IJETST- Vol.||04||Issue||08||Pages 5487-5494||August||ISSN 2348-9480 2017

International Journal of Emerging Trends in Science and Technology

IC Value: 76.89 (Index Copernicus) Impact Factor: 4.219 **DOI:** https://dx.doi.org/10.18535/ijetst/v4i8.12

Performance evaluation of TiN coated CBN inserts during hard turning of AISI 4340 steel with using Taguchi-Grey-Fuzzy approach

Authors

Sanjeev Kumar[1], Dilbag Singh[2], Nirmal Singh kalsi[2]

[1] I.K.G. Punjab Technical University, Jalandhar (PB)-India,

[2]Beant College of Engineering and Technology, Gurdaspur(PB)-143521-India

Abstract

This Hard turning finds a broad range of applications in manufacturing industries. The high wear resistance along with high dimensional accuracy is the primary attributes of the process. However, the critical setback associated with hard turning is the high heat generation at the cutting zone. It lead to earlier tool wear rate and causes the decrease in the machining performance. The cutting tool material plays a significant role in deciding the performance of hard turning. Therefore in this research work, an attempt has been made to investigate the performance of TiN coated CBN tools during machining of variable hardened AISI 4340 steel. The cutting speed, feed rate, workpiece hardness and cutting tools (uncoated CBN and TiN coated CBN) were selected as process parameters during experimentation. The cutting force, chip-tool interface temperature and material removal rate (MRR) was selected as performance parameters. The L-18 orthogonal array from Taguchi approach was chosen to perform the experimental work. The grey relational technique was used to optimize the process parameters. The results from the grey relational model were verified by using fuzzy logic. The experimental results indicate that tool material and feed rate are the significant process variables which influence the machining performance.

Keywords- Grey relational grade; Hard turning; CBN; Taguchi; Fuzzy-logic

1. Introduction

This Hard turning is an important process in the manufacturing industries. Hard turning finds a broad range of applications in manufacturing industries such as automotive, bearing, tool and die and aircraft. With the advent of new superhard cutting tool materials like CBN and PCBN, the hard turning has adequately replaced grinding and other finishing operations. CBN tools are extensively used for machining of difficult-to-cut materials such case hardened steels and superalloys due to their high thermal stability along with high wear resistance [1]. CBN tools are mostly preferred at low to moderate cutting speeds to ensure economic tool life. However, with an increase in workpiece hardness, the temperature at the cutting zone is increased which leads to rapid degradation and catastrophic failure of CBN tools [2]. Thus thermal analysis is crucial during hard turning process to evaluate the performance of CBN. Also, the hard turning is highly influenced by cutting forces during the process. The cutting forces during the machining process affect the power requirement, selection of tool materials and cutting tool geometry [3]. The high cutting forces are generated during the machining of hardened materials. The high cutting forces lead to earlier tool wear rate. It causes the deterioration of machining performance. Other than the cutting tool materials, the machining performance during hard turning depends on numbers of process parameters such as cutting parameters, tool geometry, cutting tool materials, workpiece materials, and environmental conditions. The machining performance during hard turning can be enhanced by selecting the appropriate combinations of the process parameters. Numerous studies have been carried out to analyze the performance of CBN tools during machining of different hardened materials. Chen reported that cutting forces were reduced and surface quality was increased during machining of medium hardened steel (45–55 HRC) using CBN tools [4]. Chou et al. reported that CBN and PCBN are feasible tool materials during hard turning due to high thermal stability. The studies indicate that during hard turning the temperature of cutting zone is very high, it causes the tool wear and reduction in surface quality. The coatings on cutting tool materials play a significant role in enhancing the life of tools [5]. Caydas observed that best surface quality was obtained with CBN tools followed by ceramic and then the P10-grade carbide tools during hard turning of AISI 4340 steel [6]. Bouacha et al. reported that surface roughness was extremely affected by feed rate and cutting speed. In addition, depth of cut exhibits maximum influence on the cutting forces during hard turning of AISI 52100 with CBN tool [7]. Aouici et al. reported that depth of cut and workpiece hardness shows maximum effects on cutting forces during hard turning of AISI H11 steel with CBN tools. The results also indicate that surface roughness is influenced by both feed rate and workpiece hardness. [8]. Kumar et al. studied the effect of varying hardness during machining of AISI 4340 steel with TiN coated CBN inserts. The results indicate that feed rate is the most significant parameters which affect the surface quality during hard turning [9].

