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RESEARCH

Optimization of Multiple Objectives by Genetic Algorithm for Turning of AISI 1040 Steel Using Al_2O_3 Nano Fluid with MQL

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A B S T R A C T

Multi-objective optimization requires computing the best trade-off between two or more conflicting objectives. The present study applies multi-objective optimization technique to the turning of AISI 1040 steel using Al_2O_3 nano particles with minimum quantity lubrication (MQL) technique for cutting force (CF), surface roughness (SR) and temperature (CT) using genetic algorithm. Central composite face-centered design with five factors, namely volume concentration(vol.c) of nano particles, MQL flow rate, cutting speed, feed rate and depth of cut (DOC) at three levels are used for experiments. From the developed regression model, it is found that speed, feed and DOC are the primary factors effecting the CF whereas MQL flow rate, speed and DOC are the primary factors effecting the SR and cutting temperature is predominantly affected by MQL flow rate, speed, feed rate and DOC. Based on the mathematical models, multi-objective optimization of process parameters has been performed with genetic algorithm (GA) technique. A set of confirmation experiments were conducted for randomly selected trials of pareto solutions obtained from multi-objective GA to validate the optimum values. An error percentage of 4.6%, 3.7% and 4.9% respectively for CF, SR and CT shows that the predicted optimum values are justified with the confirmation result.

1. INTRODUCTION

Manufacturing processes typically consume many natural resources that are extracted from the earth. Reliability of the product directly influences the amount of natural resources consumed during manufacturing. Muhammad et al. [1] concluded that vegetable oils have more benefits while using as lubricant for machining purposes. For ecologically sustainable manufacturing, the design and reliability of the product is highly desirable and is increasing in complexity as the products themselves are becoming complex. In this background most of the industries are aiming to produce highly complex components without compromising on safety and quality. Cutting temperature (CT), cutting force (CF) and surface roughness (SR) are some of the important responses in any machining operation which determine the quality of the product. Increase in these responses leads to high distortion and power consumption, reduces dimensional accuracy, cutting tool performance and product quality. Cutting fluid in any machining operation is used to reduce friction, to fairly reduce the workpiece temperature and to throw away chips. The CF and SR are reduced with the use of cutting fluid which also secures the surface of machining from corrosion. Though cutting fluids have number of advantages they are also accompanied by number of drawbacks. Cost and disposal of cutting fluid are the major challenges in the application of cutting fluid. In order to overcome these disadvantages, Sreejith et al. [2] conducted dry machining. However, many researchers are working on minimum quantity lubrication (MQL). MQL is a technique in which the cutting fluid is broken into small finer particles with the compressed air called aerosol in the system and this mixture of fluid and air is applied in the cutting zone under high pressure in the form of jet. Yusof et al. [3] in their work proved that MQL has more benefits compared to dry machining. The study made by Dhar et al. [4] indicated that the implementation of near dry lubrication resulted in reduction of CF and CT, appropriate tool-chip interaction, minimized tool wears, SR, and dimensional deviation. Masoudi et al. [5] concluded that the orientation of nozzle is an important factor effecting the surface roughness and cutting force. Better cutting efficiency achieved during the use of MQL technique is due to the less strain used to break up the chips because of the brittle nature of the lubricant, thus causing low friction. Dixit U S et al. [6] suggested a chip removal system and fire and explosion system in machining of light metal alloys like magnesium while using MQL technique. In order to further improve the machining process, many researchers are working on nano cutting fluids along with MQL technique. Nano cutting fluids are the fluids formed by the colloidal dispersion of nano particles in base fluid. The inclusion of nano particles in base fluid increases the thermal conductivity thus enhancing the heat transfer capacity of the base fluid. Hasan et al. [7] used nano fluids for enhancing the heat transfer capacity in CPU. The authors measured the Nusselts number and Reynolds number for Al_2O_3 nano fluid and concluded the increase in both than convention fluid (water). Khan et al. [8] developed mathematical models for predicting surface roughness and cutting temperature under MQL and nano MQL (Al_2O_3) machining conditions during milling of D2 steel. The authors showed that nano fluid MQL improved the surface roughness and reduced cutting temperature. Jamil et al. [9] used hybrid nano fluids (Al_2O_3 + MWCNT) to measure the performance characteristics of Ti–6Al–4V. The results were compared with cryogenic cooling process and reduction in surface roughness, cutting force and improved tool life were observed under nano MQL cutting conditions. Sridhara et al.[10] conducted a review on Al_2O_3 nano cutting fluids and stated that there is an enhancement of 2 % to 36 % in thermal conductivity. The responses depend on the process parameters, hence proper selection of process parameters to achieve the optimal values of responses is a tedious step. Taguchi orthogonal arrays, response surface methodology, etc. are the statistical approaches for proper selection of process parameters in order to achieve optimal values for the responses. S Settu et al. [11] discussed the implementation of Taguchi and Anova techniques to study the influence of machining parameters on tool wear and surface finish during key way milling of EN8 steel by the application of nano cutting fluid. Taguchi technique was used to predict the optimum parameters and the significant levels were found by using ANOVA. From their findings it was understood that surface finish was predominantly significant by cutting speed whereas feed rate followed by spindle speed are statistically significant for tool wear. Abbas et al. [12-13] used ANN to achieve the optimum conditions for surface roughness, machining time and processing cost while considering cutting speed, feed and depth of cut during turning of AA6061shafts and AZ61 magnesium alloy. Abbas et al. [14] used Edge worth pareto method for the first time to optimize the process parameters during turning of high strength steel. Zain et al. [15] utilized evolutionary techniques like genetic algorithm as an optimization tool for minimizing SR. Li et al. [16] used non dominated sorting genetic algorithm to optimize the production cost and surface quality simultaneously. Liu et al. [17] optimized the grinding process parameters using grey relational analysis. Venkata Rao et al. [18] used a new nature based teaching learning algorithm for optimization of turning, grinding and drilling process parameters. Iqbal et al. [19] studied tool life and surface roughness using D-optimal method and concluded that increase in rotational speed is favorable for surface roughness but unfavorable for tool life. Due to the complexity of machining process, where multiple responses must be simultaneously optimized there is a need for multi-obj optimization. Multi-obj optimization requires computing the best trade-off between two or more conflicting objectives. This method has been researched and applied to problems in many fields of science, engineering, economics and logistics. Sardinas et al. [20] remarked the benefits of multi-obj optimization over single response optimization. Azizi et al. [21] used desirability function approach to obtain the optimum machining conditions and workpiece hardness for lower SR at minimum CF. Zerti et al. [22] developed models through RSM and ANN methods through which multi-objective optimization of surface roughness, material removal rate and power consumption is achieved through desirability function. The authors concluded that feed rate is the most significant factor effecting the surface roughness and depth of cut is the most influencing factor for cutting force, cutting power and material removal rate. Aouici et al. [23] predicted the model for SR and CF respectively through which the multi-objective optimization is carried by using desirability function approach. Sathishkumar et al. [24] also conducted multi response optimization for surface roughness and cutting temperature using desirability function analysis. Raju et al. [25] used hybrid grey-fuzzy method to optimize multiple responses. Narayanan et al. [26] carried out multi response optimization on SR and material removal rate using genetic algorithm.

