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EXPERIMENTAL STUDY TO PREDICT OF TOOL WEAR IN DRY TURNING OF EN 24 STEEL USING DESIGN OF EXPERIMENT AND VERIFICATION THROUGH ANOVA AND RSM

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ABSTRACT

This research work reports the significance of influence of speed, feed and depth of cut on tool wear. In this study an experiments was carried out in kirloskar master 35- Lathe using work tool made up of ceramic with an Al_2O_3+TiC matrix and the work material is EN24 steel of hardness 48 HRC. Also, an attempt was made to fuse cutting force, cutting temperature and tool vibration (displacement), along with cutting velocity, feed and depth of cut to predict tool wear. In this work cutting force were measured by Kistler force dynamometer, cutting temperature were measured by Infra-red thermometer, tool vibration were measured by piezoelectric digital vibrometer and tool wear were measured by optical microscope. By Minitab software which is best tool for optimizing the cutting parameters such as cutting velocity, feed and depth of cut. The above study said parameters are optimized using DoE. The optimized cutting parameters using Taguchi method (L18 Mixed Design) were compared with Analysis of Variance (ANOVA) and Response Surface Methodology (RSM). In addition the results were verified with manual method for any deficiency. The above study revealed that the results obtained from ANOVA and RSM is closely matching with the results obtained from DoE.

Keywords: cutting parameters, tool wear, hard turning, minitab software, response surface methodology, analysis of variance.

INTRODUCTION

Recently, the concept of hard turning has gained considerable attention in metal cutting as it can apparently replace the traditional process cycle of turning, heat treating and finish grinding for assembly of hard wear resistant steel parts. Hard turning can possibly facilitate low process cost, low process time, better surface quality and lower waste. In hard turning, tool wear becomes an important parameter affecting the surface quality of finished parts. Turning is a common machining process used especially for the finishing of components. In machining, tool wear is a natural phenomenon that refers to the cutting tool gradually losing its cutting ability, progressively leading to tool failure. Tool wear is definitely unpleasant because as it increases to a certain value, the tool needs to be changed. Replacement with a new tool results in process interruption and rising machining cost, which is the most undesirable consequence in the manufacturing field. Therefore, to achieve high quality machining performance, machining parameter selection and control are essential. Tool wear is a highly complex phenomenon which can lead to machine downtime, product rejects and can also cause problems to person. High cutting force, excessive cutting temperature and increase in tool vibration are indications of progressing tool wear. In other words, cutting force, cutting temperature and vibration signals can be considered as symptoms of tool wear and these symptoms can be analyzed individually and collectively to predict tool wear. It is possible to predict tool wear by considering the symptoms individually. However a more accurate prediction is possible by considering cutting force, cutting temperature and displacement of tool vibration signals along with input parameters like cutting velocity, feed rate and depth of cut collectively. Sam Paul and Varadarajan [1] have developed a regression model and an artificial neural network to fuse the cutting force, cutting temperature and displacement of tool vibration signals during hard turning to predict the tool flank wear. Sam Paul [2] has conducted cutting experiments to arrive at a set of operating parameters that can offer better damping characteristics to minimize tool vibration during hard turning of AISI4340 steel using hard metal insert with sculptured rake face. Ragul and Sankar [3] have made an attempt to predict tool wear in hard turning EN24 steel with 48 HRC at a conventional lathe using multicoated hard metal inserts with sculptured rake face geometry. Palanikumar [4] has discussed the use of Taguchi and response surface methodologies for minimizing the surface roughness in machining glass fibre reinforced plastics with a polycrystalline diamond tool. Sam Paul *et al* [5] has made an attempt to reduce temperature and to improve viscosity of magnetorhelogical fluid by infusing nanoparticles along with MR fluids during hard turning process. Pang *et al* [6] have used an orthogonal array of the Taguchi method to analyze the effect of the milling parameters on the surface roughness and cutting force. Ahmed Sarhan [7] has implemented the adaptive neuro-fuzzy approach (ANFIS) and an experiment was conducted based on the Design of Experiments (DoE) technique by developing experiments with four factors at four levels corresponding to the L16 (44) experimental array to measure tool flank wear. Venkata Rao and Kalyankar [8] have proposed a new advanced algorithm for the process parameter optimization of machining process. Razfar and Zanjani Zadeh [9] have proposed a Genetically Optimized Neural Network System (GONNS) for the selection of the optimal cutting conditions during end milling glass fibre reinforced plastic. Palanikumar *et al* [10] have discussed the application of the Taguchi

method with fuzzy logic and used a Multi-Response Performance Index (MRPI) to optimize the machining parameters.

