MAT JOURNALS

Journal of Recent Activities in Production
e-ISSN: 2581-9771
Volume 4 Issue 3

Multi-Response Optimization of Turning Parameters onVanadium Micro alloyed Steel using Taguchi based Grey Relational Analysis Coupled with Principal Component Analysis

SMuniraj[1], G.Karthik[2], NMuthukrishnan[3]
[1,2,3]*Faculity, Department of Mechanical Engineering,Sri Venkateswara College of Engineering, Chennai, Tamil Nadu, India*
***Email:** mk*@svce.ac.in*
***DOI:** http://doi.org/ 10.5281/zenodo.3558472*

Abstract
An experimental investigation of MAS38MnSiVS5 to investigate the effects of machining parameters, a turning test was designed using L_{27} orthogonal array (OA) and machining was performed on the cylindrical bars using medium duty lathe of 7 kW spindle speed. The power consumption and surface roughness were measured. Grey Relational Analysis have been used for normalized the multi objective responsesWeighting values were evaluated by Principal Component Analysis (PCA) for each performance variables. The variability caused by the input parameters was apportioned using Analysis of Variance (ANOVA). Thus, the Taguchi method (TM) based GRA coupled with PCA was specifically adopted to determine the optimal combination of turning parameters. The confirmation experiment shows an average improved power consumed of 62.8 % and surface roughness of 65.4 %.

Keywords:*Grey relational analysis, micro alloy, principal component analysis.power consumed, surface roughness, turning*

INTRODUCTION
Development of light weight and high performance engineering materials like composites, alloys are one of the pioneering fields of research in material science and have been progressed through recent decades. Micro Alloy Steel (MAS) is one among them which possesses high strength to weight ratio, yield strength (above 550MPa) and zero heat treatment cycle when compared to carbon steels. Initially micro alloying technology has been utilized for developing the production of flat products and later for “long products” such as engineering bars, sections, forgings and wire rods [1]. During 1980’s the main rationale to use niobium bearing steel bars and wires was to eliminate the need for a hardening process [1,2]. The significant cost, weight reductions and energy savings features of micro alloyed steels find wider applications in automotive industry such as connecting rods, suspension components and front axle beam, etc. for the replacement of conventional heat-treated steel materials.

Few research work was reported on machinability study of the micro alloy steels, Nakumara etal. (1993) made a research on the machining of free micro alloyed steel and the micro alloyed steel with best composition of alloy elements such as C, Mn, Cr, V, S, Pb, and Ca, and their impact on fatigue strength and machinability were found as 26% higher fatigue strength than conventional free machining microalloyed steel and 15% weight reduction resulted without any reduction of mechanical or fatigue strengths[7].Cho W, et al. (1994) carried out research work on micro alloyed steel (0.4C-V Modified) intended for the production of connecting rods and wheel hubs. The research work focused on the evaluation of microstructures; tensile strength. It was found that machining performance of the micro alloyed steel was dependent on cutting conditions [8]. VSivaramanaetal.(2011) conceded a research study on chip morphology during turning of Multiphase Ferrite (F-B-M) microalloyed steel. The turning experiment was performed using Taguchi orthogonal array. For different machining parameters such that cutting speed, depth of cut and feedrate, chip morphology were studied with optical and scanning electron microscope.[9]

VSivaramanaetal. (2012) reported that the machinability of multiphase (ferrite-bainite-martensite) microalloyed steel in a high speed lathe which is similar to the mechanical propertyof quenched and tempered steel. The results exposed thatfeed rate and depth of cut had persuade on cutting force and feed rate. The only parameter which shown that, the significant effect on the surface roughness[10].

AEbrahimi, MM Moshksar (2009),carried out an experimental investigation on micro alloyed steel (30MnVS6) and quenched-tempered (QT) steels (AISI 1045 and AISI 5140), to assess the effects of factors such as hardness, feed rate and work piece material cutting force, the tool flank wear and life of coated cemented carbide inserts in the hard turning process employed with statistical analysis. Also, investigations were carried out on chips characteristics and chip/tool contact length. Chips structure was studied through Scanning Electron Microscope (SEM) images. Shear planes and micro cracks of the chips in micro alloyed steel showed that the chips of regular and discontinuous in micro alloyed steel. Using video microscope crater wear of the tool in turning process was carried out by video microscope. The results indicatedthat the tool life and machinability of the micro alloyed steel is improved than the QT steels at identical cutting condition [11]. Muniraj and Muthukrishnan (2014) carried out the optimized machining parameters on surface roughness and power consumption at the spindle of the lathe with a specimen of MAS38MnSiVS5 with Multilayer coated K20 carbide insert. The results indicated that cutting speed had estimable inverse effect on surface roughness. Higher cutting speed produced low value of surface roughness.But at advanced cutting speed increases the power consumption[12].

