Comparative analysis for the Process parameters and there effect on Surface roughness and cutting force during machining of Die Steel by TLBO and GRA

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Abstract—

Die steel has major application in aviation and automobile and industry. In both of the industry surface roughness is a major factor. Although plenty of literature is available where input parameters get optimized but very few literatures are available which compare various optimization technique for the same input parameters. In this research work we compare the parameters optimized by Teaching learning based optimization technique (TLBO) and Grey Relational Analysis (GRA). Full factorial design was used for the experiment conduction. Carbide inserts were used for the machining of die steel.

Index Terms—Grey Relational Analysis (GRA), Teaching learning based optimization (TLBO), Die Steel

1. Introduction

1.1. Work Material

Die steel having a hardness between 40 HRC to 65 HRC is widely used in aviation, die making and automobile industry. On the opposite side, due to its highly resistance nature to the wear and rust, very great fatigue strength and favorable ratio of strength to temperature, it is very tough task to machine this material[1, 2]. Because cost of machining plays a significant role in any industry, keeping the dimensional accuracy of die steel components in minimum cost is a very typical. We can perform the machining using nontraditional methods but they are very expensive compared to traditional process.[3, 4]

1.2. Surface Finish and cutting force

The role of surface finish becomes prominent when the parts are subjected to different conditions like precision, fatigue loading, fastener holes etc. In majority of organizations surface roughness is a factor which decides the product quality and on the basis of this factor machined parts may be accepted or rejected, which makes it a critical parameter during the machining. [5-7]

The final surface finish obtained on the machined parts is a result of combination of factors like tool wear, vibration of the machine tool, defects in the structure of the work piece and if not look after carefully they lead to surface distortion. Surface roughness is directly associated with the overall cost of the production and working cost of parts[8-10]. A model which is popularly used to find the surface roughness is:

$$R_a = \frac{0.0321f^2}{r}$$

Where, f is feed in mm/rev, r is the cutter nose radius in mm and Ra is the surface roughness in µm.

The depth of cut, feed, and particular cutting energy coefficient all influence cutting force. Various research paper are underway to examine this impact and build models for various tools and work materials in order to reduce power usage.[11-13]

1.3. TLBO

The use of meta-heuristic techniques to optimize various input machining parameters has expanded significantly in recent years in the realm of production. However, many of these algorithms may be efficiently implemented once a set of tuning parameters is available and can be modified to meet the needs. Optimized values of certain tuning parameters are required for the said algorithms to perform at their best, which is extremely difficult to accomplish.[14, 15]

TLBO is a population-based algorithm that simulates the teaching-learning environment in the classroom. In TLBO, no algorithm-specific control parameters are required. Various research papers are accessible for a more in-depth understanding of TLBO.[16]

The results of TLBO are compared to prior optimization approaches such as bee colony. In terms of computing time, number of generations, population size, and other factors, TLBO outperforms. The teacher and learner are the two most important core parts of TLBO, and they describe the two separate ways of learning. Learning is accomplished in two ways: first, by highly qualified individuals (teachers), and second, by student engagement.[17]

The impact of the elitism idea, as well as the number of generations and population size, on TLBO performance was investigated. This principle is used in the majority of evolutionary algorithms, where the best solution replaces the worst solution every generation.

When the learner phase ends and the elite solution replaces the worst solution in TLBO, if there is duplicity in the solution, the duplicate solution must be altered to avoid being locked in the local optimum solution.[18]

1.4. Grey Relational Analysis

Deng developed Grey System theory in 1982, which focused on decision-making with partial information and partial unknowns. Grey information is the information that exists between known and unknown information. The Grey System Theory is used to solve complex problems with complex data. Grey relation analysis is a quantitative and systematic way to solving complicated systems that is a subsystem of grey system theory.[19, 20]

GRA can be applied to financial, logistic, and process optimization. The GRA method can be used to solve problems involving multiple criteria and complicated relationships between them. It can also be used to find the best process parameter that influences two or more response variables[21].

A grey relational grade is created using this method (average sum of grey relational coefficients) described by the following relation.:-

$Y(x0 *, xi *) = Yi = (1/n)\xi i(k)$

Here, n indicate no. of process responses.

2. Experimental Plan

For three levels of parameter, a full factorial design is utilized in this article. Table I shows the specified parameter and its level.TABLE I machining parameters with their level

TABLE I MACHINING PARAMETER WITH THEIR LEVEL

S.N.	A	B	C
Factors	Speed in rpm	Feed in mm per rev	Depth of Cut in mm
Levels			
Level I	120	0.12	0.150
Level II	200	0.16	0.300
Level III	280	0.20	0.450

3. Result of Experiment and Discussion

3.1. Cutting Force and Surface Roughness

27 experiments are carried out according to the full factorial design. Table II shows the conventional full factorial design employed in the experiment with result.