SELECTION OF WORK MATERIAL

The work piece material was EN 24 steel through hardened and tempered to 48 HRC. The length of material is 380mm and diameter at 45mm. the end of 40mm in both side has 25mm diameter as shown in figure.1 and the chemical composition of work material is shown in table.1. From the literature survey it was observed that EN 24 steel is a general purpose material that has a wide range applications in aircraft, gear shaft, propeller, general purpose applications such as connecting rod, aircraft landing gears etc.,

Figure-1. Photograph of EN 24 steel.

SELECTION OF TOOL

The tool holder used had the specification PSBNR 2525 M12. Multicoated hard metal inserts with sculptured rake face geometry, having the specification SNMG 120408 MT TT5100 from M/S TaeguTec India (P) Ltd, were used as cutting tools in this investigation.

Table-1. Chemical composition of EN 24 Steel.

Chemical Composition (%)	
Carbon	0.38 - 0.44
Chromium	1.0 – 1.44
Iron	Balance
Manganese	0.45 - 0.70
Molybdenum	1.30 – 1.70
Nickel	1.65 – 2
Phosphorus	0.040 max
Silicon	0.10 - 0.35
Sulphur	0.04 max

EXPERIMENTAL SETUP

Experiments were carried out on a Kirloskar Turn master-35 lathe. A photograph of the setup used for the present investigation is shown in Figures 2 and 3. The main cutting force, flank wear, displacement of tool vibration and average cutting temperature were measured during each experiment. The main cutting force was measured using a Kistler tool force dynamometer. The tool wear was measured using optical microscope by moving cross wires to appropriate locations and noting the readings shown in figure.4. Displacement of vibration was measured using a piezoelectric-type digital vibrometer; the pickup of the vibrometer was mounted at the bottom of tool holder as shown in Figure-4. The average cutting temperature was measured using an Infra-red Thermometer (non-contacting type). This method can provide a more accurate method of predicting cutting temperature and tool wear.

Figure-2. Photograph of kistler master turn lathe.

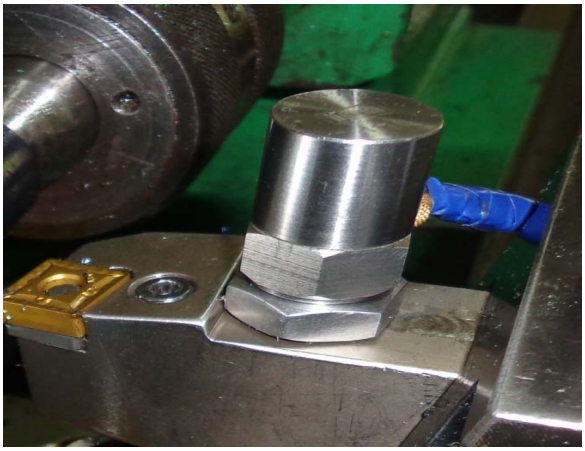

Figure-3. Piezo electric pickup device attached to tool holder.

Figure-4. Photograph of tool maker microscope.

DESIGN OF EXPERIMENTS

An 18-run experiment was designed based on the Taguchi technique in which the input variables, namely the feed and the depth of cut, were varied at three levels and cutting velocity varied at two levels. In this study, experimental work was carried out in dry turning. Feed rate and depth of cut were varied at three levels (low, medium and high) and cutting velocity varied at two levels (low and high) as shown in Table 2. The main cutting force, the average cutting temperature and the displacement of tool vibration were measured during each experiment and are presented in Table-3 and corresponding S/N ratios were shown in table.4. Three inserts were used in these experiments and each experiment lasted for 1 minute and experimental readings were taken based on the change in cutting velocity, feed and depth of cut conditions.

Table-2. Selected factors and their levels.

Variables		
Cutting velocity (V_c) m/min	**Depth of cut (d) mm**	**Feed rate (f) mm/rev**
	Level 1	Level 1
Level 1	Level 2	Level 2
Level 2	Level 3	Level 3

Table-3. Data collected during 18- run experiment.