It is observed from the previous research work that CBN cutting tools are mostly preferred during hard turning due to their high hardness and ability to perform efficient machining even at high temperature. However, at the very high hardness of the workpiece, the performance of the CBN tools was reduced. Therefore, a coating of harder materials plays a significant role in controlling the tool wear and maintaining the performance of cutting tools under extreme temperature conditions at cutting zone. Keeping this in view an attempt has been made in this research work to investigate the performance of coated CBN tools while turning hardened AISI 4340 steel under different machining conditions. The cutting force, chip-tool interfaces temperature and material removal rate is selected as performance parameters during machining. The orthogonal array form Taguchi approach was chosen to design the experimental layout. The grey relational technique was used to optimize the process parameters. The results were compared with by using the Fuzzy method.

2. Experimental details

2.1 Workpiece and cutting tool materials

Heat-treatable AISI 4340 steel is selected as workpiece material for experimentation. AISI 4340 steel has a broad range of applications in aerospace, automobile and general engineering industries. The size of the workpiece (65 mm diameter and 350 mm length) was selected to keep the L/D ratio not more than 10 as per ISO 3685 standard 1993 [10]. The workpiece materials get heat-treated (through-hardened) to hardness 40±2, 45±2 and 50±2 HRC. A grade K5625 has 65% CBN content with ISO geometry SNGA 431S0425MT of Kennametal were selected as cutting tools material, with tool holder designation ISO MSSNR2525M12. The TiN coating with 5µm thickness was provided on CBN inserts.

2.2 Selection of process parameters

Several parameters influence the performance of hard turning. In this research work, cutting speed, feed rate workpiece hardness and cutting tools (uncoated CBN and TiN coated CBN) were selected as input variables. The levels of the input variables were selected based on the previous research papers and machining handbook. The process variables with their ranges are given in Table 1.

Table 1. Input parameters with range

Symbol	Parameter	Low	Medium	High
		1	2	3
A	Cutting tool	CBN	TiN CBN	---
B	Cutting Speed (m/min)	100	125	150
C	Feed rate (mm/rev)	0.1	0.15	0.2
D	Workpiece hardness (HRC)	40	45	50

2.3. Experimental Procedure

The high rigidity of machine tool is the prime requirement for hard turning process. Therefore, highly rigid HMT made lathe was selected for experimentation. The performance of inserts was recorded online using TeLC, Germany, a high-precision lathe tool dynamometer regarding main cutting force and power consumption. The infrared thermometer (make: HTC-IRX-66, range -

30^{o}C to 1550^{o}C and an optical resolution of 30:1) was used for measuring the cutting temperature.

3. Design of Experiments

The Taguchi technique form design of experiments was selected to optimize the process parameters. Taguchi method is a valuable tool for developing the high-quality system. Taguchi uses of orthogonal arrays to conduct small, fractional factorial experiments equal to larger, full factorial experiment [11]. The L18 orthogonal array was chosen for performing the experimentations. The design matrix as per L18 orthogonal array is shown in Table 2.

Table 2. Orthogonal array L_{18}

Run No.	A	B	C	D
1.	1	1	1	1
2.	1	1	2	2
3.	1	1	3	3
4.	1	2	1	1
5.	1	2	2	2
6.	1	2	3	3
7.	1	3	1	2
8.	1	3	2	3
9.	1	3	3	1
10.	2	1	1	3
11.	2	1	2	1
12.	2	1	3	2
13.	2	2	1	2
14.	2	2	2	3
15.	2	2	3	1
16.	2	3	1	3
17.	2	3	2	1
18.	2	3	3	2

The performance parameters were selected as cutting force, chip-tool interface temperature and material removal rate (MRR). The MRR is calculated by using Eq. (1);

$$MRR = \frac{\pi \times l \times d \times Davg}{time} mm^3 / \sec \qquad (1)$$

3.1 Grey relational analysis

The hard turning process is very complicated than traditional turning process due to the several process variables involved. The grey relational analysis (GRA) provides a solution to multi-objective problems. The GRA is useful to find the optimal setting of different process variables by relating the entire range of performance parameter values into a single value [12]. The initial step in GRA is to convert the performance of all alternatives into a similarity arrangement between [0, 1], this act is known as normalization. The next step is to define the reference (ideal) order and the calculation of grey relational coefficient (GRC) among actual sequence and ideal sequence. After, then grey relational grade (GRD) is computed between the ideal sequence and every comparability sequences from GRC. The highest GRD is the best choice. For larger-the-better condition, the actual series (experimental results) is normalized by using Eq. (2);