TABLE II FULL FACTORIAL DESIGN WITH RESULTS

S.N.	Speed in rpm	Feed in mm per rev	Depth of Cut in mm	Cutting Force in Kgf	Surface Roughness in µm
1	120	0.12	0.15	27.8	2.9467
2	120	0.16	0.15	26.5	3.14767
3	120	0.2	0.15	25.1	3.69572
4	120	0.12	0.3	14.2	2.85969
5	120	0.16	0.3	25.3	3.3208
6	120	0.2	0.3	26.1	3.61916
7	120	0.12	0.45	24.6	2.87808
8	120	0.16	0.45	27.9	3.31111
9	120	0.2	0.45	28.1	3.76063
10	200	0.12	0.15	23.2	3.23411
11	200	0.16	0.15	19.3	3.18871
12	200	0.2	0.15	23.8	4.12838
13	200	0.12	0.3	36.1	3.21988
14	200	0.16	0.3	17.7	3.35085
15	200	0.2	0.3	19.5	3.97017
16	200	0.12	0.45	20.3	3.2177
17	200	0.16	0.45	28.7	3.42755
18	200	0.2	0.45	41.6	4.11726
19	280	0.12	0.15	15.8	2.8383
20	280	0.16	0.15	27.6	3.12085
21	280	0.2	0.15	28.4	3.84063

22	280	0.12	0.3	26.1	2.97032
23	280	0.16	0.3	22.8	3.38311
24	280	0.2	0.3	27.2	3.80415
25	280	0.12	0.45	23.5	2.94496
26	280	0.16	0.45	30.6	3.2074
27	280	0.2	0.45	34.4	3.73835

3.2. Grey Relational Analysis

Step I: Table III standardizes cutting force and surface roughness data. Using the smaller-is-better quality criteria, the following equation is used to normalize the original sequence for both cutting force and surface roughness.

$$z_i^*(x) = \frac{max\, b_i(x) - b_i(x)}{max\, b_i(x) - min\, b_i(x)}$$

TABLE III GREY RELATIONAL NORMALIZATION

S.N.	Cutting Force	Surface Roughness	S.N.	Cutting Force	Surface Roughness
1	0.503	0.91597	15	0.806	0.12263
2	0.551	0.76019	16	0.777	0.70591
3	0.602	0.33537	17	0.470	0.54324
4	1	0.98342	18	0	0.00862
5	0.594	0.62599	19	0.941	1
6	0.565	0.39472	20	0.510	0.78098
7	0.620	0.96916	21	0.481	0.22304
8	0.5	0.63350	22	0.565	0.89766
9	0.492	0.28506	23	0.686	0.57769
10	0.671	0.69319	24	0.525	0.25132
11	0.813	0.72838	25	0.660	0.91732
12	0.649	0	26	0.401	0.71389
13	0.200	0.70422	27	0.262	0.30233
14	0.872	0.60269			

Step II : Examine the variation sequence for each of the table IV responses.

TABLE IV FOR EACH OF THE RESPONSES, CALCULATION OF DEVIATION SEQUENCE Δ_{OI} WITH REFERENCES SEQUENCES = 1

S.N.	Cutting Force	Surface Roughness	S.N.	Cutting Force	Surface Roughness
1	0.496	0.08402	15	0.193	0.87736
2	0.448	0.23980	16	0.222	0.2940
3	0.397	0.66462	17	0.529	0.45675
4	0	0.01658	18	1	0.99138
5	0.405	0.37400	19	0.058	0
6	0.434	0.60528	20	0.489	0.21901
7	0.379	0.03083	21	0.518	0.77695
8	0.5	0.36649	22	0.434	0.10233
9	0.507	0.71494	23	0.313	0.42230
10	0.328	0.30681	24	0.474	0.74867
11	0.186	0.27161	25	0.339	0.08267
12	0.350	1	26	0.598	0.28610
13	0.799	0.29578	27	0.737	0.69767
14	0.127	0.39730			

Step III: For cutting force and surface roughness, calculate the Grey relational Coefficient. It can be calculated using the formula:

$$\xi\left(z_0^*(x), z_i^*(x)\right) = \xi_i(x) = \frac{\Delta min + \mu * \Delta max}{\Delta_{0i}(x) + \mu * \Delta max}$$

