and MRR 6544.79 mm^3/min. The percentage of error observed between predicted and experimental is 13% for surface roughness and for MRR it is 5.33%.
- The Pareto front plot provides minimum surface roughness and maximum MRR. The Pareto optimum solution is better than any other. The combinations obtained are satisfactory and can be varied according to need. The range obtained for speed in MOGA is 1146.52–1197.12 rpm, whereas in DOE it is 1000–1450 rpm, hence from MOGA the reduced range is obtained. Maintaining a lower speed and feed rate with a higher depth of cut, the least surface roughness, and a higher material removal rate can be attained.
- The predicted value of surface roughness by GRA is 3.8 μm and by MOGA is 2.3 μm. In comparison, MOGA provides a better predicted value. The improvement of surface roughness is observed in Soft Computing Technique MOGA as compared to the statistical technique GRA.

- The minimum surface roughness of AISI 4340 is attainable at a lower feed rate and speed and a higher depth of cut in the turning process. The hardness of the material and speed of cutting are the most influential factors for surface roughness as well as MRR.

Nomenclature

SR (Ra)	Surface Roughness in μm
MRR	Material Removal Rate in mm^3/min
S (SS)	Speed in rpm
DOC	Depth of Cut in mm
FR	Feed Rate mm/rev
MOGA	Multi Objective Genetic Algorithm
GRA	Grey Relational Analysis
GRG	Grey Relation Grade
ANN	Artificial Neural network
MQC	Minimum quantity of coolant
OF	Objective function
CNC	Computer Numerical Control
OA	Orthogonal Array
w/p	Work piece

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Data availability of statement

The data was collected from original research work and optimisation of data is done with a genetic algorithm and GRA process.

Code availability

The datasets generated during and/or analysed during the current study are available from the corresponding author upon reasonable request.

References

[1] Banker VJ, Mistry JM, Patel MH. Experimental investigation of cutting parameters on surface roughness in hard turning of AISI 4340 alloy steel. In: Advanced engineering optimization through intelligent techniques. Singapore: Springer; 2020. p. 727–737. doi: 10.1007/978-981-13-8196-6_64

[2] Jena J, Panda, A., Behera, A. K., et al. Modeling and optimization of surface roughness in hard turning of AISI 4340 steel with a coated ceramic tool. In: Innovation in materials science and engineering. Singapore: Springer; 2019. p. 151–160. 10.1007/978-981-13-2944-9_15.