$$yi(k) = \frac{xi(k) - \min xi(k)}{\max xi(k) - \min xi(k)} \qquad (2)$$

Where, *xi*(*k*) is the actual series, *yi*(*k*) series after normalization, max *xi*(*k*) and min *xi*(*k*) indicate the highest and lowest value of *xi*(*k*). For smaller-the-better condition, the actual series is normalized by applying Eq. (3);

$$yi(k) = \frac{\max xi(k) - xi(k)}{\max xi(k) - \min xi(k)} \qquad (3)$$

After the normalization of data then grey relational coefficient (GRC) is calculated. The GRC is indicating the correlation among actual and ideal normalized values. The ideal sequence is represented by yo(k) and it is taken as 1. The GRC is calculated from the ideal sequence yo(k) and the actual sequence yi(k). GRC show the correlation between ideal and actual sequence. The larger the GRC closer the yi(k) and yo(k) are. The GRC is calculated by using Eq. (4);

$$\zeta i = \frac{\Delta \min + \delta \Delta \max}{\Delta ij + \delta \Delta \max} \qquad (4)$$

In above Eq. (4), ζi is represented the coefficient of grey relational between yi(k) and yo(k); Δij= | yo(k) – yi(k) | deviation sequences; Δmin = minimum from Δi(k); Δmax = maximum from Δi(k); δ is the distinctive coefficient, δ ϵ [0,1]. The role of the distinctive coefficient is to increase or decrease the range of the GRC. The range of distinctive coefficient δ is chosen between [0,1]. Usually, δ =0.5 is used because it offers reasonable distinctive outcome and constancy [13]. The next step after calculating the GRC is to calculate the Grey relational grade (GRD) by using following Eq. (5);

$$\gamma i = \frac{1}{n} \sum_{k=1}^{n} \zeta i(k) \qquad (5)$$

In Eq. (5), ϒi is the GRD between yij and yoj. The GRD designate the degree of resemblance between the actual and the ideal series. The higher value of GRD indicates that corresponding cutting parameter is closer to optimal. In other words, optimization of the complex multi responses problems is transformed into optimization of a single GRD. The values of GRD are fallen within [0, 1].

3.2 Fuzzy Inference Systems

The fuzzy-logic process includes fuzzification of the input data followed by establishing the rules for the database, then make a decision on rule-based by the control unit and then de-fuzzification [14]. The database in fuzzy logic defines the membership function, these membership function used in formulating the fuzzy rules. These established rules utilized by decision-making unit to perform the inference operations. In the last step is defuzzification of the fuzzy results into crisp output [15].

4. Results and Discussion

All The experimental outcomes are represented given in Table 3. The grey relational model is prepared from the results obtained. The experimental data first converted between (0,1), this is known as normalization. Normalization of chip-tool interface temperature and cutting force are carried out by using Eq.(3). The Eq. (2) is used for normalizing the data for MRR. The normalized data is represented in Table 4. The next step is to calculate the grey relational coefficient (GRC) from the normalized data. The estimated value of GRC shows the correlation between the ideal and actual (experimental) data. The Eq. (4) is used to derive the GRC. The calculated GRC is represented in Table 5. Then the last step is to calculate the grey relational grade (GRD). For the calculation of GRD, the significance of all performance characteristics was assumed to be equal. The weights of the three performance characteristics were all the same (1/3). The GRD can be calculated by using Eq. (5). The calculated GRD for each run is given in Table (5). Based on the calculated GRD the rank is prepared to recognize the excellent input arrangement. It is observed that run no 16 has highest GRD of 0.746. Higher GRD signifies the input parameters corresponding to run no 16 provide superior performance.

