International Journal of Innovative Technology and Exploring Engineering (IJITEE)
ISSN: 2278-3075 (Online), Volume-8 Issue-5, March 2019

Teaching-Learning based Optimization (TLBO) for the Process Parameters During Turning of Die Steel

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Abstract**:** ***Die steel is extensively used in making die in automobile and aircraft industry. The objective of this work is to optimize the surface roughness. TLBO is used as the optimization technique for finding the suitable cutting parameter for the machining of die steel. Experiments were conducted using full factorial design. In this work effect of input parameters on surface roughness has been calculated. As turning of die steel using carbide insert is a majorly used machining operation, the result of this study would significantly contribute in optimizing the input machining parameters.***

I. INTRODUCTION

Work Material

Die steel is extensively used in moulds, die making, automobile and aerospace industry having a hardness range of 45 HRC to 60 HRC. On the other side, because it possesses high resistance to wear and corrosion, high fatigue strength and better ratio of strength to temperature, it is very challenging to machine. [1]. It is a very challenging task to maintain the dimensional accuracy and high quality of die steel components keeping the low cost of manufacturing. As machining of die steel is very expensive by using non-traditional methods, it will be very helpful if we can obtain better surface finish and Higher MRR by using lathe machine.

Surface Finish

Impact of surface finish is very high for the machined parts especially when it is subjected to fatigue loads, fastener holes, precision fits etc. Product quality is measured by Surface roughness and is a crucial parameter in a material removal process. Many Factors like machine tool vibration, defect in work piece structure, chip irregularities, tool wear etc. contribute towards surface finish distortion during machining. Production cost and Working of mechanical parts is directly linked with the surface roughness [2, 3]. The following model is popularly used for calculating the surface roughness

$$R_a = \frac{0.0321 f^2}{r} \text{ ----------- (1)}$$

Where, Ra = surface roughness(µm), r = cutter nose radius(mm) and f = feed (mm/rev).

TLBO

In recent time in the field of production, optimization of different input machining parameters by the meta-heuristic techniques has been considerably increased. But many of these algorithms can performed effectively when a set of tuning parameters is there and can be adjusted as per the requirements. For the said algorithms to perform best, optimized values of those tuning parameters is required which is very difficult to obtain.

TLBO, which simulates teaching - learning environment of the classroom is a population-based algorithm. There is no need of algorithm- specific control parameters in TLBO [4]. For detailed knowledge of TLBO, various research papers are available.

Results obtained from TLBO are compared with previous techniques of optimization such as bee colony. TLBO gives better results in terms of computational time, number of generations, population size etc. The two most crucial key elements of TLBO are teacher and learner and it explain the two distinct way of learning. In first way the learning is by highly qualified one (teacher) and in the second way by the student interaction [5].

The effect of elitism concept along with number of generation and population size on the performance of TLBO was also studied. This concept is used in majority of the evolutionary algorithms where in every generation elite solution replaced the poorest solution. In TLBO, when learner phase end and the elite solution replaced the worst solution, if the duplicity in solution exist then to avoid stuck in the local optimum solution, duplicate solution must be changed [6-8].

Material & Machine

Machine: The experiments were conducted on the centre lathe.

Work piece: diameter- 30mm, length - 300mm.

Tool: Carbide insert

Manuscript published on 30 March 2019.
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For the measurement of surface roughness, specimen is checked at four locations around the circumference and the average value is assigned for roughness. For measurement of roughness Mitutoyo Surftest SJ 301 model is used.

II. EXPERIMENTAL WORK

A. Experimental plan

Full Factorial design is used in this study for 3 level of parameter.

TABLE 1 Process parameter and level

S.N.	A	B	C
Factors	Speed	Feed	Depth of Cut
Levels	3	3	3
1	120	0.12	0.150
2	200	0.16	0.300
3	280	0.20	0.450
Units	Rpm	mm/rev	mm

B. Surface Roughness

The standard full factorial design used in the experiment with process parameter and experimental results for Surface Roughness are given in Table II.