Trail No	V_c (m/min)	d (mm)	F (mm/rev)	F_c (N)	T_c (^{0}C)	a (mm)	V_b (mm)
1	60	0.3	0.05	157.7	62.26	0.01172	0.06
2	60	0.3	0.06	259.0	51.35	0.00776	0.04
3	60	0.3	0.07	191.4	54.54	0.01123	0.06
4	60	0.4	0.05	149.4	53.64	0.01050	0.07
5	60	0.4	0.06	180.7	52.43	0.01290	0.08
6	60	0.4	0.07	186.7	56.76	0.01451	0.108
7	60	0.5	0.05	516.6	61.56	0.01332	0.086
8	60	0.5	0.06	134.0	57.87	0.00973	0.089
9	60	0.5	0.07	186.2	64.8	0.01332	0.103
10	70	0.3	0.05	170.7	61.4	0.01267	0.105
11	70	0.3	0.06	302.1	64.8	0.00786	0.102
12	70	0.3	0.07	201.5	63.5	0.01382	0.105
13	70	0.4	0.05	101.6	67.4	0.00786	0.106
14	70	0.4	0.06	130.2	61.2	0.02465	0.095
15	70	0.4	0.07	256.7	65.4	0.01123	0.134
16	70	0.5	0.05	348.0	71.3	0.01134	0.157
17	70	0.5	0.06	137.7	68.4	0.01654	0.196
18	70	0.5	0.07	191.7	70.3	0.01654	0.182

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Table-4. Tabulated S/N Ratios.

Trial No.	F_c(N)	T_c (^{0}C)	a (mm)	V_b (mm)
1	-43.95	-35.88	38.62	24.43
2	-48.26	-34.21	42.20	27.95
3	-45.63	-34.73	38.99	24.43
4	-43.48	-34.58	39.57	23.09
5	-45.13	-34.39	37.78	21.93
6	-45.42	-35.08	36.76	19.33
7	-54.26	-35.78	37.50	21.31
8	-42.54	-35.24	40.23	21.01
9	-45.39	-36.23	37.50	19.74
10	-44.64	-35.76	37.94	19.57
11	-49.60	-35.23	42.09	19.82
12	-46.08	-36.05	37.18	19.74
13	-40.13	-35.57	42.09	19.49
14	-42.29	-35.73	32.16	20.44
15	-48.18	-36.31	38.99	17.45
16	-50.83	-37.06	38.90	16.08
17	-42.77	-37.70	35.62	14.15
18	-45.65	-36.93	35.62	14.79

ANALYSIS OF VARIANCE (ANOVA)

Analysis of variance (ANOVA) is a collection of statistical models used in order to analyze the differences among group means and their associated procedures (such as "variation" among and between groups), developed by statistician and evolutionary biologist Ronald Fisher. In the ANOVA setting, the observed variance in a particular variable is partitioned into components attributable to different sources of variation. In its simplest form, ANOVA provides a statistical test of whether or not the means of several groups are equal, and therefore generalizes the t-test to more than two groups. As doing multiple two-sample t-tests would result in an increased chance of committing a statistical type I error, ANOVAs are useful in comparing (testing) three or more means (groups or variables) for statistical significance. Analysis of variance (ANOVA) describes the partition of the response variable sum of squares in a linear model into 'explained' and 'unexplained 'components. A single categorical explanatory variable (factor or classification)corresponds to one-way analysis of variance; two factors to two-way analysis of variance; three factors to three-way analysis of variance; and so on.

The experimental results were analyzed using Minitab 16 software. It is a powerful tool for determining the percentage influence of input parameters.

RESPONSE SURFACE METHODOLOGY (RSM)

Response surface methodology (RSM) is a collection of mathematical and statistical techniques for empirical model building. By careful design of experiments, the objective is to optimize are spouse (output variable) which is influenced by several independent variables (input variables). An experiment is a series of tests, called runs, in which changes are made in the input variables in order to identify their sons for changes in the output response. In RSM, the errors are assumed to be random. The application of RSM to design optimization is aimed at reducing the cost of expensive analysis methods (e.g. finite element method or CFD analysis) and their associated numerical noise.

In this process all the out parameters obtained in the first experiment were plotted and the software determines the best cutting parameters for minimizing the values of output parameter. The figure shows the screen shot of the software in which the values are tabulated for plotting the result. The graph obtained from the RSM result is shown in figure. .From the graph it is seen that the RSM predicted values for best cutting performance is that the velocity should be kept at 60 m/mm, feed at 0.05 mm/rev and depth of cut at 0.3 mm.