From the literature survey the following gaps in research were identified:

1. In existing literature, volume concentration and MQL were analyzed as one-factor-at-a-time, thereby increasing the number of experiments and also precise solutions are also not obtained. The present study considers DOE technique to reduce the total number of experiments as well to get more accurate results.
2. Most of the multi-objective optimization is carried out using Desirability approach. This only suggests the best among the available options, whereas genetic algorithm can find out untested optimal options.

In the present work, AISI 1040 steel was machined with Tungsten carbide. Al_2O_3 nano particles of size 40nm were dispersed in de-ionized water and used as a cutting fluid under MQL conditions. The effect of volume concentration, MQL flow rate, speed, feed rate, DOC on cutting force, surface roughness and cutting temperature were studied through response surface methodology. Regression equations were developed for all the three responses and the effecting parameters were studied. Finally, optimum cutting conditions were obtained through genetic algorithm.

2. MATERIALS AND METHODS

2.1 Experimental set up

Kennametal made Tungsten-carbide insert whose standard designation TNMG160408H with six working triangular edges was used for turning AISI 1040 carbon steel of size 300mmx40mm. This steel is primarily used for automobile components such as axles, bolts, forged connecting rods, crankshafts, torsion bars, light gears, guide rods etc. The chemical compositions of AISI 1040 carbon steel and Tungsten-carbide insert are shown in Table 1 and Table 2 respectively. Because of the high carbon content, the steel is hard thus generates stronger frictional forces, thereby increasing the cutting temperature. Due to high cutting temperature, product quality degrades and cutting tool wears out quickly. To avoid this, usage of a coolant is mandatory during machining. Al_2O_3 nano particles have been chosen because of properties such as high conductivity, wear resistance and good lubricating properties. The Al_2O_3 nano particles were dispersed in de-ionized water, the resulting colloidal solution was used as cutting fluid. MTJNR 1616H16 was used for holding the inserts. Moreover, variable high-speed precision lathe machine with Kenco MQL set up was used for conducting the experiments. Experimental setup is displayed in Fig. 1.