TABLE 2 Full Factorial Design and experimental results

Experiment No.	Spindle Speed V (rpm)	Feed rate F (mm/rev)	DOC (mm)	Surface Roughness Ra (µm)
1	120	0.12	0.15	1.9467
2	120	0.16	0.15	2.14767
3	120	0.2	0.15	2.69572
4	120	0.12	0.3	1.85969
5	120	0.16	0.3	2.3208
6	120	0.2	0.3	2.61916
7	120	0.12	0.45	1.87808
8	120	0.16	0.45	2.31111
9	120	0.2	0.45	2.76063
10	200	0.12	0.15	2.23411
11	200	0.16	0.15	2.18871
12	200	0.2	0.15	3.12838
13	200	0.12	0.3	2.21988
14	200	0.16	0.3	2.35085
15	200	0.2	0.3	2.97017
16	200	0.12	0.45	2.2177
17	200	0.16	0.45	2.42755
18	200	0.2	0.45	3.11726
19	280	0.12	0.15	1.8383
20	280	0.16	0.15	2.12085
21	280	0.2	0.15	2.84063
22	280	0.12	0.3	1.97032
23	280	0.16	0.3	2.38311
24	280	0.2	0.3	2.80415
25	280	0.12	0.45	1.94496
26	280	0.16	0.45	2.2074
27	280	0.2	0.45	2.73835

C. Teaching–learning based optimization (TLBO)

Teacher phase: In this part the learner learns from the teacher. The mean output of the class is tried to increase by teacher from any value A1 to his/her level (TA). But practically the output cannot be increased to the teachers level so mean of the class is move to any other better value A2 depending on his/her capability. Let Fi be the teacher at any interaction i and Aj is the mean. Now the existing mean Aj will be improved toward Fi so the new mean will be designated as AN and the difference between the new mean and existing mean is given in eq 2:

Difference Meani = RNi (AN – FFAj)

In above equation FF denotes the teaching factor and RNi denotes any random number, the range of which lies between 0 and 1. The value of mean to be changed is decided by teaching factor. FF can be either 1 or 2 and is randomly decided with equal probability as:

AF = round [1 + rand (0,1) {2 -1}]

During the algorithm FF is randomly generated in the previously defined range, where 1 represent unchanged level of knowledge and 2 shows all knowledge transfer. For simplification teaching factor should be either 1 or 2. It depends on how the in between values are neglected. However, any value of AF in between 1 and 2 can be used.

Based on this Difference Mean, the existing solution is changed by using Equation 4

SN,i = So,i + Difference Meani

whereSN,i= new solution; So,i = existing solution

Learner phase: In this part, knowledge of the learner is increased when they interact among themselves. The interaction is of random nature. If the other learners have more knowledge than the learner will learn new thing.

consider Pi and Pj as two different learners, and i ≠j

ZN,i = Zo,i + RNi (Pi - Pj) if f(Pi) < f (Pj) (5)

ZN,i = Zo,I + RNi (Pj - Pi) if f(Pj) < f (Pi) (6)

Accept Znew if function value given by it is better.

In the above equation Pi and Pj are two learners (independent) with different level of knowledge, and have interact to improve level of knowledge. [9-11]

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III. RESULTS AND ANALYSIS

A. *Modeling and Optimization*

2nd order mathematical model is represented in Equation 7

$$SR = 1.395 + 0.01605s - 18.86f + 0.171d - 0.000039s^2 + 92.6f^2 \quad (7)$$

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

B. *Analysis of Variance:*

ANOVA from MINITAB 17 is applied on the recorded data. The confidence level of 95% is used in ANOVA test.

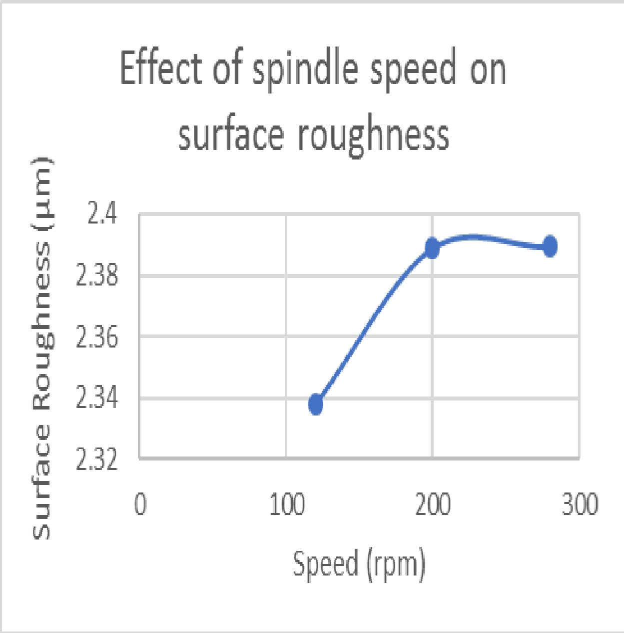
Source	Degree of freedom	Adjusted sum of squares	Adjusted mean squares	F-Value	P-Value
Regression	I. 5	3.88615	0.77723	72.09	0
S	II. 1	0.39062	0.39062	36.23	0
f	III. 1	0.05308	0.05308	4.92	0.038
D	IV. 1	0.01186	0.01186	1.1	0.306
S*S	V. 1	0.37861	0.37861	35.12	0
f*f	VI. 1	0.13183	0.13183	12.23	0.002
Error	VII. 21	0.22641	0.01078	VIII.	IX.
Total	X. 26	4.11256	XI.	XII.	XIII.

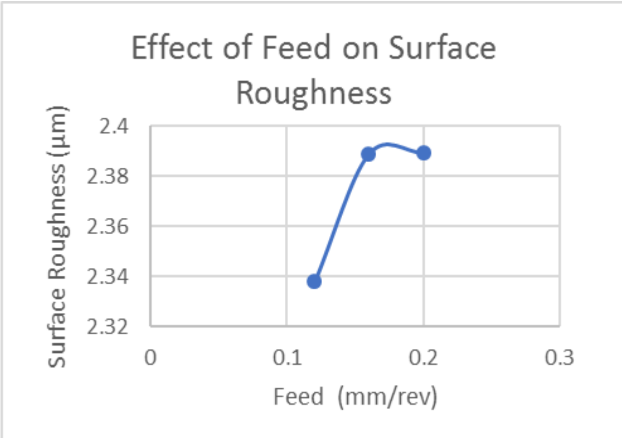
Summary of the Model

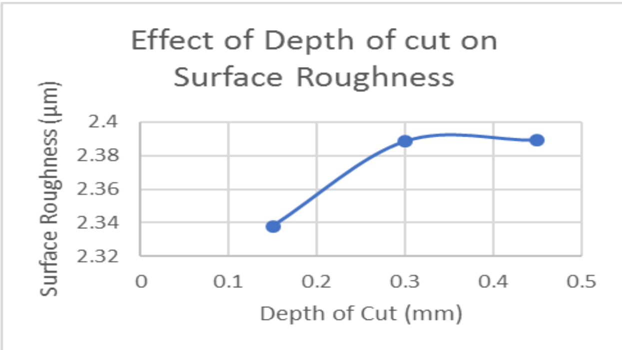
S	R-sq	R-sq(adj)	R-sq(pred)
0.103834	94.49%	93.18%	90.92%

As the R2 and adjusted R2 value is more than 90 % in the developed model, it indicates that the relationship between the input parameters and surface roughness provided by regression model is excellent.

C. VARIATION OF SURFACE ROUGHNESS WITH INPUT PARAMETERS







D. OPTIMIZATION BY TLBO

The execution steps for TLBO technique is given below.

Step 1: Initialization and evaluation of population and design variables of the problem which is to be optimized with random generation.
Step 2: For teacher role select the best learner For each subject and in each subject determine the mean result of learners.
Step 3: find the difference between current and best mean result according to Eq. 2 by utilizing the teaching factor (TF).

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Step 4: By the use of teacher's knowledge updating the learners' knowledge according to Eq. 4

Step 5: By using the knowledge of some other learner updating the learners' knowledge according to Eqs. 5 and 6.

Step 6: Repeat from step 2 to step 5 till the criterion for termination is met.

Optimal parametric condition and the corresponding response value are produced, in each of the TLBO run. The obtained individual optimal parametric condition by TLBO is shown in Table 5.

S.N.	Optimized Parameter	TLBO response	Experimental Result
1	Spindle Speed (A) – 120 rpm	Surface Roughness = 1.8553 µm	Surface Roughness = 1.9467 µm
2	**Feed Rate (B) – 0.120 mm/rev**		
3	**Depth of Cut (C) – 0.150 mm**		

IV. CONCLUSION

The following conclusions may be drawn from the results of the experiments:

1. For surface roughness 2nd order mathematical model is developed by regression analysis.
2. From ANOVA results, it is confirmed that all the input parameters and square combinations of spindle speed and feed rate are significant on surface roughness.
3. From TLBO, the optimized value of input parameters are: speed = 120 rpm, DOC = 0.15 mm and feed = 0.12 mm/rev.
4. Predicted value of surface roughness by TLBO is 1.8553 µm.
5. Predicted input parameters proved with confirmatory test results.
6. TLBO can be useful for the optimization of surface roughness during turning of die steel.

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