MunirajS,MuthukrishnanN(2015), investigatedabout a study on optimum levels of turning parameters on MAS using single layer coated K20 Insert. It shown that the influences of cutting speed, feed rate and depth of cut on the surfacefinish andthe spindle power consumption[13]. MunirajS, MuthukrishnanN(2015), studied the machining performance of MAS38MnSiVS5 using uncoated K20 insert. The results showed the optimized cutting parameters of turning operation for the better surface value of the MAS micro alloyed steel bar[14].Chang NC Hwang,CT Chung(2009),who conducted a research work on rough cutting process of high-speed end milling on SKD61 tool steel. The major characteristics selected to evaluate the performance indexes were tool life and metal removal rate, and the corresponding cutting parameters are milling type, spindle speed, feed per tooth, radial depth of cut, and axial depth of cut. Grey relation analysisgrey relation grade adapted for optimal machining parameters combination.Principal component analysis was employed for weighing the performance index. This studyconcluded that this approach got hold ofthe optimal cutting parameters combinations[15].RRamanujam,K Venkatesan, VimalSaxena, Rachit Pandey(2014), investigated minimum machinability properties in turning operationof Inconel 625by using fuzzy based principal component function coupled with Taguchi's design of experiment is used for optimization of machining parameters for minimum surface roughness, and power

Journal of Recent Activities in Production
e-ISSN: 2581-9771
Volume 4 Issue 3

consumption, and maximum material removal rate[16].SanjitMoshat (2010) investigated the optimization of CNC end milling process parameters to provide better surface finish as well as high MRR. The GRA based Taguchi method has been applied toamulti objective optimization problem. Successfully used for simultaneous optimization of large number of responses[17].Tzeng et al. (2009), investigated the optimization of CNC turning operation for SKD11 using GRA based Taguchi method. In this study the GRA is applied to find how the turning operation parameter influences the quality target of work piece. Additionally the ANOVA is also applied to identify the most significant factor[18].Hag AN, MarimuthuP,Jeyapaul R(2008),employed the grey relational analysis in Taguchi method to evaluate the optimized machining parameters in drilling of Al/SiC metal matrix composites. It was concluded that the method is most effective one[19].

In the view of above machining problems, the main objective of the present work is to investigate the influence of different cutting parameters on surface finish and power consumed criterion. The Taguchi L_{27} orthogonal array is utilized for experimental planning for turning of MAS 38MnSiVS5. Fig.1a shows the microstructure of the specimen, shows uniform grains of pearlite in ferrite matrix.Fig. 1b shows the experimental setup.Table 1 shows the chemical composition of the work piece.

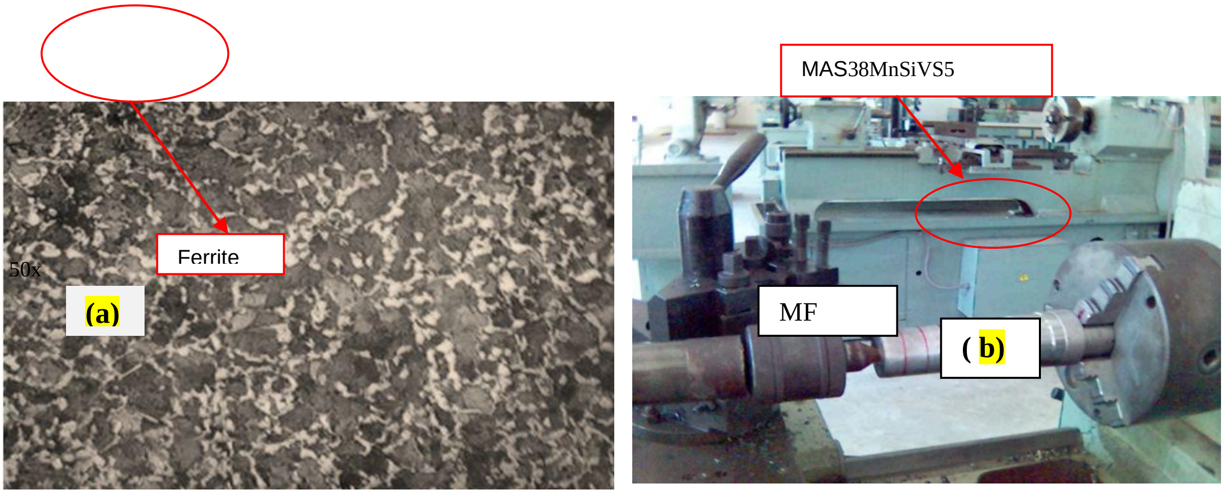


Figure 1:*a) Microstructure of MAS 38MnSiVS5.b) Experimental set up.*

Table 1:*Chemical composition of MAS 38MnSiVS5.*

Elements	%C	%Cr	%Si	%Mn	% Ni	%Cu	%Mb	%Zn	%Ti	%V	% Fe
Micro Alloyed Steel 38MnSiVS5	0.41	0.002	0.40	1.38	0.001	0.08	0.02	0.08	0.05	0.18	Balance