Table 3. Machining results for each run

Run No.	T (ºC)	F (N)	MRR (mm^3/sec)
1	460	454.54	44.40
2	515	602.23	39.8
3	570	852.21	36.57
4	500	310.14	47.82
5	543	456.15	46.05
6	615	705.14	35.52
7	555	349.17	73.14
8	590	552.53	65.11
9	620	489.06	82.89
10	450	541.23	49.73
11	435	385.12	54.06
12	500	600.54	51.81
13	460	275.27	73.14
14	510	423.59	59.11
15	529	396.25	65.44
16	520	348.45	103.63
17	500	225.37	77.71
18	580	412.47	88.81

Table 4. Linear normalization of the responses

Run No	T (ºC)	F (N)	MRR (mm3/min)
1	0.865	0.635	0.130
2	0.568	0.399	0.06
3	0.271	0	0.02
4	0.649	0.865	0.19
5	0.417	0.632	0.16
6	0.028	0.235	0
7	0.352	0.803	0.56
8	0.163	0.479	0.44
9	0	0.580	0.70
10	0.919	0.497	0.21
11	1	0.746	0.28
12	0.649	0.403	0.23
13	0.865	0.921	0.56
14	0.595	0.684	0.35
15	0.492	0.728	0.43
16	0.541	0.804	1
17	0.649	1	0.62
18	0.217	0.702	0.79

Table 5. Grey relational coefficient and grade

Run No.	Grey relational coefficient			Grey relational grade	Rank
	T (ºC)	F (N)	MRR (mm^3/min)		
1.	0.787	0.578	0.364	0.576	7
2.	0.536	0.454	0.347	0.445	15
3.	0.406	0.333	0.337	0.358	17
4.	0.587	0.787	0.381	0.585	5
5.	0.461	0.576	0.374	0.470	14
6.	0.339	0.395	0.333	0.355	18
7.	0.435	0.717	0.532	0.561	9
8.	0.373	0.489	0.472	0.444	16
9.	0.333	0.543	0.625	0.501	12
10.	0.860	0.498	0.387	0.581	6
11.	1	0.663	0.409	0.690	4
12.	0.587	0.455	0.393	0.478	13
13.	0.787	0.863	0.532	0.727	2
14.	0.552	0.612	0.435	0.533	11
15.	0.496	0.647	0.467	0.536	10
16.	0.521	0.718	1	0.746	1
17.	0.587	1	0.569	0.718	3
18.	0.389	0.626	0.704	0.573	8

The fuzzy logic technique utilized to forecast the unpredictability in outcomes response which is indeterminate, incomplete response and vagueness

[16]. The decrease of improbability present in the GRD can be carried out by formulating Grey-fuzzy reasoning grade (GFRD) using the fuzzy inference system [17]. The fuzzy approach method is accessible to a single GFRD than considering the complex system with several responses. Input information and fuzzified output are evaluated to attain high-quality accuracy to forecast. These fuzzified outputs are utilized by the expert systems to respond the unclear and inaccurate problems and illustrate the methods of conveying function to fuzzy membership values. Mamdani's system of fuzzy logic is selected for attaining membership function using fuzzy inference system (FIS). The FIS used to for formulating combinations of fuzzy rules. The centroid technique is utilization for defuzzification for better accuracy than other techniques used in fuzzy. The grey relational grades formulated by using fuzzy techniques are more accurate than made by the standard grey relational approach. The GFRD indicate the higher value than normal GRD due to the reduction in fuzziness data's. For the generation of GFRD, the inputs to the fuzzy inferences system are GRC of chip-tool interface temperature, cutting force and MRR as given in Table 5. Three inputs to the fuzzy inference system are selected with GFRD as output. Fig (1) shows the complete setup of FIS system. The triangular membership function is chosen for each input data with three subsets.

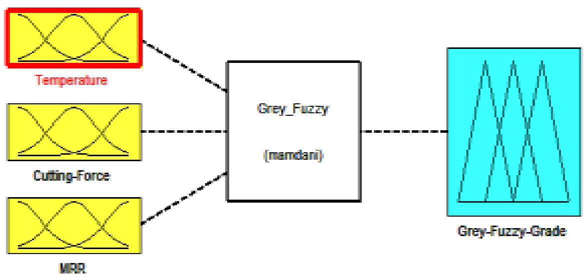

Figure 1. Fuzzy editor in FIS

For the better accuracy of the output i.e. GFRD, the single output i.e. GFRD is separated into five subsets as given in Table 6.