Fig.1. Experimental set up.

Table 1. Chemical composition of AISI 1040 steel.

Element	C	Si	Mn	P	S	Fe
% in wt.	0.473	0.295	0.738	0.022	0.007	98.465

Table 2. Chemical composition of Tungsten-Carbide Insert.

Element	W	C	Ni	Cr	Fe
% in wt.	Balance	4.8-5.6	8.5-11.5	4.4-5.6	<0.3

Aluminum-oxide (Al_2O_3) nano particles of size 40nm were purchased from Nano Research Lab, Jamshedpur. The cutting fluid required for turning operation was prepared by mixing Al_2O_3 nano particles with de-ionized water.

2.2 Preparation of nano fluid

For the preparation of Al_2O_3 nano fluid two-step method was used as it is economical when prepared in large scale. The foremost step was to obtain dried nano particles. For this process, Al_2O_3 nano particles were purchased from Nano Research Lab, Jamshedpur, India. Al_2O_3 nano particles were spherical in form and had an average grain size of 40 nm. These were then suspended in different volume concentration percentages (0.2, 0.4 and 0.6 %) in base fluid. Moreover, the base fluid used in this work was de-ionized. The quantity of nano particles required for preparation of nano fluid was calculated by using rule of mixtures.

$$\% \, \boldsymbol{volume\ concentration} = \frac{\frac{\boldsymbol{WAl2O3}}{\boldsymbol{\rho Al2O3}}}{\frac{\boldsymbol{WAl2O3}}{\boldsymbol{\rho Al2O3}} + \frac{\boldsymbol{Wbf}}{\boldsymbol{\rho bf}}} \quad (1)$$

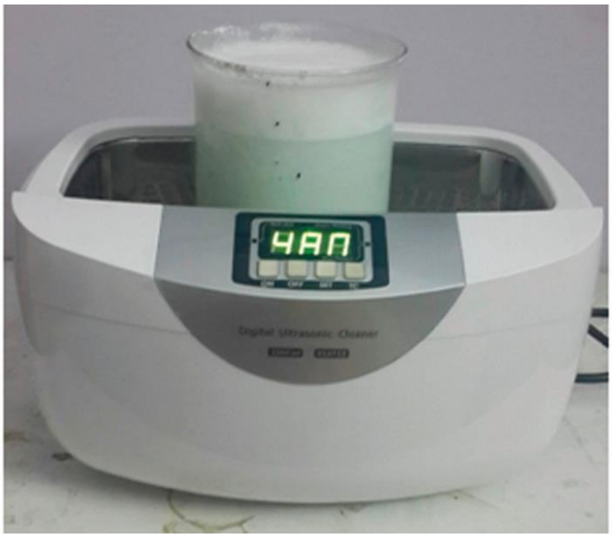

Fig. 2. Sonication of Nano Fluid.

SDBS was used in de-ionized water for the purpose of increasing the stability in nano particles. Ali et al. [27] in their work proved that surfactant (SDBS) also improves the surface roughness. The quantity of SDBS taken was also calculated using rule of mixtures. The desired quantity of SDBS was taken and mixed gradually in a step-up-step process with de-ionized water. The mixture was set for magnetic stirring for a period of 15min to ensure proper dissolving of surfactant. The premeasured quantity of nano particles was added meticulously to the above mixture. This mixture was set for sonication at a frequency of 60 Hz for 60 min for proper dispersion of nano particles. Sonication of nano fluid is shown in Fig. 2. The CF, SR and CT are measured by using Kistler piezoelectric dynamometer with Type 5070 charge amplifier, Taylor Hobson Surtronic S128 and infrared pyrometer respectively.

2.3 Design of Experiments

Central Composite Face Centered (CCF) design with five factors namely volume concentration (vol.c), MQL flow rate (LFR), speed, feed and DOC at three levels is used for conducting experiments. CCF design requires fewer runs for five factors at three levels than full factorial designs and other central composite designs. The design also enables us to find the optimal values. CCF design contains 16 fractional factorial points, 10 axial points and 2 center points making a total of 28 runs for five factors at three levels. The parameters to be studied and their levels are presented in Table 3. CCF design along with responses CF, SR and CT are displayed in Table 4.

Table 3. Process parameters at three levels.