Table 2:*Machining parameters and their levels.*

Symbol	Machining parameter	Unit	Level 1	Level 2	Level 3
A	Cutting Speed	rpm	500	775	1200
B	Feed	mm/rev	0.04	0.042	0.046
C	Depth of cut	mm	0.5	1.0	1.5

Grey Relation Analysis

The grey relational theory provides an efficient management upon the uncertainty, multi input and discrete data. A grey relational grade is obtained to evaluate the multi responses. As a result, optimization of the responses can be converted into optimization of a single relational grade [19–21]. A flow chart for the grey relational analysis procedure is shown in Fig.2.

In GRA, when the range of a response variable is large or the standard value is enormous, the fluctuation of variables may be neglected. Since the response variables and their units are different, it is necessary to preprocess the data so that they can be normalized in the range between zero and one. The normalization was done to the response variables using Eqns. (1) and (2). For smaller the better, the normalized the experimental results x_{ij} can be expressed as:

$$x_{ij} = \frac{max_j y_{ij} - y_{ij}}{max_j y_{ij} - min_j y_{ij}} \quad (1)$$

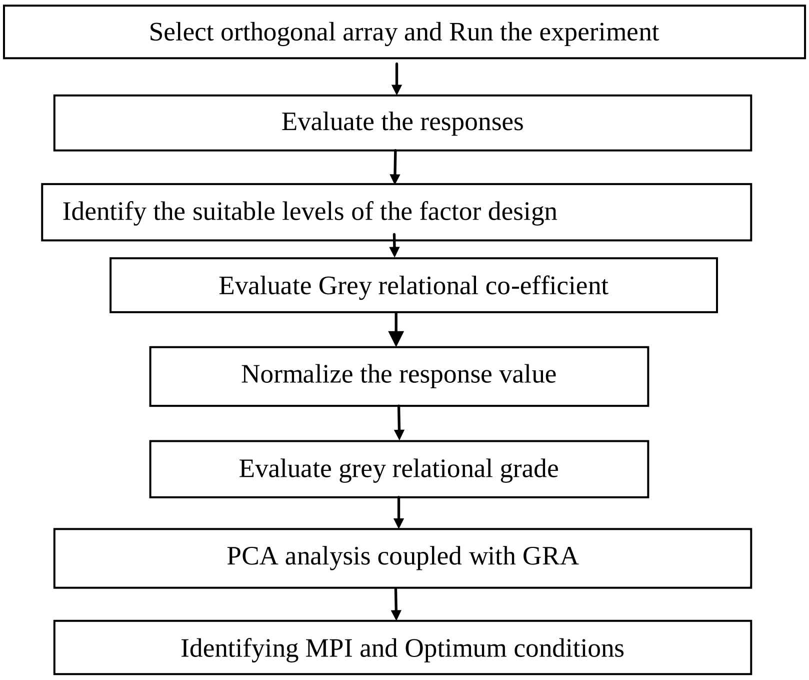


Figure 2:*Flow diagram for grey relational analysis and PCA.*

Forhigher – the –better, the normalized experimental results Xij can be expressed as:

$$x_{ij} = \frac{y_{ij} - min_j y_{ij}}{max_j y_{ij} - min_j y_{ij}} \quad (2)$$

Where, *yij* is the experimental result of the i^{th} run for the j^{th} response variable. The larger normalized results correspond to the better performance and the best-normalized results are equal to one. Next, the grey relational coefficient (GRC) is calculated to display the relationship between the optimal and actual normalized experimental results,It(ξ_{ij})can be expressed as:

$$\xi_{ij} = \frac{\min_i \min_j \left| x_i^o - x_{ij} \right| + \xi \max_i \max_j \left| x_i^o - x_{ij} \right|}{\left| x_i^o - x_{ij} \right| + \xi \max_i \max_j \left| x_i^o - x_{ij} \right|} \quad (3)$$

Where X_i^0 is the ideal normalized results for i^{th} response variable and ç is the distinguishing coefficient and lies between 0 and 1. In general it is set as 0.5.Table 3 shows the experimental layout.