RESULT AND DISCUSSIONS

The results obtained from Minitab 16 for Taguchi method, Analysis of Variance and Response surface methodology were shown in below table 5-23 and figure.5-9 for optimization of minimum (Cutting force, cutting temperature, Tool vibration and Tool wear).

Optimized parameter for minimum cutting force

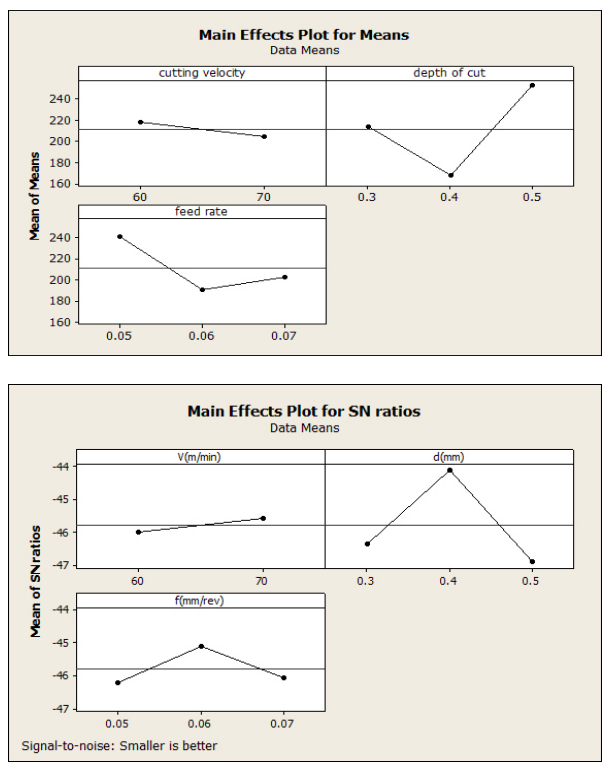


Figure-5. Graph showing cutting force at each level.

Table-5. Response table for means.

level	V	d	f
1	217.9	213.7	240.6
2	204.5	167.5	190.6
3		252.3	202.4
Delta	13.5	84.8	50.0
Rank	3	1	2

Table-6. Response table for signal to noise (S/N) ratios.

level	v	d	f
1	-46.01	-46.37	-46.22
2	-45.58	-44.11	-45.10
3	0	-46.91	-46.06
Delta	0.43	2.80	1.12
Rank	3	1	2

Smaller is better

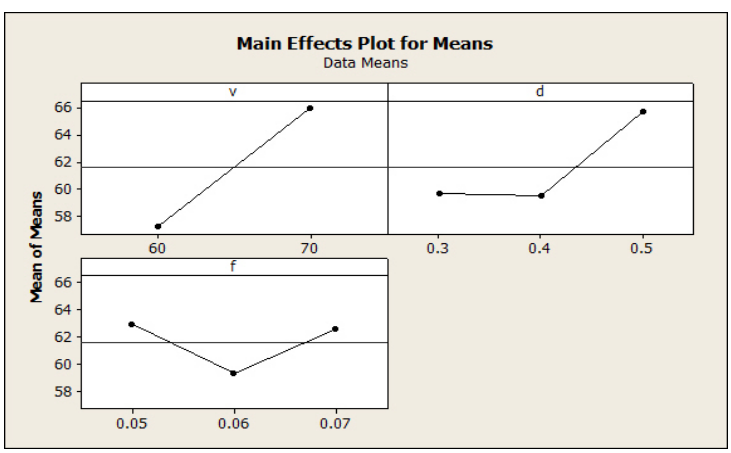
Table-7. Analysis of variance for means.

Source	Seq SS	Adj SS	Adj SS	F	P
cutting velocity	333.36	333.36	166.68	*	12.89%
depth of cut	2119.93	2119.93	1059.96	*	62.91%
feed rate	679.72	679.72	339.86	*	20.17%
Total	3133.07				4.03%

Table-8. Analysis of Variance for S/N ratios.