Table 6. Separation of fuzzy subsets for grey-fuzzy grade

Sr. No.	Range of sub-set	State of subset	Membership function
1	[-0.25, 0, 0.25]	very low	
2	[0, 0.25, 0.50]	low	
3	[0.25, 0.5, 0.75]	Medium	Triangular function
4	[0.5, 0.75, 1]	High	
5	[0.75, 1, 1.25]	Very high	

n fuzzy inference systems (FIS) modelling, If-Then rule statements are utilized to forecast outcomes. The inputs to the system are assigning the values of the GRC as mentioned in Table 5. The result is assigned with five membership functions their range as mention in Table 6. The set of rules is established to predict the GFRD. The FIS review every experimental run. Fig (2), illustrates the fuzzy-rule editor for calculating the GFRD, for all the range given input. The GFRD is compared with GRD as shown in Table 7. It has been observed that there is improvement in the grades determined from fuzzy logic approach than the grey relational grade. Therefore higher grades of fuzzy interference system are due to the reduction in vagueness and fuzziness. The comparison of GRD and GFDR is shown in Fig 3. It is evident from the plot that values of grade obtained with fuzzy-logic are higher than grey relational. However, the value of higher rank in both cases is at same experimental run no 16. There-fore fuzzy logic approach gives superior performance than grey relational approach.

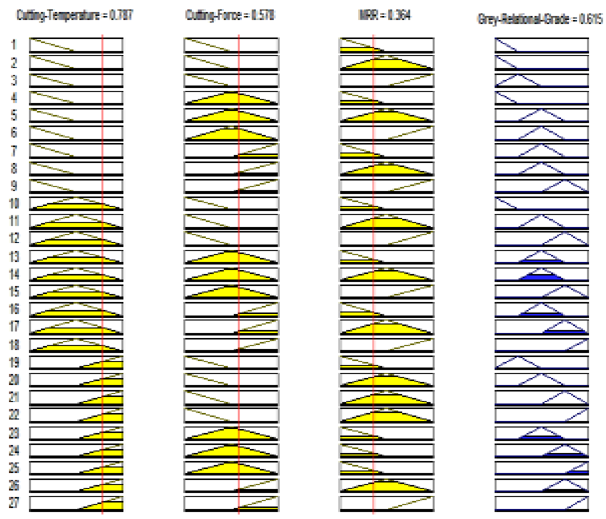

Figure 2. Fuzzy rule editors in FIS

Table 7 Comparisons of grade generated with fuzzy.

Run no	GRD	GFRD	% increase	Rank
1	0.576	0.615	06.77	8
2	0.445	0.493	10.78	15
3	0.358	0.405	13.12	18
4	0.585	0.645	10.25	5
5	0.470	0.521	10.85	14
6	0.355	0.406	14.36	17
7	0.561	0.613	09.26	9
8	0.444	0.479	07.88	16
9	0.501	0.578	15.36	11
10	0.581	0.623	07.22	6
11	0.690	0.711	03.04	4
12	0.478	0.528	10.46	13
13	0.727	0.751	04.61	3

14	0.533	0.569	06.75	12
15	0.536	0.579	08.02	10
16	0.746	0.775	03.88	1
17	0.718	0.752	04.73	2
18	0.573	0.617	07.67	7

To investigate the significance of input parameters the analysis of variance (ANOVA) is carried out by using GFRD. The ANOVA for GFRD is shown in Table 8.

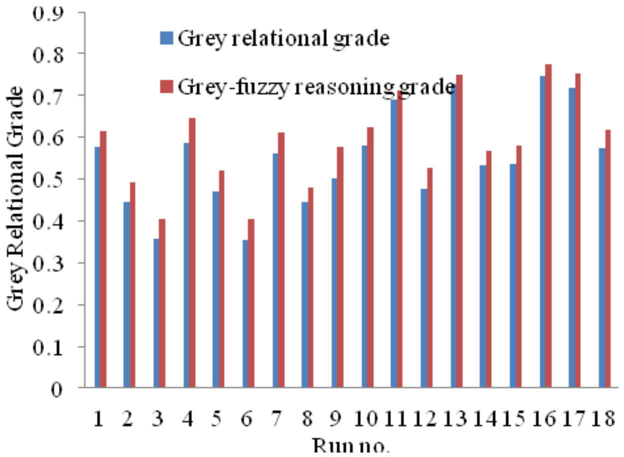

Figure 3. Comparison among GRD and GFRD

The ANOVA for GFRD shows the percentage contribution of each factor. From the ANOVA table, it has been observed that cutting tool materials and feed rate are the primary important factor which influences the machining performance. From the grey fuzzy logic grade response table is generated to identify the optimum combinations of the parameters. The response for a grey-fuzzy logic grade is given in Table 9.

Table 8. ANOVA for GFRD

Source	df	SS	MS	F_{cal}	P	%C
A	1	0.070	0.070	59.84	0.000	35.37
B	2	0.018	0.009	7.09	0.009	09.34
C	2	0.065	0.032	27.74	0.000	32.79
D	2	0.032	0.016	14.03	0.001	16.58
residual error	10	0.011	0.0011			05.92
Total	17	0.198				

The optimal levels of the input parameters which maximize the machining performance are A1B3C1D1. Therefore the optimal condition of input is TiN coated CBN tools with cutting speed 150 m/min, feed rate 0.1 mm/rev and workpiece hardness 40 HRC. Main effects plot for means of GFRD is shown in Fig 4.

Table 9 Response table for Grey fuzzy reasoning grade.

Level	A	B	C	D
1	0.5283	0.5625	0.6660	0.6467
2	0.6532	0.5742	0.5875	0.5828
3		0.6357	0.5188	0.5428
Delta	0.1249	0.0732	0.1472	0.1038
Rank	2	4	1	3

It has been observed from the plot that high cutting speed with low feed rate, low workpiece hardness and TiN coated CBN tools maximize the grey-fuzzy relation-al grades which in turn maximize the machining performance.

5. Prediction and validation of the optimum result

After selecting the optimal level of a process variable, the next step is to predict the machining performance using optimal level of the process variable. A verification test is carried out to analyze performance. The outcome from the grey-fuzzy analysis (Grey-fuzzy reasoning grade) is utilized to validate the experiment results. The Eq.(6) used to estimate the predicted mean (μpredicted) of GFRD using optimum level of process variables.

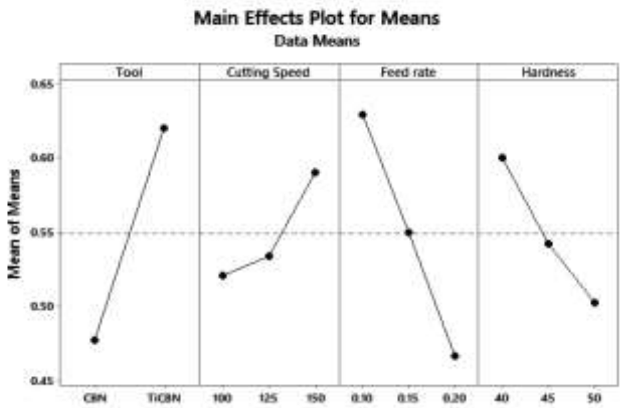

Figure 4. Main effects plot for mean of GFRD

$$\mu_{predicted} = A_{2m} + B_{1m} + C_{1m} + D_{1m} - 3\mu_{mean} \qquad (6)$$

Where A2m, B1m, C1m and D1m are the mean of the optimal level of the process variables and μmean is the total mean of GFRD. At optimal level of input variables, the μpredicted = 0.835. The validation of the test is carried out at same experimental setup. I was observed that cutting temperature was reduced from 460 oC to 380oC; the cutting force was reduced from 454.54 N to 325.15 N and the material removal rate was increased to 44.40 mm3/min from 53.20 mm3/min. The experimental value of GFRD = 0.771, it indicates an improvement by 21.77 %.

5. Conclusions

In this research work the tests are performed to analyze the effects of process variables such as cutting speed, feed rate, workpiece hardness and cutting tool materials on cutting force, cutting temperature and material removal rate during hard turning of AISI 4340 steel. The grey-fuzzy based multi- objective optimization is carried out to get the optimum value of the process variables. The following conclusions are drawn from the present research work:

- The performance of TiN coated CBN cutting tool inserts was better as compared to uncoated CBN inserts.
- The optimal values of process variables are 150 m/min, cutting speed, 0.1 mm/rev feed rate, 40 HRC workpiece hardness and TiN coated CBN tool.
- ANOVA results show that the cutting tool material and feed rate are the relevant parameters which affect the machining performance.
- This study indicated that grey-fuzzy based multi-objective optimization technique is efficient and reliable for optimization.

Acknowledgement
The authors are highly thankful to I.K.G. Punjab Tech-nical University, Kapurthala for continuous technical support in this research work.

Nomenclature

T : Cutting Temperature (^{o}C)
F : Cutting (N)
GRC :Grey relational coefficient
GRD :Grey relational grade
GFRD :Grey fuzzy reasoning grade
df :Degree of freedom
SS :Sum of sequare
MS :Mean sum of square
P :Probability
%C :Percentage Contribution
xi(k) : Actual Series
yi(k) : Series after normalization
yo(k) : Ideal sequence
ζi *:Grey relational coefficient between yi(k) and yo(k)* ϒi : GRD between yij and yoj.