Table 3: *Experimental layout and the response variables using L27 OA.*

Exp.No	Machining parameters and their levels			Response variable		
	A	***B***	***C***	***Ra***	***Rz***	***Pc***
1	1	1	1	3.4433	17.8167	0.1300
2	1	1	2	3.4920	17.8020	0.1300
3	1	1	3	2.9160	16.3320	0.1400
4	1	2	1	2.9867	15.6067	0.1400
5	1	2	2	3.4380	19.5080	0.1400
6	1	2	3	2.8920	16.4460	0.1400
7	1	3	1	3.4133	20.2600	0.1400
8	1	3	2	2.9840	17.2280	0.1400
9	1	3	3	2.7760	16.8320	0.1500
10	2	1	1	2.2300	12.6533	0.2300
11	2	1	2	3.1320	17.4860	0.2000
12	2	1	3	3.0920	17.5120	0.1900
13	2	2	1	2.3433	13.0267	0.2400
14	2	2	2	3.4500	17.9720	0.2000
15	2	2	3	2.9560	16.8360	0.2000
16	2	3	1	2.2600	11.9067	0.2300
17	2	3	2	3.7000	19.5500	0.2100
18	2	3	3	3.3340	18.2600	0.2000
19	3	1	1	1.4500	7.4000	0.3400
20	3	1	2	2.6980	14.5780	0.2900
21	3	1	3	2.9980	15.3680	0.2900
22	3	2	1	1.2700	6.6300	0.3500
23	3	2	2	2.7540	14.1140	0.3000
24	3	2	3	2.8140	16.0340	0.3000
25	3	3	1	1.4500	7.4933	0.3500
26	3	3	2	3.2400	16.5600	0.3100
27	3	3	3	2.9340	15.6840	0.3200

Table 4: *Results of grey with principle component analysis(PCA).*

Exp. No	Normalized *Ra*	Normalized *Rz*	Normalized *Pc*	Grey coefficient*Ra*	Grey coefficient*Rz*	Grey coefficient*Pc*	MPI	Rank
1	0.1056	0.1793	1.0000	0.3586	0.3786	1.0000	0.3658	22
2	0.0856	0.1803	1.0000	0.3535	0.3789	1.0000	0.3615	25
3	0.3226	0.2882	0.9545	0.4247	0.4126	0.9167	0.4265	12
4	0.2936	0.3414	0.9545	0.4144	0.4316	0.9167	0.4203	14
5	0.1078	0.0552	0.9545	0.3591	0.3461	0.9167	0.3612	26
6	0.3325	0.2798	0.9545	0.4283	0.4098	0.9167	0.4291	11
7	0.1180	0.0000	0.9545	0.3618	0.3333	0.9167	0.3617	24
8	0.2947	0.2225	0.9545	0.4148	0.3914	0.9167	0.4151	17
9	0.3802	0.2515	0.9091	0.4465	0.4005	0.8462	0.4430	9
10	0.6049	0.5581	0.5455	0.5586	0.5308	0.5238	0.5545	4
11	0.2337	0.2035	0.6818	0.3949	0.3857	0.6111	0.3951	19
12	0.2502	0.2016	0.7273	0.4001	0.3851	0.6471	0.3997	18
13	0.5583	0.5307	0.5000	0.5310	0.5158	0.5000	0.5287	6
14	0.1029	0.1679	0.6818	0.3579	0.3753	0.6111	0.3621	23
15	0.3062	0.2512	0.6818	0.4188	0.4004	0.6111	0.4176	15
16	0.5926	0.6129	0.5455	0.5510	0.5636	0.5238	0.5526	5
17	0.0000	0.0521	0.6364	0.3333	0.3453	0.5789	0.3367	27
18	0.1506	0.1467	0.6818	0.3705	0.3695	0.6111	0.3721	21
19	0.9259	0.9435	0.0455	0.8710	0.8985	0.3438	0.8711	2
20	0.4123	0.4169	0.2727	0.4597	0.4616	0.4074	0.4596	7
21	0.2889	0.3589	0.2727	0.4128	0.4382	0.4074	0.4163	16
22	1.0000	1.0000	0.0000	1.0000	1.0000	0.3333	0.9953	1
23	0.3893	0.4509	0.2273	0.4502	0.4766	0.3929	0.4534	8
24	0.3646	0.3101	0.2273	0.4404	0.4202	0.3929	0.4373	10
25	0.9259	0.9367	0.0000	0.8710	0.8876	0.3333	0.8695	3
26	0.1893	0.2715	0.1818	0.3815	0.4070	0.3793	0.3850	20
27	0.3152	0.3357	0.1364	0.4220	0.4295	0.3667	0.4227	13