Source	Seq SS	Adj SS	Adj MS	F	P
cutting velocity	4.245	4.245	2.1922	*	12.12%
depth of cut	8.977	8.977	8.9765	*	61.23%
feed rate	4.387	4.387	2.133	*	20.19%
Total	17.609				6.46%

Optimized parameter for minimum cutting temperature



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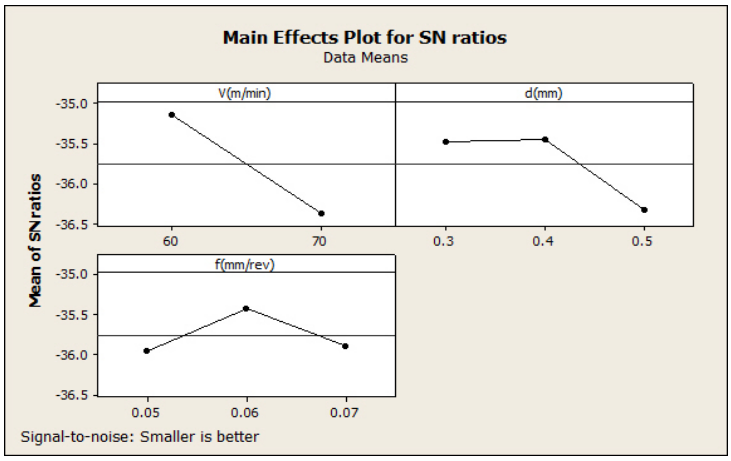

Figure-6. Graph showing cutting temperature at each level.
Smaller is better

Table-9. Response table for means.

level	v	d	f
1	57.25	59.65	62.93
2	65.97	59.47	59.34
3		6.23	62.56
Delta	8.72	6.23	3.59
Rank	1	2	3

Table-10. Response table for signal to noise (S/N) ratios.

level	v	d	f
1	-35.13	-35.48	-35.94
2	-36.37	-35.45	-35.42
3		-36.33	-35.39
Delta	1.25	0.88	0.52
Rank	1	2	3

Table-11. Analysis of variance for means.

Source	Seq SS	Adj SS	Adj MS	F	P
cutting velocity	441.82	441.82	441.824	*	64.44%
depth of cut	151.10	151.10	75.549	*	24.067%
feed rate	46.67	46.67	23.335	*	7.43%
Total	639.10			*	4.06%

Table-12. Analysis of variance for S/N ratios.

Source	Seq SS	Adj SS	Adj MS	F	P
cutting velocity	7.977	7.977	7.9765	*	64.15%
depth of cut	2.989	2.989	1.4946	*	23.19%
feed rate	1.001	1.001	0.5005	*	7.769%
Total	11.963			*	4.89%

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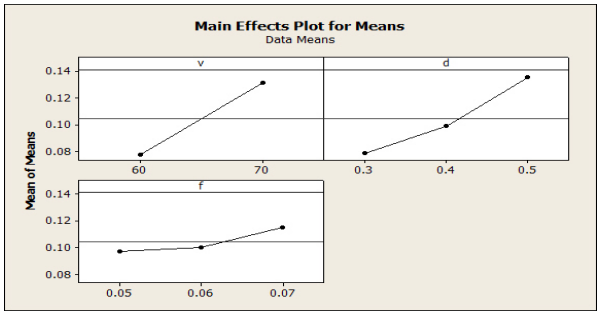
Optimized parameter for minimum tool wear



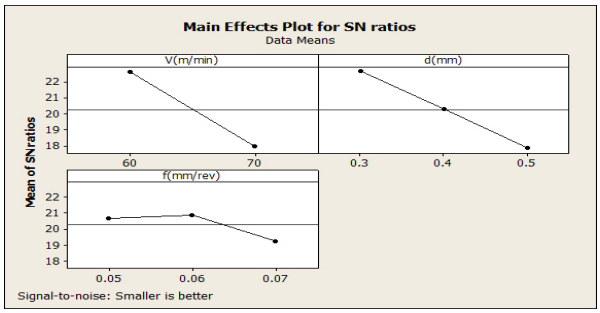


Figure-7. Graph showing tool wear at each level.