References

[1] Davim, J. Paulo, ed. Machining of hard materials. Springer Science & Business Media, 2011.

[2] Huang, Yong, Y. Kevin Chou, and Steven Y. Liang. "CBN tool wear in hard turning: a survey on research progresses." The International Journal of Advanced Manufacturing Technology 35, no. 5-6 (2007): 443-453.

[3] [Mandal, Nilrudra, Biswanath Doloi, and Biswanath Mondal. "Force prediction model of Zirconia Toughened Alumina (ZTA) inserts in hard turning of AISI 4340 steel using response surface methodology." International Journal of Precision Engineering and Manufacturing 13, no. 9 (2012): 1589-1599.

[4] Chen, Wuyi. "Cutting forces and surface finish when machining medium hardness steel using CBN tools." International journal of machine tools and manufacture 40, no. 3 (2000): 455-466.

[5] Chou, Y. Kevin, Chris J. Evans, and Moshe M. Barash. "Experimental investigation on cubic boron nitride turning of hardened AISI 52100 steel." Journal of Materials Processing Technology 134, no. 1 (2003): 1-9.

[6] Çaydas, U. "Machinability evaluation in hard turning of AISI 4340 steel with different cutting tools using statistical techniques." Proceedings of the Institution of Mechanical Engineers 224, no. B7 (2010): 1043.

[7] Bouacha, Khaider, Mohamed Athmane Yallese, Tarek Mabrouki, and Jean-François Rigal. "Statistical analysis of surface roughness and cutting forces using response surface methodology in hard turning of AISI 52100 bearing steel with CBN tool." International Journal of Refractory Metals and Hard Materials 28, no. 3 (2010): 349-361.

[8] Aouici, Hamdi, Mohamed Athmane Yallese, Kamel Chaoui, Tarek Mabrouki, and Jean-François Rigal. "Analysis of surface roughness and cutting force components in hard turning with CBN tool: Prediction model and cutting conditions optimiza-tion." Measurement 45, no. 3 (2012): 344-353.

[9] Kumar, Sanjeev, Dilbag Singh, and Nirmal Singh Kalsi. "Surface quality evaluation of AISI 4340 steel having varying hardness during machining with TiN-coated CBN inserts." Proceedings of the Institution of Mechanical Engineers, Part J: Journal of

Engineering Tribology (2016): 1350650116684243.

[10] Anonim, I. S. O. "3685: 1993 (E)." Tool-life testing with single point tools (1993).

[11] Ross, Phillip J. "Taguchi techniques for quality engi-neering: loss function, orthogonal experiments, pa-rameter and tolerance design." (1988).

[12] Park, Hong-Seok, Trung-Thanh Nguyen, and Xuan-Phuong Dang. "Multi-objective optimization of turning process of hardened material for energy effi-ciency." International Journal of Precision Engi-neering and Manufacturing 17, no. 12 (2016): 1623-1631.

[13] Lin, Sue J., I. J. Lu, and Charles Lewis. "Grey relation performance correlations among economics, energy use and carbon dioxide emission in Taiwan." Energy Policy 35, no. 3 (2007): 1948-1955.

[14] Shu-Jen, Chen, and Hwang Chin-Lai. Fuzzy multiple attribute decision making. Berlin etc.: Springer, 1992.

[15] Loetamonphong, Jiranut, Shu-Cherng Fang, and Robert E. Young. "Multi-objective optimization problems with fuzzy relation equation con-straints." Fuzzy Sets and Systems 127, no. 2 (2002): 141-164.

[16] Lian, Ruey-Jing, Bai-Fu Lin, and Jyun-Han Huang. "A grey prediction fuzzy controller for constant cut-ting force in turning." International Journal of Ma-chine Tools and Manufacture 45, no. 9 (2005): 1047-1056.

[17] Rajasekaran, T., V. N. Gaitonde, and J. Paulo Davim. "Fuzzy modeling and analysis on the turning parame-ters for machining force and specific cutting pressure in CFRP composites." In Materials Science Forum, vol. 766, pp. 77-97. Trans Tech Publications, 2013.

Corresponding Author; **Sanjeev Kumar**; Research Scholar. I.K.G. Punjab Technical University- Kapurthala- Punjab (India).
e-mail sk_74@rediffmail.com ;
Mobile no. 919463048804