The GRC for the present study were calculated and listed in Table 4. The GRG for each experimental run is computed from the average GRC of the response variable. GRG is used to show the relationship among the experimental runs. Higher the GRG more important the experimental run which isgiven in theEqn.4.

$$\gamma_i = \frac{1}{n}\sum_{j-1}^{n} w_j \,\xi_{ij} where \sum_{j-1}^{n} w_j = 1 \quad (4)$$

Where,'γ_i' is the weighted – Grey relation grade (GRG) for the i^th experiment, n is the number of response variables and w_j represents the normalized weighting value of the j^th response variable.

Principle Component Analysis Coupled With Grey

This is a most effective statistical approach to make linear combinations of response variables into structured variance-covariance [16,24,25].The multi objective response matrix is formed by Eqn.4.

$$X = \begin{bmatrix} x_1(1) & x_1(2)\cdots & x_1(n) \\ \vdots & \ddots & \vdots \\ x_m(1) & x_m(2)\cdots & x_m(n) \end{bmatrix} (4)$$

Wherex_i (j), i = 1,2,....m number of experiments, j=1,2,.....n number of response variable. In this study, m=27, n=3 and$x$ is the GRC response variable from Table4. The correlation coefficient matrix is obtained by the Eqn.(5).

$$R_{jl} = \left(\frac{Cov(x_i(j), x_i(l))}{\sigma_{x_i}(j) \times \sigma_{x_i}(l)}\right) (5)$$

Where,Cov(x_i(j),x_i(l)) is the covariance of sequences of $x_i(j)$and,$x_i(l)$is the standard deviation ofthe sequence of$x_i(j)$ and $\sigma_{x_i}(l)$ standard deviation of the sequence $x_i(l)$. Then the eigen values and eigen vectors are estimated from the correlation coefficient matrix by Eqn.(6).

$$(R - \lambda_k I_m)V_{ik} = 0 \qquad (6)$$

Where,

$$\sum_{k=1}^{n} \lambda_k = n, \qquad k = 1,2,3,$$

$V_{ik} = [a_{k1} a_{k2} \dots \dots a_{kn}]^T$ Eigenvectors corresponding to the eigenvalue $\lambda_k$the uncorrelated principal component (PC) is formulated as:

$$Y_{mk} = \sum_{i=1}^{n} X_m(i).V_{ik} (7)$$

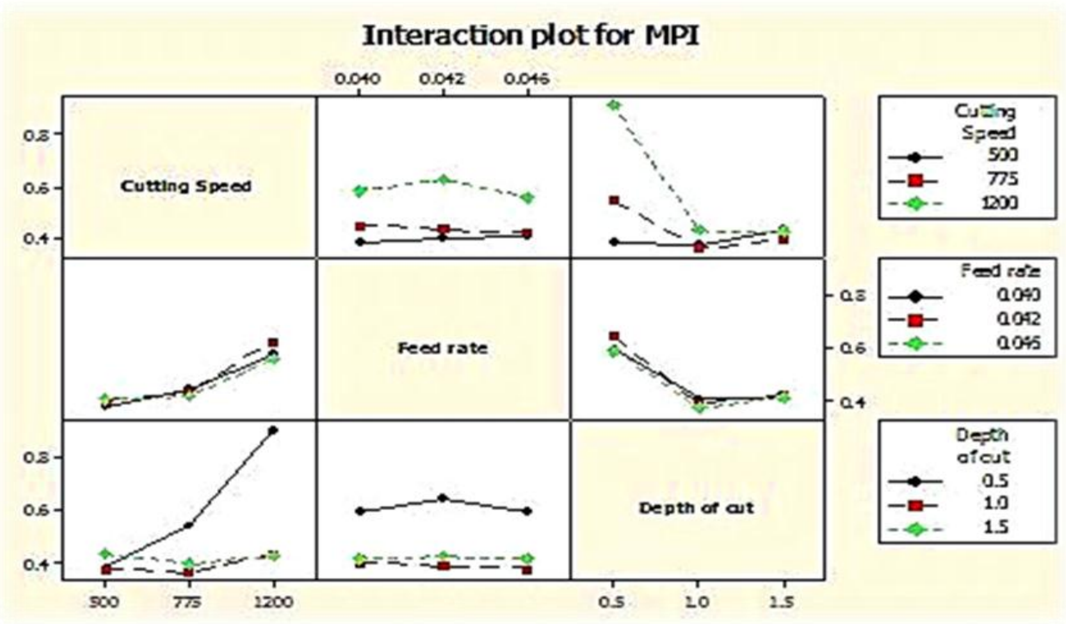


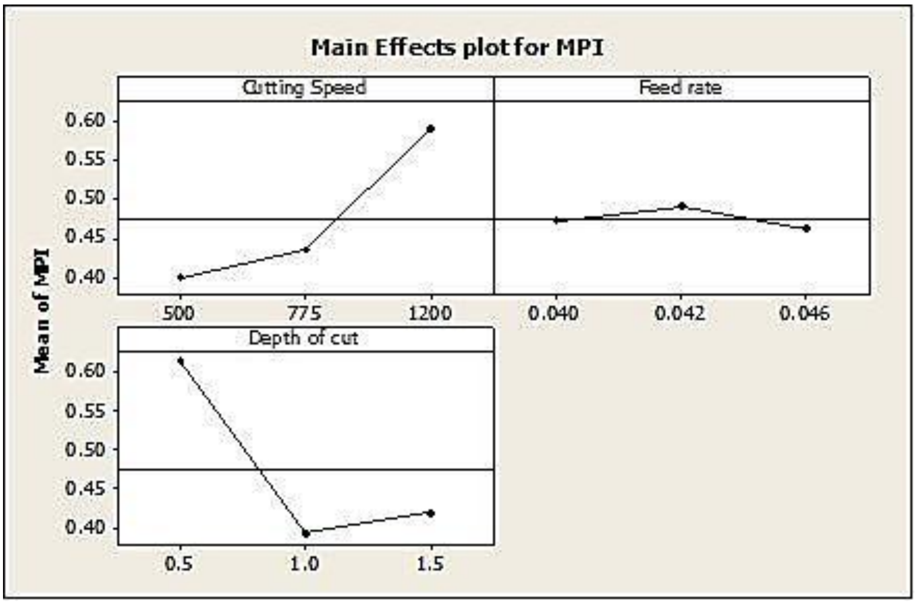
Figure 3: *Interaction plot for MPI.*

MAT JOURNALS

Journal of Recent Activities in Production
e-ISSN: 2581-9771
Volume 4 Issue 3

Where Y_{mk} is called the first PC, Y_{m2} is called the second PC, and soon.For the present study, w_j were obtained from the PCA. In this study, the elements GRC and the results Grey coupled with Principal component analysis listed in Table 5.

Interaction plot for Multi performance index is shown in Fig.3, for three levels of cutting speed, feed rate and depth of cut. The response table for the MPI is given in Table 5.



***Fiure 4:** Main effect plot for multi performance index.*

***Table 5:**Response table for multi performance index.*

Cutting Speed(rpm)	**Mean**
500	0.3982
775	0.4355
1200	0.5900
Feed rate(mm/rev)	Mean
0.040	0.4722
0.042	0.4894
0.046	0.4620
Depth of cut(mm)	Mean
0.5	0.6133
1.0	0.3922
1.5	0.4183

By using this table main effect plot for Multi performance index(MPI) is drawn as shown belowFig.4.

***Table6:**Eigen values for the principle components.*

Principle Components	**First Component**	**Second Component**	**ThirdComponent**
Eigen Values	2.5642	0.4138	0.0221
Contribution in %	85.5	13.8	0.7

Table6 showed the Eigenvalues for the three principle components which are Ra, Rz and Pc respectively. The contributions of these components revealed that the first component has greater influence on the performances.The second and third

Journal of Recent Activities in Production
e-ISSN: 2581-9771
Volume 4 Issue 3

components are also showing their significance on the work as in their order.

ANALYSIS OF VARIANCE FOR MULTI PERFORMANCE INDEX

It is a statistical tool for apportioning the variability of an output to various inputs. It is used to determine which input parameter significantly influences the output [26,27]. The total variability among weighted GRG measured by the sum of squared deviations from the total men of weighted –GRG are decomposed into two sources: the sum of squared deviations due to each machining parameter are the sum of squared error. The fisher's F –test can be used to identify which machining parameter have significantly effect on the weighted – GRG. The results of ANOVA for the weighted – GRG were tabulated as shown in Table 7. It shows that three machining parameters are found to be the most influential on the power consumed and surface roughness.