Table-13. Response table for means.

level	v	d	f
1	0.07733	0.7867	0.09733
2	0.11883	0.11883	0.12033
3		0.13550	0.11533
Delta	0.0415	0.05683	0.01800
Rank	2	1	3

Smaller is better

Table-14. Response table for signal to noise (S/N) ratios.

level	v	d	f
1	22.59	22.64	20.67
2	17.93	21.29	21.89
3		17.85	19.22
Delta	4.65	4.79	1.67
Rank	2	1	3

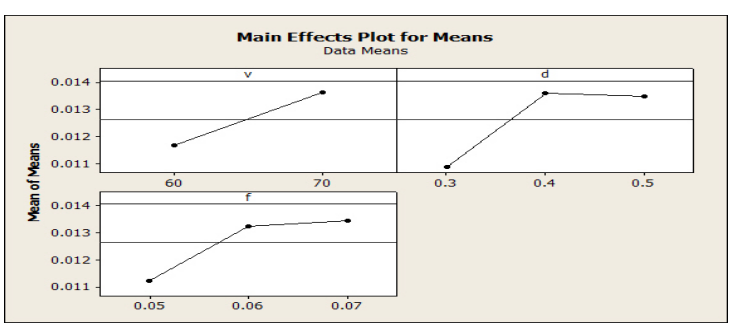
Table-15. Analysis of variance for means.

Source	Seq SS	Adj SS	Adj MS	F	P
cutting velocity	0.013122	0.013122	0.013122	*	34.81%
depth of cut	0.009962	0.009962	0.004981	*	55.86%
feed rate	0.001116	0.001116	0.000558	*	3.91%
Total	0.02422				5.42%

Table-16. Analysis of variance for S/N ratios.

Source	Seq SS	Adj SS	Adj MS	F	P
cutting velocity	97.314	97.314	97.314	*	34.01%
depth of cut	68.710	68.710	34.355	*	58.17%
feed rate	9.807	9.807	4.904	*	4.85%
Total	175.831				2.97%

Optimized parameter for minimum tool vibration



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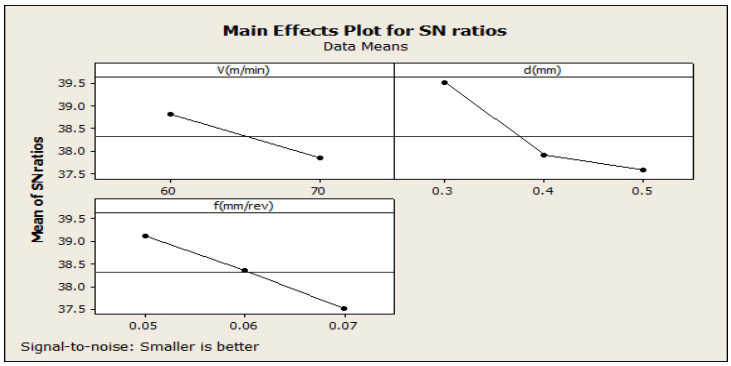

Figure-8. Graph showing Tool vibration at each level.

Table-17. Response table for means.

level	V	d	f
1	0.01167	0.01084	0.01124
2	0.01361	0.01361	0.01344
3		0.01347	0.01344
Delta	0.00195	0.00276	0.00221
Rank	3	1	2

Smaller is better

Table-18. Response table for signal to noise (S/N) ratios.

level	v	d	f
1	38.80	39.51	39.11
2	37.85	37.90	38.35
3		37.57	37.51
Delta	0.95	1.94	1.60
Rank	3	1	2

Table-19. Analysis of variance for means.

Source	Seq SS	Adj SS	Adj MS	F	P
cutting velocity	0.00231	0.00231	0.00110	*	4.12%
depth of cut	0.008834	0.008834	0.003911	*	54.23%
feed rate	0.01324	0.01324	0.01311	*	35.16%
Total	0.024384				6.49%

Table-20. Analysis of variance for S/N ratios.

Source	Seq SS	Adj SS	Adj MS	F	P
cutting velocity	10.304	10.304	10.235	*	4.21%
depth of cut	98.243	98.243	98.132	*	58.03%
feed rate	69.276	69.276	69.270	*	35.10%
Total	177.823				2.65%