[3] Santhosh AJ, Tura AD, Jiregna IT, et al. Optimization of CNC turning parameters using face centred CCD approach in RSM and ANN-genetic algorithm for AISI 4340 alloy steel. Results Eng. 2021 Sep 1;11:100251. doi: 10.1016/j.rineng.2021.100251
[4] Kumar S, Singh D, Kalsi NS. Performance evaluation of TiN-coated CBN tools during turning of variable hardened AISI 4340 steels. In: Advanced engineering optimization through intelligent techniques. Singapore: Springer; 2020. p. 847–857. doi: 10.1007/978-981-13-8196-6_76
[5] Chen S-H, Hsu C-H. Using uniform design and regression methodology of turning parameters study of a nickel alloy. Int J Adv Manuf Technol. 2021;116(11):3795–3808. doi: 10.1007/s00170-021-07584-4
[6] Zhou G, Xu, C., Wang, X., et al. Determination of tooltip steady-state temperature in dry turning process based on artificial neural network. J Manuf Processes. 2022;79:600–613. doi: 10.1016/j.jmapro.2022.05.021
[7] Saravana Kumar A, Rajeshkumar, L., Sisindri Reddy, G., et al. Multi-response optimization of turning parameters for AZ91D magnesium alloy using gray-based Taguchi approach. In: Recent advances in mechanical engineering. Singapore:Springer; 2023. p. 389–397. 10.1007/978-981-16-9057-0_41.
[8] Ben Fathallah B, Saidi, R., Mabrouki, T., et al. Multi-optimization of stellite 6 turning parameters for better surface quality and higher productivity through RSM and grey relational analysis. In: International conference design and modeling of mechanical systems. Springer: Cham; 2019. doi: 10.1007/978-3-030-27146-6_41
[9] Jozić S, Bajić D, Celent L. Application of compressed cold air cooling: achieving multiple performance characteristics in the end milling process. J Clean Prod. 2015;100:325–332. doi: 10.1016/j.jclepro.2015.03.095
[10] Dinesh S, Vijayan, V., Parthiban, A., et al. Modeling and optimization of machining parameters for turning of mild steel using single-point cutting tool made of P20 tool steel. In: Advances in industrial automation and smart manufacturing. Singapore:Springer; 2021. p. 285–295. 10.1007/978-981-15-4739-3_24.
[11] Mukherjee S, Kamal A, Kumar K. Optimization of material removal rate during turning of SAE 1020 material in CNC lathe using Taguchi technique. Procedia Eng. 2014;97:29–35. doi: 10.1016/j.proeng.2014.12.221
[12] Gupta A, Singh H, Aggarwal A. Taguchi-fuzzy multi-output optimization (MOO) in high-speed CNC turning of AISI P-20 tool steel. Expert Syst Appl. 2011;38(6):6822–6828. doi: 10.1016/j.eswa.2010.12.057
[13] Saravanakumar A, Karthikeyan SC, Dhamotharan B. Optimization of CNC turning parameters on aluminum alloy 6063 using Taguchi Robust design. Mater Today Proc. 2018;5(2):8290–8298. doi: 10.1016/j.matpr.2017.11.520
[14] Kumar MV, Kiran Kumar BJ, Rudraksha N. Optimization of machining parameters in CNC turning of stainless steel (EN19) by Taguchi's orthogonal array experiments. Mater Today Proc. 2018;5(5):11395–11407. doi: 10.1016/j.matpr.2018.02.107
[15] Prakash PB, Raju, K. B., Subbaiah, K. V., et al. Application of Taguchi based grey method for multi aspects optimization on CNC turning of AlSi7 mg. Mater Today Proc. 2018;5(6):14292–14301. doi: 10.1016/j.matpr.2018.03.011
[16] Gadekula RK, Potta, M., Kamisetty, D., et al. Investigation on parametric process optimization of HCHCR in CNC turning machine using Taguchi technique. Mater Today Proc. 2018;5(14):28446–28453. doi: 10.1016/j.matpr.2018.10.131
[17] Bharathi SS, Ravindran, D., Moshi, A. A. M., et al. Multi-objective optimization of CNC turning process parameters with Acrylonitrile Butadiene Styrene material. Mater Today Proc. 2020;27:2042–2047. doi: 10.1016/j.matpr.2019.09.055
[18] Ravuri M, Reddy YSK, Harsha Vardhan D. Parametric optimization of face turning parameters for surface roughness on EN 31 material using RSM and Taguchi method. Mater Today Proc. 2021;37:769–774. doi: 10.1016/j.matpr.2020.05.816

[19] Muthuram N, Christo Frank F. Optimization of machining parameters using artificial intelligence techniques. Mater Today Proc. 2021;46:8097–8102. doi: 10.1016/j.matpr.2021.03.045

[20] Osorio-Pinzon JC, Abolghasem, S., Maranon, A., et al. Cutting parameter optimization of al-6063-O using numerical simulations and particle swarm optimization. Int J Adv Manuf Technol. 2020;111(9):2507–2532. doi: 10.1007/s00170-020-06200-1

[21] Surya MS, et al. Optimization of cutting parameters while turning Ti-6Al-4 V using response surface methodology and machine learning technique. Int J Interact Des Manuf (IJIDeM). 2021;15(4):453–462. doi: 10.1007/s12008-021-00774-0

[22] Subramanian M, Sakthivel, M., Sooryaprakash, K, et al. Optimization of cutting parameters for cutting force in shoulder milling of Al7075-T6 using response surface methodology and genetic algorithm. Procedia Eng. 2013;64:690–700. doi: 10.1016/j.proeng.2013.09.144

[23] Sivaiah P, Chakradhar D. Modeling and optimization of sustainable manufacturing process in machining of 17-4 PH stainless steel. Measurement. 2019;134:142-152, ISSN 0263–2241. doi: https://doi.org/10.1016/j.measurement.2018.10.067

[24] Saha S, Zaman PB, Tusar M, et al. Multi-objective genetic algorithm (moga) based optimization of high-pressure coolant assisted hard turning of 42CrMo4 steel. Int J Interact Des Manuf (IJIDeM). 2022;1–20. doi: 10.1007/s12008-022-00848-7

[25] Kuntoğlu M, Acar O, Gupta MK, et al. Parametric optimization for cutting forces and material removal rate in the turning of AISI 5140. Machines. 2021;9(5):90. doi: 10.3390/machines9050090

[26] Abbas AT, Al-Abduljabbar AA, Alnaser IA, et al. A closer look at precision hard turning of AISI4340: multi-objective optimization for simultaneous low surface roughness and high productivity. Materials. 2022;15(6):2106. doi: 10.3390/ma15062106

[27] Hegab H, Salem A, Rahnamayan S, et al. Analysis, modeling, and multi-objective optimization of machining inconel 718 with nano-additives based minimum quantity coolant. Appl Soft Comput. 2021;108:107416. doi: 10.1016/j.asoc.2021.107416

[28] de Melo SA, Pereira RBD, da Silva Reis AF, et al. Multi-objective evolutionary optimization of unsupervised latent variables of turning process. Appl Soft Comput. 2022;120:108713. doi: 10.1016/j.asoc.2022.108713

[29] Mondal N, Mandal S, Mandal MC. FPA based optimization of drilling burr using regression analysis and ANN model. Measurement. 2020;152:107327. doi: 10.1016/j.measurement.2019.107327

[30] Dutta S, Narala SKR. Optimizing turning parameters in the machining of AM alloy using Taguchi methodology. Measurement. 2021;169:108340. doi: 10.1016/j.measurement.2020.108340

[31] John V, Aggarwal S, Arora RK, et al. Forecasting the output using ANN models and effect of input factors on machinability of Duplex steel 2205 in dry-turning operation for high strength and anti-corrosive applications. Adv Mater Process Technol. 2022;1–12. doi: 10.1080/2374068X.2022.2140941

[32] Zaman PB, Sultana MN, Dhar NR. Multi-variant hybrid techniques coupled with Taguchi in multi-response parameter optimization for better machinability of turning alloy steel. Adv Mater Process Technol. 2021;8(3):1–21. doi: 10.1080/2374068X.2021.1945302

[33] Subbaiah KV, Raju C, Suresh C. Parametric analysis and optimization of hard turning at different levels of hardness using wiper ceramic insert. Measurement. 2020;158:107712. doi: 10.1016/j.measurement.2020.107712

[34] Singh BK, Roy H, Mondal B, et al. Measurement of chip morphology and multi criteria optimization of turning parameters for machining of AISI 4340 steel using Y-ZTA cutting insert. Measurement. 2019;142:181–194. doi: 10.1016/j.measurement.2019.04.064

[35] Touggui Y, Uysal A, Emiroglu U, et al. Evaluation of MQL performances using various nanofluids in turning of AISI 304 stainless steel. Int J Adv Manuf Technol. 2021;115(11–12):3983–3997. doi: 10.1007/s00170-021-07448-x

[36] Thakur A, Manna A, Samir S. Multi-response optimization of turning parameters during machining of EN-24 steel with SiC nanofluids based minimum quantity lubrication. Silicon. 2020;12(1):71–85. doi: 10.1007/s12633-019-00102-y
[37] Ali S, Pervaiz S. Machinability analysis of AZ31 magnesium alloys using the Taguchi gray relational analysis. Int J Adv Manuf Technol. 2023;126(9–10):1–20. doi: 10.1007/s00170-023-11354-9
[38] Huang PB, Inderawati MMW, Rohmat R, et al. The development of an ANN surface roughness prediction system of multiple materials in CNC turning. Int J Adv Manuf Technol. 2023;1–19. doi: 10.1007/s00170-022-10709-y