Table 7:*Analysis of variance MPI, using adjusted SS for tests.*

Factor	Degrees of Freedom	Sum of squares	Mean Squares	Test F	Contribution %
Cutting Speed (*V*)	2	0.18613	0.093065	89.58	25.31
Feed (*f*)	2	0.003452	0.001726	1.66	0.4694
Depth of cut (*D*)	2	0.262780	0.131390	126.48	35.75
*V**f*	4	0.006222	0.001555	1.49	0.8461
V D*	4	0.264909	0.066227	63.75	36.02
*f*D*	4	0.003496	0.008740	8.41	0.4754
Error	8	0.008311	0.0010388		1.13
Total	26	0.735332			100

Confirmation Experiment

Once the optimal level of machining parameters is selected ($A_1B_1C_1$), the final step is to predict and verify the improvement of the performance characteristics using the optimal level of the machining parameters. The estimated grey relational grade $\hat{\gamma}$ using the optimum level of the machining parameters can be calculated as:

$$\hat{\gamma} = \gamma_m + \sum_{i-1}^{q} (\bar{\gamma}_j - \gamma_m) \qquad (8)$$

Where,γ_m is the total mean of the grade, $\bar{\gamma}_j$ is the mean of the Grey relational grade at the optimum level and q is the number of machining parameters that significantly affects the multiple performance characteristics.

Based on Eqn. (5) the estimated grey relational grade using the optimal machining parameters can then be obtained. Table8 shows the results of the confirmation experiment using the optimal machining parameters. As shown inTable8 predicted values of combined grey relational grade is 1.188.

Table 8:*Results of confirmation experiment.*

	Initial machining parameters	Optimal machining parameters	
		Prediction	Experiment
Setting level	$A_1B_1C_1$	$A_3B_2C_1$	$A_3B_2C_1$
Surface roughness (Ra) in µm	3.44	------	1.27
Power consumed (kW)	0.13	---------	0.35
Multi performance index	--------	0.741	0.949

CONCLUSION

In this investigation, Taguchi method based GRA coupled with PCA was used for optimizing the machining parameters of machining micro alloy steel using single layer(TiN) coated K 20 carbide insert.

The micro alloy MAS38MnSiVS5 was chosen for the study. The power consumed by main spindle and the surface roughness that are measured were considered as multi-objective response variables.

GRA was used to convert these multi-objectives into a single weighted-GRG where PCA was used to determine the weighting values of each response variable and thereby the multi objectives were converted into a weighted-GRG. Thus, optimization of complicated multi-objective response variables can be greatly simplified through this method.

From the proposed method, it is found that improved power consumed and surface roughness can be obtained by setting the optimal combination of the forming parameters as A_3 B_2 C_1.

ACKNOWLEDGEMENT

Theauthorswishes to thank M/s, Kalyani Carpenter Special steel, Pune andChennai, Indiaanda special thanks to Mr. PCUnikrishnan, Senior VP,for the support of rawmaterial(38MnSiVS5) as round bars to execute the turning experimental work aSri Venkateswra College of Engineering., Debarment of mechanical engineering,SriprumbudurChennai, India.

REFERENCES

1. Michel Korchynsky (2001), “A New Role for Micro alloyed Steels-Adding Economic Value. The use of Vanadium in Steel- Proceedings of the Vanitec Symposium”, pp. 26−35, China.
2. Yang L, Fatemi A, Rhoda D, Tripp J (1996), “An Overview of Microalloyed Steels, Part II: Their Mechanical Behavior”, SAE Technical Paper, 960309, DOI:10.4271/960309.
3. Eder Costa, NelisLuiz, Marcio da Silva, Emmanuel Ezugwu, “Influence of tellurium addition on drilling of microalloyed steel (DIN 38mns6)”, Indutrial Lubrication and Tribology, Volume 63, pp. 420−426.
4. L Yrmg, A Fatemi, DA Rhoda, JE Tripp (1996), “An overview of microalloyed steels. II. Their mechanical behaviour. New Steel Products and Processing for automotive application”, pp. 89−100, Detroit, USA.
5. Masayuki Hashimura, Hiroshi Hirata, Hideo Kanisawa, Kenichiro Naito (2003), “Development of lead free microalloyed steel for crank shafts”, Nippon steel technical report No. 88, UDC669.14.018.23:669.775.
6. Kurtomi H, Uchino M, Kurebayashi Y, Namiki K et al. (1990), “Development of lightweight connecting rod based on fatigue resistance analysis of micro alloyed steel”, SAE Technical Paper, 900454.doi: 10.4271/900454.
7. Nakamura S, Mizuno K, Matsubara T, Sato Y (1993), “Development of high fatigue strength free machining microalloyed steel for connecting rods”, SAE Technical Paper, 930619. DOI:10.4271/930619.
8. Cho W, Kim K, Jo E, Oh S (1994), “Development of medium carbon microalloyed steel forgings for automotive ccomponents”, SAE Technical Paper, 940785, DOI:10.4271/940785.
9. V Sivaraman, S Sankaran, Vijayaraghavan L (2011), “Chip Formation during turning multiphase micro alloyed Steel”, World Academy of Science, Engineering and Technology, Volume 59, pp. 776−778.
10. Sivaramana S, Sankaran, Vijayaraghavan L (2012), “Machinability of multiphase micro