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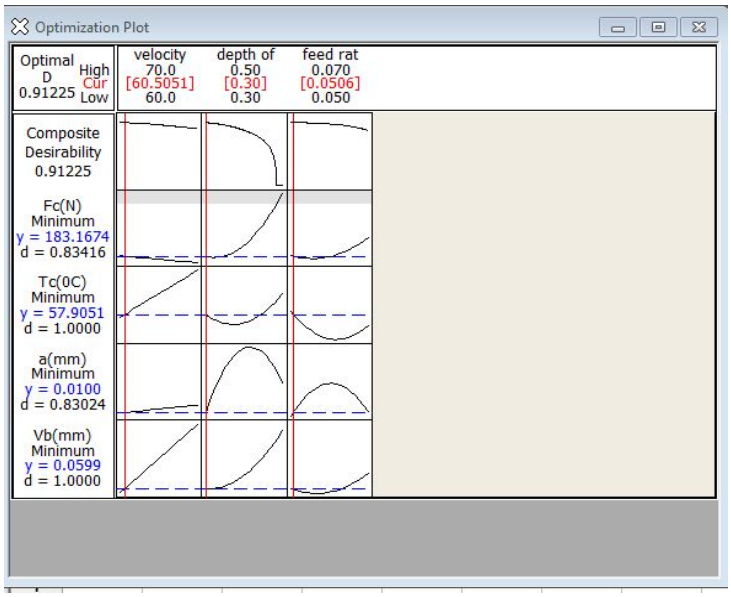

Figure-9. Graph showing optimal values for best result.

The predicted values obtained from software is again checked for the actual values by conducting a cutting experiment by keeping the above values constant and the results were plotted. Figure. shows the tabulation for RSM prediction of the input values. In this method all the output variables are compared along with all input variables and best input values are chosen for keeping tool vibration, surface finish, cutting force and tool wear to minimum. The results obtained from the confirmatory experiment conducted RSM predicted input values.

Starting Point

Velocity = 60
Depth of cut = 0.3
Feed rate = 0.05

Global Solution

Velocity = 60.5051
Depth of cut = 0.3
Feed rate = 0.0506061

Predicted Responses

Fc (N) = 183.167, desirability = 0.834163
Tc (^{0}C) = 57.905, desirability = 1.000000
a (mm) = 0.010, desirability = 0.830242
V_b (mm) = 0.060, desirability = 1.000000
Composite Desirability = 0.912250

Table-21. Optimized of V, d, f by response surface methodology (RSM).

Parameters	Starting value	Optimized response
Cutting velocity(V_C)	60	60.50
Depth of cut(d)	0.3	0.3
Feed rate(f)	0.05	0.050

The error calculated between the predicted and actual value is done using the equation %error = (1-predicted value/actual value)* 100

Table-22. Percentage error between predicted and actual value.

Predicted Response	Predicted value	Actual value	% Error
Cutting force (N)	183.167	189.85	3.52
Cutting temperature (^{0}C)	57.905	61.02	5.10
Tool vibration (mm)	0.01000	0.0101	0.99
Tool wear (mm)	0.060	0.062	3.22

Table-23. Optimized parameters for the Minimum Tool Wear by Experiment.

Parameters	DoE	RSM
Cutting velocity	60	60.50
Depth of cut	0.3	0.30
Feed rate	0.05	0.05

It is evident from table 23 that the optimal parameter for minimum Tool Wear through DoE is 60 m/min (V_C), 0.05mm/rev (f), 0.3mm (d). Similarly the optimized parameter from RSM is 60.50m/min (V_C), 0.0505mm/rev (f), 0.3mm (d). It is observed that the result obtained from RSM is closely matching with the result obtained from DoE (Taguchi technique). In addition a comparison was made in Analysis of Variance (ANOVA)

to confirm the above parameters. It is evident from ANOVA result that the Depth of cut (55%) and Cutting velocity (34%) are the critical parameter which contributes for minimum Cutting Tool Wear.

CONCLUSIONS

In the present study, DoE, ANOVA and RSM approaches were used to predict tool wear during hard turning of 817M40 (EN 24) steel having a hardness of 48HRC. Parameters such as cutting velocity, feed rate, depth of cut, cutting force, cutting temperature and displacement due to tool vibration were measured by means of a 18 -run Taguchi's experimental design. The data obtained were used to develop tool wear models. From the present study, the following conclusions were drawn:

- Tool wear can be predicted better by considering a number of appropriate symptoms collectively rather than when they are considered individually.
- Response Surface Methodology (RSM) can predict tool wear better than Design of Experiments (DoE) and Analysis of Variance (ANOVA).
- The above three methods can form an economical and viable technique for predicting tool wear and timing the replacement of worn tools, so that the surface finish can be maintained within the tolerance limits. This is possible by developing a tool for measuring cutting force, cutting temperature and displacement due to tool vibration.
- The result obtained from DoE and ANOVA confirms closely with the result given by the Response Surface Methodology (RSM).

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