Factor symbol	Factor	Level 1 (-1)	Level 2 (0)	Level 3 (+1)
A	Volume Concentration (%)	0.2	0.4	0.6
B	MQL Flow rate(ml/min)	3	4	5
C	Cutting Speed V_c(m/min)	80	100	120
D	Feed Rate f (mm/rev)	0.051	0.102	0.153
E	DOC d (mm)	0.25	0.5	0.75

Table 4. Central composite design in coded form with responses.

Ex. No	Volume concentration (%)	MQL flow rate (ml/min)	Cutting speed V (m/min)	Feed rate f (mm/rev)	Depth of cut d(mm)	Surface roughness R_a(μm)	Cutting force F_z (kgf)	Temperature T(^{0}C)
1	-1	-1	-1	-1	+1	0.90	131.8	55.00
2	-1	-1	-1	+1	-1	2.20	159.0	46.10
3	-1	-1	+1	-1	-1	2.46	086.7	54.95
4	-1	-1	+1	+1	+1	1.65	339.0	92.50
5	-1	+1	-1	-1	-1	2.25	102.5	36.55
6	-1	+1	-1	+1	+1	2.00	415.6	59.90
7	-1	+1	+1	-1	+1	1.80	209.4	49.80
8	-1	+1	+1	+1	-1	1.34	121.0	50.45
9	+1	-1	-1	-1	-1	1.76	084.9	38.75
10	+1	-1	-1	+1	+1	1.30	404.0	67.40
11	+1	-1	+1	-1	+1	1.45	191.2	70.50
12	+1	-1	+1	+1	-1	1.48	155.0	54.90
13	+1	+1	-1	-1	+1	2.00	205.5	40.25
14	+1	+1	-1	+1	-1	2.45	153.0	42.30
15	+1	+1	+1	-1	-1	1.80	074.8	37.90
16	+1	+1	+1	+1	+1	1.40	296.6	88.55
17	-1	0	0	0	0	1.97	212.3	68.75
18	+1	0	0	0	0	1.83	222.7	64.35
19	0	-1	0	0	0	1.40	196.5	74.70
20	0	+1	0	0	0	1.13	165.5	61.90
21	0	0	-1	0	0	1.56	243.0	63.40
22	0	0	+1	0	0	1.29	206.0	55.00
23	0	0	0	-1	0	1.59	136.6	52.50
24	0	0	0	+1	0	1.60	251.4	53.50
25	0	0	0	0	-1	1.40	117.8	56.90
26	0	0	0	0	+1	1.09	337.0	72.80
27	0	0	0	0	0	1.15	204.9	65.00
28	0	0	0	0	0	1.21	201.8	68.51

3. RESULTS AND DISCUSSION

The responses CF, SR and CT are evaluated from the experiments in order to study the influence of volume concentration, MQL flow rate, cutting speed, feed and depth of cut on the process. The effect of individual process variables on responses are studied using multi linear backward regression model.

3.1 Analysis of Variance

Anova is the most powerful tool in order to understand the effect of process parameters on the responses. The analysis of the present study has been carried out using the coded form of data in SPSS software. Anova for CF, SR AND CT are shown in Tables 5a, 6a and 7a respectively and the estimated coefficients are displayed in Tables 5b, 6b and 7b respectively.

3.2 Regression equation for cutting force

From Table 5a R^2 value of 0.975 indicates the adequacy of the model in determining the output response i.e. cutting force. The data from Table 5b shows that speed, feed and DOC are the predominating parameters for cutting force. In addition, interaction terms vol.c*LFR, LFR*speed, LFR*feed, speed*feed, feed*DOC also signify their effect on cutting force. The presence of square term LFR^2 indicates the quadratic nature of the equation. The developed mathematical equation for cutting force is given as:

$$CF = 214.633 - 12.2 * speed + 59.511 * feed + 81.867 * DOC - 20.633 * LFR^2 - 14.825 * vol.c * LFR - 10.437 * LFR * speed - 10.525 * LFR * feed - 16.088 * speed * feed + 29.888 * feed * DOC \quad (2)$$

It can be observed from Equation 2 that DOC is having more effect on cutting force followed by feed rate and speed. Hwang et al. [28] have also come to the same conclusion in their study. The increase in DOC and feed rate increases the cutting force. This may be due to the removal of more amount of material. Whereas, the cutting force decreases with increase in cutting speed which is coinciding with established theory. A possible explanation to this phenomenon is that chip flow increases when cutting speed increases, thereby minimizing the coefficient of friction at the area of contact between tool and workpiece. Another possibility is that the chip thickness reduces due to higher cutting speed. At lower cutting speeds, there is less shearing and plastic deformation, which explains the low cutting force.

Table 5a. ANOVA for cutting force.

Model	Sum of squares	df	Mean square	F	Significant
Regression	215380.536	9	23931.171	72.837	0.000
Residual	5585.510	17	328.559		
Total	220966.047	26			

R^2 – 0.975

Table 5b. Estimated coefficients for cutting force.

Variable	Parameter Estimate	Standard Error	t	Sig.
Constant	214.633	6.764	35.523	0.000
C	-12.2	4.272	-2.856	0.011
D	59.511	4.272	13.929	0.000
E	81.967	4.272	19.185	0.000
B^2	-20.633	7.400	-2.788	0.013
AB	-14.825	4.532	-3.272	0.004
BC	-10.437	4.532	-2.303	0.034
BD	-10.525	4.532	-2.323	0.033
CD	-16.088	4.532	-3.550	0.002
DE	29.888	4.532	6.595	0.000

3.3 Model equation for surface roughness

From Table 6a R^2 value of 0.849 indicates that the model is able to explain 84.9% variation in output response i.e. surface roughness with respect to input parameters. As we can see from Table 6b, MQL flow rate, speed and DOC have significant primary effect on surface roughness. Fratila et al. [29] have observed the same factors as dominating factors. Also, other terms like vol.c*LFR, LFR*speed, LFR*DOC, speed*feed, speed*DOC have a secondary effect on surface roughness. We can clearly see that it is a quadratic equation, as the square term vol.c^2 exists. The developed mathematical equation for surface roughness is given as:

$$SR = 1.356 + 0.087 * LFR - 0.097 * speed - 0.198 * DOC + 0.425 * vol.c^2 + 0.092 * vol.c * LFR - 0.202 * LFR * speed + 0.123 * LFR * DOC - 0.167 * speed * feed + 0.105 * speed * DOC \quad (3)$$

Table 6a. ANOVA for surface roughness.

Model	Sum of squares	df	Mean square	F	Significant
Regression	3.747	9	0.416	10.6	0.000
Residual	0.668	17	0.039		
Total	4.415	26			

R2 – 0.849

From Equation 3, it can be observed that increase in speed and DOC reduces surface roughness whereas roughness increases with increase in MQL flow rate. This may be due to the presence of some unknown or noise factors. At higher cutting speeds, the heat generated at the machining zone decreases the chances of generating the built-up edges. This prevents the chip fracture, because of which the surface roughness is reduced.

Table 6b. Estimated coefficients of parameters for surface roughness.

Variable	Parameter Estimate	Standard Error	t	Sig.
Constant	1.356	0.066	20.520	0.000
B	0.087	0.047	1.861	0.080
C	-0.097	0.047	-2.075	0.053
E	-0.198	0.047	-4.228	0.001
A^2	0.425	0.081	5.252	0.000
AB	0.092	0.050	1.861	0.080
BC	-0.202	0.050	-4.081	0.001
BE	0.123	0.050	2.479	0.024
CD	-0.167	0.050	-3.375	0.004
CE	0.105	0.050	2.126	0.048

3.4 Regression equation for cutting temperature

From Table 7a R^2 value of 0.864 indicates that the model is 86.4% adequate in determining the relation between output response i.e. cutting temperature and process parameters. Table 7b MQL flow rate, speed, feed and DOC have significant primary effect on surface roughness. Also, other terms like speed*DOC, feed*DOC have significant correlation with cutting temperature. The presence of square term feed^2 clearly shows that it is a quadratic equation. The developed mathematical equation for cutting temperature is given as

$$CT = 64.756 - 4.844 * LFR + 5.828 * speed + 6.633 * feed + 9.883 * DOC - 9.656 * feed^2 + 2.769 * speed * DOC + 4.2 * feed * DOC \quad (4)$$

From Equation (4) it is observed that cutting temperature increases with increase in speed, feedrate and DOC and decreases with increase of MQL flow rate. As the feed rate increases, the chip size increases and leading to increased friction at the tool-workpiece interface. This leads to higher temperature in the cutting zone. Increase in cutting speed causes higher friction, causing the temperature to raise. When MQL flow rate increases, the nanoparticle-based mist forms a stable thin film in the machining zone. The water evaporates quickly, leaving behind the thin nano particles which form a tribological film which improves lubrication, and reduces further heating. While the water evaporates, it takes away a lot of heat from the machining zone which leads to drop in temperature. Similar observations were made by Ul Haq et al. [30].

Table 7a. ANOVA for cutting temperature.

Model	Sum of squares	df	Mean square	F	Significant
Regression	4548.309	7	649.758	17.180	0.000
Residual	718.612	19	37.822		
Total	5266.921	26			

R^2-0.864

Table 7b. Estimated coefficients for cutting temperature.

Variable	Parameter Estimate	Standard Error	t	Sig.
Constant	64.756	2.050	31.588	0.000
B	-4.844	1.450	-3.342	0.003
C	5.828	1.450	4.020	0.001
D	6.633	1.450	4.576	0.000
E	9.883	1.450	6.818	0.000
D^2	-9.656	2.511	-3.846	0.001
CE	2.769	1.537	1.801	0.088
DE	4.200	1.537	2.732	0.013

3.5 Genetic Algorithm

The theory of genetic algorithms (GA) was proposed by Holland J H[31]. GA is based on the theory of evolution which is the most convincing theory that explains the origins of various species. In the natural world, the species evolve or become extinct based on natural selection. Species which adopt to changes in their environment survive and spawn newer generations. The adaptability is determined by the genes contained by the species. Genes evolve in two methods, crossover or mutation. Crossover is the process where strong genes from parents are passed to children. Mutation is the process where genes get modified.

The theory of evolution is applied to optimization problems in the following manner. The set of possible solutions is called a population. An individual solution is made up of multiple genes. Crossover function selects genes from two fit parent individual solutions into offspring. The parents are selected from fitness functions. By iterating over the population, selecting parents using fitness function, the offspring tends to be alike and converges towards an optimal solution. The mutation operator has the opposite effect. It tries to introduce diversity in the population so that the solution set is not just satisfied by local optima and attempts to find a global optimum solution.

The theory of Genetic Algorithm described above is applied to a problem which has a single objective. However, most real-life situations involve choosing the best compromise among a set of multiple orthogonal objectives. The same genetic algorithm approach can be applied even to multiple objective solutions as described in the next section.

3.6 Multi-objective optimization using Genetic Algorithm

In multi-objective optimization, the GA can be applied in multiple ways depending upon the problem domain [32]. Some of the well-known approaches are: weighted fitness function, altering objective functions and pareto ranking approach. In MATLAB, the pareto ranking approach known as non-dominated sorting genetic algorithm is available as function gamultiobj. This function is used to find the pareto optimal solutions. The rank is given to the population as per rule of dominance. Afterwards, each solution is given a fitness value based on the population rank. The following steps illustrate multi-objective problem solving using non-dominated sorting genetic algorithm (NSGA).

Step 1: Randomly generate the initial population P_1 (set of possible solutions)

Step 2: Iterate over each generation as follows (until stop criteria is reached)

- Step 2.1: Evaluate objective values
- Step 2.2: Rank the solutions according to Pareto Dominance Rule
- Step 2.3: For non-dominated individuals, assign dummy fitness and compute shared fitness
- Step 2.4: When entire population is classified, reproduce according to dummy fitness
  - Step 2.4.1: Apply Crossover operator
  - Step 2.4.2: Apply Mutation operator
- Step 2.5: Check stop criteria (number of generations, functional tolerance etc.)

Step 3: End

GA in MATLAB (R2018b version) software is used to find the minimum CF, SR and CT. The regression equations for CF, SR and CT are considered as the objective functions in GA.

Problem formulation:
The present problem is formulated as to minimize CF, SR and CT. Fitness function considered is shown in Equations 5, 6 and 7.

$$Minimize\ Fz = 214.633 - 12.2 * x\,(3) + 59.511 * x\,(4) + 81.867 * x\,(5) - 20.633 * x(2)^2 - 14.825 * x\,(1) * x\,(2) - 10.437 * x\,(2) * x\,(3) - 10.525 * x\,(2) * x\,(4) - 16.088 * x\,(3) * x\,(4) + 29.888 * x\,(4) * x\,(5) \quad (5)$$

$$Minimize\ SR = 1.356 + 0.087 * x(2) - 0.097 * x(3) - 0.198 * x(5) + 0.092 * x(1) * x(2) - 0.202 * x(2) * x(3) + 0.123 * x(2) * x(5) - 0.167 * x(3) * x(4) + 0.105 * x(3) * x(5) + 0.425 * x(1)^2 \quad (6)$$

$$Minimize\ CT = 64.756 - 4.844 * x(2) + 5.828 * x(3) + 6.633 * x(4) + 9.883 * x(5) - 9.656 * x(4)^2 + 2.769 * x(3) * x(5) + 4.2 * x(4) * x(5) \quad (7)$$

Where x (1), x (2), x (3), x (4), x (5) are vol. c, LFR, speed, feed and DOC respectively.

Limits:
-1 ≤ Vol.c ≤ 1
-1 ≤LFR ≤ 1
-1 ≤ Speed ≤ 1
-1 ≤ Feed rate ≤ 1
-1 ≤ DOC ≤ 1

The limits are considered from their levels. -1 and +1 are considered for lower bound and upper bound respectively. The other parameter setting for multi-objective optimization is shown in Table 8. The multi-objective optimization is carried out using GA optimization tool box. Since it is a multi-objective optimization, there are number of solutions which we call them as pareto solutions. The pareto solutions are shown in Table 9 and 3D pareto plot is illustrated in Figure 3. The pareto front is the set of optimal solutions that are non-dominated. For all the points on the pareto front, it is not possible to improve one objective without sacrificing another objective.

Table 8. GA multi-obj parameter settings.

Subject	Values
Population size	100
Crossover rate	0.8
Mutation rate	0.1
No. of generations	500

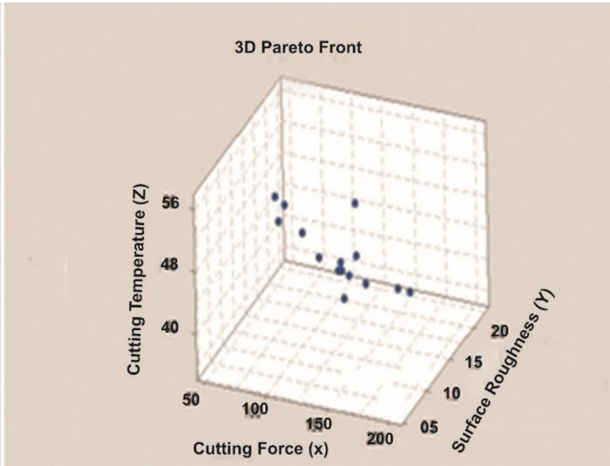

Fig. 3. 3D pareto front.

Table 9. Pareto solutions from GA.

A (%)	B (ml/min)	C (m/min)	D (mm/rev)	E (mm)	CF (Kgf)	SR (μm)	CT (°C)
0.43	3.10	80.50	0.06	0.75	188.22	0.65	54.62
0.60	4.95	118.88	0.06	0.26	77.76	1.78	44.14
0.60	4.96	80.83	0.05	0.26	88.23	2.24	35.96
0.43	4.97	118.76	0.12	0.38	140.14	1.13	60.24
0.43	3.31	81.29	0.06	0.65	174.96	0.88	52.03
0.60	4.96	80.84	0.05	0.26	88.14	2.25	35.97
0.39	4.97	119.08	0.09	0.39	133.09	1.19	58.26
0.34	3.10	80.80	0.06	0.75	182.64	0.72	54.90
0.60	4.96	104.44	0.06	0.26	82.04	1.96	41.38
0.51	4.96	83.33	0.05	0.32	106.17	1.86	37.21
0.32	3.45	80.79	0.05	0.63	162.93	1.05	48.62
0.41	4.08	81.01	0.06	0.66	197.05	1.15	47.72
0.55	4.95	109.22	0.06	0.27	86.09	1.72	42.76
0.59	4.84	85.09	0.05	0.28	97.90	2.14	38.43
0.46	4.96	118.44	0.07	0.33	104.09	1.33	49.24
0.39	4.92	114.97	0.06	0.47	143.17	1.33	51.19
0.37	3.88	80.82	0.06	0.52	159.61	1.27	46.24
0.35	4.96	117.77	0.08	0.38	132.91	1.23	56.28

Table 10. Confirmation results.

A	B	C	D	E	Confirmation values			Predicted values			Error %		
					CF	SR	CT	CF	SR	CT	CF	SR	CT
0.59	4.96	80.83	0.052	0.255	91.65	2.16	37.8	88.23	2.24	35.96	3.73	3.7	4.9
0.51	4.96	83.33	0.052	0.316	103.2	1.94	39.14	106.17	1.86	37.21	2.9	4.1	4.9
0.59	4.84	85.09	0.054	0.28	102.6	2.08	36.8	97.9	2.14	38.43	4.6	2.9	4.4

3.7 Confirmation experiments

Three runs are randomly selected from pareto solutions to verify and validate the proposed model for prediction of CF, SR and CT. The results obtained from confirmation tests are in reasonable agreement with the predicted values with error percentage of less than 5 % for all the responses i.e. CF, SR and CT. Table 10 shows the results of confirmation tests along with predicted values and percentage of error. Figs. 4-6 depicts the results pictorially. From Fig. 4 the average cutting force value for confirmation experiments and predicted value are 99.15 Kgf and 97.43 Kgf respectively. The relative error is less than 2 %. From Fig. 5 the average surface roughness value for confirmation experiments and predicted are 2.06 μm and 2.08 μm respectively. The relative error is approximately 1 %. From Fig. 6 the average cutting temperature for confirmation experiments and predicted are 37.91 °C and 37.2 °C respectively. The relative error is nearly 2 %.

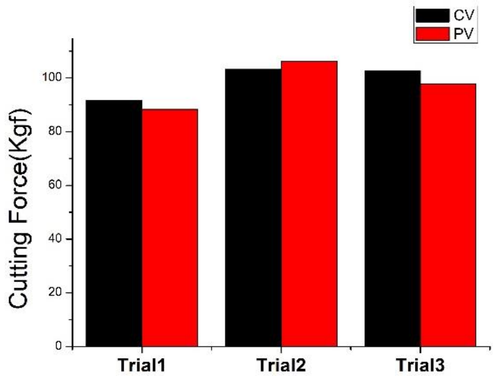

Fig. 4. Comparative bar chart of experimental and optimum predicted values for cutting force.

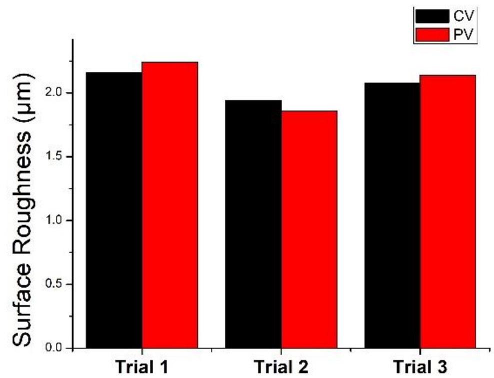

Fig. 5. Comparative bar chart of experimental and optimum predicted values for surface roughness.

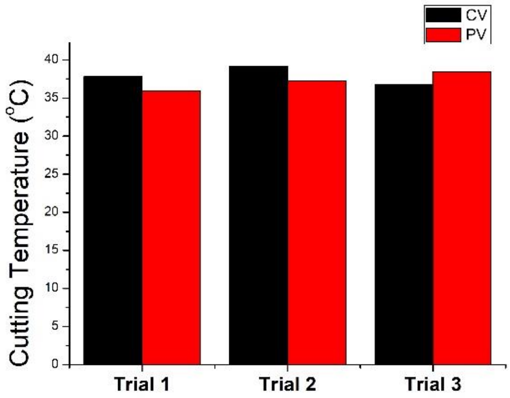

Fig. 6. Comparative bar chart of experimental and optimum predicted values for temperature.

4. CONCLUSIONS

In the present work, multi-objective optimization of process parameters has been carried while machining AISI 1040 steel using Al_2O_3 nano particles with MQL technique. The following conclusions were drawn:

1. Speed, feed and DOC are the predominant factors effecting on the cutting force where as MQL flow rate, speed and DOC are the primary factors effecting on the SR and cutting temperature is predominantly affected by MQL flow rate, speed, feed and DOC.
2. R^2 values of 0.975, 0.849 and 0.864 for CF, SR and CT respectively shows that the developed quadratic model can effectively determine the relation between response and process variables.
3. The optimum process values for all the responses are obtained through the developed quadratic equations. By applying the technique of GA, multi-objective optimization is carried out for minimizing CF, minimizing SR and also for minimizing CT to detect the optimum process parameters for turning of AISI 1040 steel using MQL technique.
4. Confirmation experiments were conducted by randomly selecting the pareto solutions obtained from GA and error percentages of 4.6%, 3.7% and 4.9% respectively for CF, SR and CT shows that the predicted optimum values are justified with the confirmation result.

Several existing studies have already shown the benefits of using Al_2O_3 nano fluids via MQL. The Genetic algorithm outlined in the current study provides the global optimum parameters for the given problem. Using this approach reduces cost of production and improves the quality of the performance characteristics. Application of DOE reduces the requirement of resources and also experimental effort.

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Nomenclature

ANOVA	analysis of variance
CCF	central composite face centered
CF, F_z	cutting force (Kgf)
CT	cutting temperature (°C)
DOC, d	depth of cut (mm)
DOE	design of experiments
f	Feed rate(mm/rev)
GA	genetic algorithm
LFR	MQL flow rate (ml/min)
MQL	minimum quantity lubrication
Multi-obj	multi-objective
NSGA	non-dominated sorting genetic algorithm
SR	surface roughness (μm)
Vc	cutting speed (m/min)
vol.c	volume concentration (%)