Here, $\Delta_{0i}\ (x)$ is a deviation sequence.

$$\Delta_{0i}(x) = \mid z_0^*(x) - z_i^*(x) \mid$$

The smallest value of $\Delta_{0i}\,(x) is\ \Delta_{min}$ and the largest value of $\Delta_{0i}\,(x)\ is\ \Delta_{max}$.

$$\Delta_{0i}(x) = \Delta\,min = \ min \mid z_0^*(x) - z_i^*(x) \mid$$

$$\Delta_{0i}(x) = \Delta\,max = \ max \mid z_0^*(x) - z_i^*(x) \mid$$

Here, $\mu*$ is the identification coefficient $0 \leq \mu* \leq 1$

Cutting force and surface roughness, the value of Δ_{max} and Δ_{min} is 1 and 0 respectively.

For cutting force, the identification coefficient (μ) is 0.25, while for surface roughness, it is 0.65. The grey relationship coefficient of performance parameter is shown in Table V.

TABLE V EACH PERFORMANCE CHARACTERISTIC'S GREY RELATIONSHIP COEFFICIENT

S.N.	Cutting Force for μ = 0.25	Surface Roughness for μ = 0.65	S.N.	Cutting Force for μ = 0.25	Surface Roughness for μ = 0.65
1	0.3767	0.781198	15	0.6079	0.254806
2	0.4005	0.555754	16	0.5740	0.504974
3	0.4299	0.311002	17	0.3617	0.39643
4	1	0.947627	18	0.2307	0.23231
5	0.4254	0.445099	19	0.8370	1
6	0.4085	0.331389	20	0.3802	0.578015
7	0.4414	0.906796	21	0.3666	0.278564
8	0.375	0.450115	22	0.4085	0.745648
9	0.3716	0.295584	23	0.4887	0.415336
10	0.4773	0.494388	24	0.3873	0.286075
11	0.6171	0.524825	25	0.4691	0.783951
12	0.4612	0.230769	26	0.3338	0.511853
13	0.2729	0.503541	27	0.2892	0.300701
14	0.7013	0.43023			

Step IV: Calculate the grey relational grade overall. Cutting force and surface roughness are the two reactions, and the value of n should be taken as 2. The total grey relationship grade of both process parameters is shown in Table VI.

TABLE VI OVERALL GREY RELATIONAL GRADE (GRG)

S.N.	Overall GRG	S.N.	Overall GRG
1	0.578958	15	0.431397
2	0.47817	16	0.539498
3	0.370459	17	0.379113
4	**0.973813**	18	0.231539
5	0.435282	19	0.918534
6	0.369969	20	0.479109
7	0.674128	21	0.3226
8	0.412557	22	0.577098
9	0.333597	23	0.45202
10	0.48587	24	0.336723
11	0.570971	25	0.626564
12	0.346024	26	0.422864
13	0.388225	27	0.294967
14	0.565798		

Table VI shows that trial number 4 yields the highest overall GRG rating. So, The earliest arrangement of process parameters $V_1F_1D_2$ is based on the greatest value of GRG.

Step V**:** Calculate the GRG mean now. It's the average of the grey relationship coefficients, which are calculated as follows:

$\Upsilon(z_0^*, z_i^*) = \Upsilon_i = \frac{1}{n}\sum_{x=1}^{n} \xi_i(x)$

Here, n is the number of process responses. Mean of the GRG shown in the table VII.

TABLE VII MEAN OF THE OVERALL GRG

Level	Speed in rpm	Feed in mm per rev	Depth of Cut in mm
1	0.514104	0.640298781	0.505632855
2	0.485697	0.466209321	0.503369498
3	0.438993	0.337475079	0.434980827
Delta	0.075111	0.302823702	0.070652028
Rank	2	1	3

The difference between the minimum and maximum mean values of GRG indicates the significance of the process parameters; the wider the gap, the greater the significance. As can be seen in table VII, Feed (F) contributes the most to GRG, with the greatest differential value, followed by Depth of Cut (DOC), and Cutting Speed (V).

The ideal combination of process parameters based on this GRG table is V1F1D1, i.e. cutting speed 120, feed 0.12, and cut depth 0.15.

Table VIII displays the initial and optimal machining results based on the researched factors.

TABLE VIII OPTIMUM PARAMETERS

V	F	DOC	F_C	R_a
120	0.12	0.15	27.8	2.859

3.3. Teaching–learning based optimization (TLBO)

Teacher phase: The student receives instruction from the teacher in this section. The teacher tries to raise the class's average output from any value P1 to his or her level (TA). However, because the output cannot be increased to the level of the teacher, the average of the class is moved to a better value P2 based on his or her ability.[22]

Allow Mi to be the instructor in any engagement, and Pj to be the average. Now that the previous mean Pj has been improved toward Mi, the new mean will be denoted as PN, and the difference between the new and old means will be presented as: RNi (PN – MFPj)

In the said equation, M_F stands for the teaching factor, while RNi stands for any random number between 0 and 1. The teaching factor determines the value of the mean to be adjusted. M_F can be 1 or 2 and is determined at random with the same chance as:

$$P_F = \text{round}\ (1 + \text{rand}\ (0,1))$$

M_F is generated at random during the procedure in the previously established range, where 1 represents unmodified knowledge and 2 represents complete knowledge transfer. The teaching factor should be either 1 or 2 for simplicity. It depends on how the values in between are treated. Any P_F value between 1 and 2 can be used, though[23, 24].

The existing solution will be changed as: A_N,i = Ao,i + Difference Meani, here, A_N,i represents the new solution while Ao,i represents the old solution

Learner phase: The learner's knowledge is increased in this section when they interact with one another. The interaction is a haphazard one. If the other students have more knowledge than the learner, the learner will pick up new information[25].

consider Gi and Gj are two distinct learners, and i ≠ j

$Y_{New,i} = Y_{Old,i} + RNi\ (Gi - Gj)$ if f(Gi) < f (Gj)

$Y_{New,i} = Y_{Old,i} + RNi\ (Gj - Gi)$ if f(Gj) < f (Gi)

Accept Ynew if function value given by it is better.

Where Gi and Gj are two learners (independent) with different levels of knowledge who have interacted to improve their degree of knowledge in the preceding equation.

3.4. Modelling & Optimization

2nd order mathematical model is represented in Equation given below

$$\boldsymbol{SR = 1.295 + 0.01505s - 18.96f + 0.169d - 0.000040s^2 + 92.5f^2}$$

Where SR = surface roughness, d = depth of cut, f = feed rate and s = speed

3.5. Analysis of Variance

On the recorded data, MINITAB's ANOVA is used. The ANOVA test is carried out using a 95% confidence level.

TABLE IX ANNOVA TABLE

Source	Degree of freedom	Adjusted sum of squares	Adjusted mean squares	F-Value	P-Value
Regression	5	3.88615	0.77723	72.09	0.000
S	1	0.39062	0.39062	36.23	0.000
f	1	0.05308	0.05308	4.92	0.038
D	1	0.01186	0.01186	1.10	0.306
S*S	1	0.37861	0.37861	35.12	0.000
f*f	1	0.13183	0.13183	12.23	0.002
Error	21	0.22641	0.01078		
Total	26	4.11256			

TABLE X MODEL SUMMARY

S	R-sq	R-sq(adj)	R-sq(pred)
0.103834	94.49%	93.18%	90.92%

Table shows the R^2 value and corrected R^2 of the developed model (greater than 90 percent). It shows that the regression model's association between the input variables and surface roughness (response) is excellent.

3.6. Optimization through TLBO

- The TLBO technique's execution steps are listed below.
- Initialization and evaluation of the problem's population and design variables, which will be optimized by random generation.
- Choose the ideal learner for the role of instructor. Determine the mean outcome of learners for each subject and within each subject.
- Using the teaching factor, determine the difference between the current and best mean outcome (TF).
- By utilizing the teacher's knowledge, the learners' knowledge is updated.
- By utilizing the knowledge of another learner, the learners' knowledge is updated.
- Steps 2 through 5 should be repeated until the termination criteria is reached.

In each TLBO run, the optimal parametric condition and the matching response value are generated. Table shows the TLBO-acquired individual optimal parametric condition and the solution provided by GRA.

TABLE XI SUMMARY

S.N.	Optimized parameter by TLBO	Optimized parameter by GRA	TLBO Response	Experiment Result
1	Speed = 120 rpm	Speed = 120 rpm	Surface Roughness = 2.185	Surface Roughness = 2.859
2	Feed = 0.120 mm/rev	Feed = 0.120 mm/rev	Cutting Force = 24.5	Cutting Force = 27.8
3	DOC = 0.150 mm	DOC = 0.150 mm		

4. Conclusion

Although both optimization techniques anticipate the same initial setting, the experimental result differs from the value predicted by TLBO. By using regression analysis, a 2nd order mathematical model for surface roughness is built, and ANOVA findings show that all input parameters, as well as square combinations of spindle speed and feed rate, have a substantial impact on surface roughness.

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