alloyed Steel", Proc. CIRP, Volume 2, pp. 55−59.
11. Ebrahimi A, Moskar MM (2009), "Evaluation of machinability in turning of micro alloyed and quenched-tempered steel: Tool wear, statistical analysis, chip morphology", J of mat. Proc. Tech., Volume 209, pp. 910−921.
12. Muniraj S, Muthukrishnan N (2014), "Experimental investigations on machining micro alloy steel(mas 38mnsivs5) using k 20 multicoated carbide insert", App. Mech. and Mat., Volume 59, pp. 15−18.
13. Muniraj S, Muthukrishnan N (2015), "An experimental study on machinability of micro alloyed steel with k20 single layer (ti-n)coated carbide insert", Appl. Mechanics and Mat., Volume 787, pp. 465−469.
14. Muthukrishnan N, Muniraj S (2015), "Optimization of cutting parameters on machining micro alloy steel (mas 38mnsivs5) by desirability analysis", Int. J. of the Balk. Trib.Asso., Volume 21, pp. 775−786.
15. CK Chang, NC Hwang, CT Chung (2009), "Grey relational analysis coupled with principal component analysis for optimization design of the cutting parameters in high-speed end milling", Journal of Material Processing Technology, Volume 209, Issue 8, pp. 3808−3817, DOI:10.1016/j.jmatprotec.2008.08.03.
16. R Ramanujam, K Venkatesan, VimalSaxena, RachitPandey (2014), "Optimization of Machining Parameters Using Fuzzy Based Principal Component Analysis during dry turning operation of Inconel 625 – A hybrid approach Procedia Engineering", Volume 97, pp. 668−676,DOI:10.1016/j.proeng.2014.12.296.
17. Moshat S, Datta S, Bandyopadhyay A, Pal P (2010), "Parametric optimization of CNC end milling using entropy measurement technique combined with grey-Taguchi method", Int. J. of Engg, Sci. and Tech., Volume 2, Issue 2, pp. 1−12.
18. Tzeng CJ, Lin YH, Yang YK, Jeng MC (2009), "Optimization of turning operations with multiple performance characteristics using the Taguchi method and Grey relational analysis", Journal of materials processing technology, Volume 209, Issue 6, pp. 2753−2759.
19. Hag AN, Marimuthu P, Jeyapaul R (2008), "Multi response optimization of machining parameters of drilling Al/SiC metal matrix composites using grey relational analysis in Taguchi method", In.l J. of Adv. Manuf. Tech., Volume 37, pp. 250−255.
20. Mahamannai A, Muthukrishnan N, Ananda Krishnan V (2012), "Determination of optimum paprameters for multi- performance characteristic in turning of Al6061-6%ZrB2 in situ metal matrix composite using grey relational analysis", Int. J. of Manuf, mat. and Mech. Engg., Volume 2, Issue 1, pp. 11−29.
21. AmanAggarwal, Hari Singh, Pradeep Kumar, Manmohan Singh (2008), "Multi-characteristics Optimization of CNC turned parts using principal component analysis", Int.J of Machin.andMachinabi. of Mater., Volume 3, Issue ½, pp. 208−223, DOI: 10.1504/IJMMM.2008.017634.
22. PJ Ross (1996), "Taguchi Techniques for Quality Engineering", First Ed, McGraw-Hill, New York.
23. Roy RA (1990), "Primer on Taguchi Method. Van Nostrad Reinhold", New York.
24. Deng Julong (1988), "Introduction to Grey System Theory", The journal of Grey system, Volume 1, Issue 5, pp. 1−24.
25. Fung HC, Kang PC (2005), "Multi-response optimization in friction

properties of PBT composites using Taguchi method and principal component analysis", J. Mater. P. Technol., Volume 170, pp. 602−610.
26. Kribes Nabil, HessainiaZahia, M.A. Yalles, N. Ouelaa.(2012) Statistical analysis of surface roughness by design of experiments in hard turning. MECHANIKA.18 (5): 605-611. http://dx.doi.org/10.5755/j01.mech.18. 5.2704 9. 27. BerilEker, BülentEkici, Mustafa Kur, BarkınBakı. (2014).Sustainable machining of the magnesium alloy materials in the CNClathe machine and optimization of the cutting conditions.MECHANIKA. 20(3): 310-316 http://dx.doi.org/10.5755/j01.mech.20. 3.4702 .

Cite this article as: