International Journal of Multidisciplinary Research and Modern Education (IJMRME)
ISSN (Online): 2454 - 6119
(www.rdmodernresearch.org) Volume II, Issue I, 2016

OPTIMIZATION OF TURNING PROCESS THROUGH TAGUCHI AND SIMULATED ANNEALING ALGORITHM

S. Ganapathy
Assistant Professor, Department of Mechanical Engineering,
Jayaram College of Engineering and Technology, Thuraiyur, Trichy, Tamilnadu

Abstract:

In the manufacturing industries, the correct selection of manufacturing conditions is one of the most important aspects and it is considered here in the Turning process. The aim of this work is to optimize the process parameters for multi objective in the Turning process through Taguchi method and simulated annealing algorithm (SA). The experiments were conducted based on L_9 taguchi orthogonal array. The experiments were carried out for different combination of process parameters like cutting speed; feed, depth of cut and corresponding response variables material removal rate (MRR) and flank wear (FW) were measured. The results indicate that the depth of cut significantly affects the multiple performance characteristics.

Simulated annealing is well known stochastic global optimization technique for obtaining high quality solutions to difficult optimization problems. From the experimental data, using MINITAB software, the mathematical model for the objective function has been developed. Simulated annealing algorithm is applied to obtain the optimal process parameter setting in turning process. A program has been developed in C++ to obtain the optimal process parameter settings for the required objective through simulated annealing algorithm.

Introduction:

The optimization of cutting parameter is the key component in planning of machining processes. The manufacturing processes are characterized by a multiplicity of dynamically interacting process variables. Optimization of machining parameter not only increases the utility for machining economics, but also the product quality to a great extent. However, deep analysis of cutting involves certain costs, particularly in case of small series. In case of individual machining it is particularly necessary to shorten as much as possible the procedure for determination of the optimum cutting parameters, otherwise the cost of analysis might exceed the economic efficiency which could be reached if working with optimum conditions. From optimization of the machine operations the quantitative methods have been developed with consideration of a single objective, such as minimization of cost or maximization of profit etc. For the process of the single objective optimization several different techniques have been proposed, such as the differential calculus, regression analysis, linear programming, geometric and stochastic programming, computer simulating. While most researches hitherto are based on the single-objective optimization, there have been some successful attempts also with the multi-objective optimization. In many real applications the process designers face on regular basis the problem of simultaneous optimization of several objectives. Those objectives are often conflicting and incomparable. The objective of this work to achieve high material removal rate (MRR) and low flank wear width (FWW) by setting process parameter at optimal level through Taguchi method worth multi performance characteristics and simulated annealing algorithms (SA). Taguchi method is a systematic application of design and analysis of experiments for the purpose of designing and improving product quality. Taguchi method is used to achieving high quality without increasing cost. The experiments were performed on Centre Lathe Machine. Mild steel with a diameter of 49mm was used as the work piece and High Speed Steel was used as the cutting tool.

The experiments were conducted based on L_9 taguchi orthogonal array. The experiments were carried out for different combination of process parameters like cutting speed; feed, depth of cut and corresponding response variables material removal rate (MRR) and low flank wear width (FWW) were measured. Taguchi method with multi performance characteristics is adopted to obtain optimal process parameter in turning process. Furthermore, statistical analysis of variance (ANOVA) is performed to see which process parameters are statistically significant. From the experimental data, the mathematical model of the objective function is developed using multiple regression analysis. By using MINITAB software, the objective function of the problem is obtained. In order to judge, whether the objective function is significant or not by using the following method the co-efficient of determination, square of residual (R^2) and average error of the mathematical model.

Simulated annealing algorithm is used for solving minimization problem. The simulated annealing method resembles the cooling process of metals through annealing process. That means, it is an algorithm that gets final global optimal solution by gradually going from one solution to next solution. The objective function of the problem is considered for multi objective problem. In simulated annealing algorithm, the initial point is generated randomly and the neighborhood points are found out by using random interchange perturbation scheme. This method is implemented in C++ language. This method will give minimum tool wear by setting of process parameters for optimal/near-optimal level in turning operation.

Objective:

The objective of this work is to achieve high material removal rate (MRR) and low flank wear width (FWW) in turning process by settings of optimal/near-optimal process parameter (cutting speed, feed, depth of cut) through taguchi method with multiple performance characteristics and simulated annealing algorithm

The major steps involved in multi objective optimization problem in turning process:

To set the levels for the process parameter values with in the variable bounds range.

The experiments were conducted based on L9 taguchi orthogonal array.

To predict optimal process parameter in turning process by using Taguchi method with multiple performance characteristics.

To predict, which parameter significantly affects the overall performance characteristics.

To develop mathematical model for the objective function using Regression analysis.

To solve the non-linear problem using non-traditional optimization algorithm SA.

Simulated annealing algorithm is implemented in C++ to obtain high material removal rate (MRR) and low flank wear width (FWW) by setting optimal/near optimal level of process parameters like cutting speed, feed, depth of cut.

Primarily for pumping and a higher speed machine resembling an eggbeater.

Experimental Investigation:

Experimental Setup:

Experiments were conducted on centre lathe machine. In this project, mild steel work piece of 80mm length and diameter of 49mm was turned using single point HSS turning tool and flank wear were measured with help of tool maker's microscope.

Experimental Condition:

Machine tool	Centre lathe
Cutting tool	High speed steel (HSS)
Work material	Mild steel
Environment	Dry condition (coolant not used)

Tool Maker's Microscope Specification:

Model	METZ-1395
Magnification	30X(standard)
Objective	2X
Eyepiece	W.F 15X with cross slide
Field of view	8mm Diameter
Working distance	115mm (approximately)

Process Parameters and levels:

The process parameters are considered in this work and their levels are tabulate below

Table1: Process parameters and levels

Factors	**Symbol**	**Level 1**	**Level 2**	**Level 3**
Cutting speed (m/min)	A	55	85	115
Feed (mm/rev)	B	0.18	0.20	0.22
Depth of cut (mm)	C	0.5	1.0	1.5

Experimental Data:

Table 2: Experimental data of MRR and FWW

TRAIL NO	**SPEED (A) (m/min)**	**FEED (B) (mm/rev)**	**DOC (C) (mm)**	**MRR (mm^3/min)**	**FWW (mm)**
1	55	0.18	0.5	4550	0.055
2	55	0.20	1.0	8647	0.735
3	55	0.22	1.5	12200	0.975
4	85	0.18	1.0	11470	0.725
5	85	0.20	1.5	16150	0.945
6	85	0.22	0.5	4840	0.745
7	115	0.18	1.5	18150	0.950
8	115	0.20	0.5	7340	0.760
9	115	0.22	1.0	14300	0.780

Results and Discussion:

Analysis of Results Obtained from Taguchi Method:

The experiments were performed on Centre Lathe Machine and the response variables measured.

Process Parameters and Levels:

The process parameters are considered in this work and their levels are tabulated once again

Table 3: Process parameters and levels

Factors	Symbol	Level 1	Level 2	Level 3
Cutting speed (m/min)	A	55	85	115
Feed (mm/rev)	B	0.18	0.20	0.22
Depth of cut (mm)	C	0.5	1.0	1.5

Experimental Data:

The experiments were conducted based on L_9 taguchi orthogonal array. The experiments were carried out for different combination of process parameters like cutting speed; feed, depth of cut and corresponding response variables material removal rate (MRR) and flank wear width (FWW) were measured.

Table 4: Experimental Data

S.No	A	B	C	E	MRR (mm^3/min)	FWW (mm)
1	1	1	1	1	4550	0.055
2	1	2	2	2	8647	0.735
3	1	3	3	3	12200	0.975
4	2	1	2	3	11470	0.725
5	2	2	3	1	16150	0.945
6	2	3	1	2	4840	0.745
7	3	1	3	2	18150	0.95
8	3	2	1	3	7340	0.76
9	3	3	2	1	14300	0.78

Analysis of the Multi-Response S/N Ratio:

Each performance characteristic may belong to a different category in the analysis of the S/N ratio. The engineering unit for descending each performance characteristic may not be the same. The importance of each performance characteristic in the overall performance evaluation ma be different. To obtain Optimal machining performance, the higher-the-better performance characteristic for MRR must be taken. On the other hand, the lower-the-better performance characteristic for FWW should be taken for obtaining optimal machining performance. For the higher-the-better performance characteristic, the loss function can be expressed as

$$L_{ij} = 1/n\,(1/y_1^2 + 1/y_2^2 + 1/y_3^2))$$

Where Lij is the loss function of ith performance characteristic in the j^{th} experiment, n the number of tests, and y_{ijk} is the experimental value of the i^{th} performance characteristic in jth experiment at the test.

The loss function L_{ij} for the lower-the-better performance characteristic can be expressed as

$$L_{ij} = 1/n\,(y_1^2 + y_2^2 + y_3^2))$$

The loss function of each performance characteristic is calculate and tabulated give below.

Table 5: Loss Function

S.No.	MRR $*10^{-8}$	FWW
1	4.83	0.0030
2	1.337	0.5402
3	0.672	0.9506
4	0.760	0.5256
5	0.383	0.9120
6	4.27	0.5550
7	0.304	0.9025
8	1.856	0.5776
9	0.489	0.6084

As a result, the application of the parameter design of the Taguchi method in a process with multiple performance characteristics cannot be straightforward. To solve these problems, the loss function corresponding to each performance characteristic is first normalized,

i.e, $S_{ij}=L_{ij}/L_i$

Where, Sij is the normalized loss function for the ith performance characteristic in the jth experiment, Lij the loss function for the ith performance characteristic in jth experiment and Li is the average loss function for the ith performance characteristic. The normalized loss function of each performance characteristic is calculated and tabulated given below

Table 6: Normalized Loss Function

S.No	MRR	FWW
1	2.9174	0.0048
2	0.8076	0.8721
3	0.4059	1.5347
4	0.4590	0.8486
5	0.2313	1.4724
6	2.5785	0.8960
7	0.1836	0.9371
8	1.1210	0.9325
9	0.2954	0.9822

A weighting method is then used to determine the importance of each normalized loss function. Based on the weighting method, the total loss function TLJ in the jth experiment is defined as

$$T_{Lj}=\sum w_i sij$$

Where, w_i is the weighting factor for the ith performance characteristic and m is the number of performance characteristics. In this work, FWW is very important factor in turning process. Therefore the weighting factor for FWW is taken as .4 and MRR taken as .6. The Total loss function of the overall performance characteristic is calculated and tabulated given below

Table 7: Total Loss Function

S.No	Total Loss Function
1	1.7523
2	0.8334
3	0.8574
4	0.6148
5	0.7277
6	1.9055
7	0.6930
8	1.0456
9	0.4726

The total loss function is further transformed into a multi-response S/N ratio. In the Taguchi method, the S/N ratio is used to measure the performance characteristic deviation from the desired value. Therefore, the multi-response S/N ratio η_j in the jth experiment can be expressed as

$$\eta_j = -10 \log T_{Lj}$$

The multi response S/N ratio, table and response graph of the overall performance characteristic is calculated and tabulated given below

Table 8 Multi Response S/N Ratio:

S.No	Multi response S/N ratio
1	-2.4361
2	0.7915
3	0.6682

4	2.1127
5	1.3805
6	2.8000
7	1.5927
8	-0.1937
9	3.2551

The multi response S/N ratio table is shown in below and also the graph between mean multi response S/N ratio and number of level are shown in Fig 6.1

Table 9: Multi Response S/N Ratio Table

Symbol	Process parameter	Mean multi response S/N ratio table (db)			
		Level 1	Level 2	Level 3	Max-Min
A	Cutting speed	-0.3124	0.2311	1.9961	1.6837
B	Feed	0.7117	1.0653	0.5294	0.5359
C	Depth of cut	-0.3510	2.2309	2.4266	2.0756

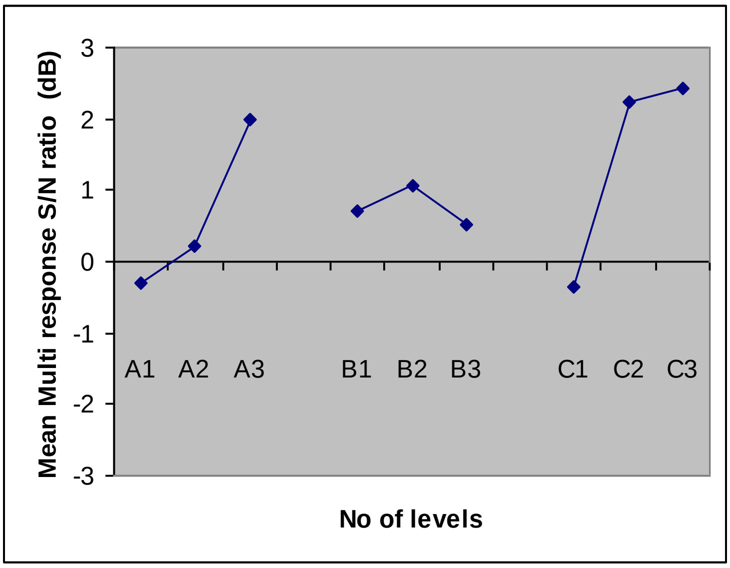

Figure 1: Multi Response Graph

Analysis of Variance (ANOVA):

The purpose of the ANNOVA is to investigate which of the process parameter significantly affect the performance characteristics. This is accomplished by separating the total variability of the multi-response S/N ratios, which is measured by the sum of the squared deviations from the total mean of the multi-response S/N ratio, into contributions by each of the process parameters and the error. First, the total sum of the squared deviations SS_T from the total mean of the multi-response S/N ratio η_m can be calculated as

$$SS_T = \sum (\eta_j - \eta_m)^2$$

Where p is the number of experiments in the orthogonal array and η_j is the mean of the multi-response S/N ratio for jth experiment.

The total sum of the squared deviations SS_T is decomposed into two sources: the sum of the squared deviations SS_d due to each process parameter and the sum of the squared error SS_e. The percentage contribution ρ by each of the process parameters in the total sum of the squared deviations SST can be calculated.

Statistically, there is a tool called the F-test named after Fisher to see which process parameters have a significant effect on the performance characteristic. In performing the F-test, the mean of the squared deviations SS_m due to each process parameter needs to be calculated. The mean of the squared deviations SS_m is equal to the sum of the squared deviations SS_d divided by the number of degrees of freedom associated with the process parameter. Then, the F value for each process parameter is simply a ratio of the mean of the squared deviations SS_m to the mean of the squared error SS_e. Usually, the larger the F value, the greater the effect on the performance characteristic due to the change of the process parameter.

Table 6.8 shows the result of ANOVA, depth of cut and cutting speed are significantly affecting the multiple performance characteristics.

Table 10: ANOVA Table

Symbol	Process parameter	Degree of freedom	Sum of Squares	Mean Square	F-ratio	Contribution ratio
A	Cutting speed	2	50.1788	25.089	3.135	15.63
B	Feed	2	31.9980	15.999	1.999	10.00
C	Depth of cut	2	222.9337	111.467	13.92	69.42
Error		2	16.0081	8.004		4.95
Total		8	321.1182			100.00

Confirmation Tests:

Once the optimal level of the process parameters is selected, the final step is to predict and verify the improvement of the performance characteristic using the optimal level of the process parameters. The estimated S/N ratio ή using the optimal level of the process parameters can be calculated as,

$$\eta = \sum (\eta_i - \eta_m)$$

Where, η_m is the total mean of multi-response S/N ratio, η_i the men of the multi-response S/N ratio at the optimal level, and q is the number of the process parameters that significantly affect the multiple performance characteristics. The estimated multi-response S/N ratio using the optimal cutting parameters can then be obtained

$$\acute{\eta} = \hat{\eta}\ A3 + \hat{\eta}\ B2 + \hat{\eta}\ C2 - 2n_m$$
$$= 3.828 \text{ dB}$$

The confirmation experiment is very important in parameter design. The purpose of the confirmation experiment in this study was to validate the optimum sparking conditions (A_3 B_2 C_2) that were suggested by the experiment, that correspond with the predicted value. In this study the confirmation runs with optimum sparking conditions (A_3 B_2 C_2). The confirmation experiment conducted at optimum process parameter and measures corresponding response values of like MRR is 12992.6 mm^3/min and FWW is 0.741 mm

Mathematical Model Developed by Multiple Regression Analysis:

From the experimental data, mathematical modeling is crated by multiple regression analysis is an iterative process; MINITAB is used to obtain the mathematical model. The mathematical model for objective function is given below,

$$MRR = 54870 - 400 * A - 413198 * B + 15139 * C - 515000 * B^2 + 2383 * A * B$$
$$189292 * B * C$$

$$FWW = -5.2765 + 0.011 * A - 21.6111 * B + 6.1456 * C + 0.00001 * A^2 - 0.0127 *$$

A * B + 0.0153 * A * C - 22 * B * C

Where, A –Speed in m/min
B – Feed in mm/rev
C –Depth of cut in mm
MRR–Material removal rate in mm^3/min
FWW –Flank wear width in mm

Validating Mathematical Model:

In order to judge whether the equation obtained in this model is significant or not in explaining the relationship between X and Y, the coefficient of determination, R^2 method was used. The formula for correlation coefficient is,

$$R^2 = [\sum (y_i-y_a)^2] / [(\sum (\tilde{y}_i-y_b)^2]$$

y_i = response obtained by experiment
y_a = average response (experiment)
$\tilde{y}_i$ = response obtained by equation
y_b = average response (by equation)
i = experiment number
R_2 is the correlation coefficients and its value range from 0 to 1.

The average error is found by,

$$E = 1/n \ (\sum(I\, y_e - y_p\, I * 100/y_e))$$

Where, n - number of data
y_e - Response by experiment
y_p - Response by equation

For the best fit of the equation, R^2 value should be near to one and the error should be as minimum as possible. From the Table 6.9 it is found that the percentage of error for model values of MRR varies within 1.2%. But their average error is in the acceptable range is shown in Table 6.9 the variations of the experimental and predicted values are shown in Fig 6.2

Table 11: Percentage of Error for MRR

Term	Co-efficient	R^2	Error (%)
Constant	54870	99.4%	1.20%
A	-400		
B	-413198		
C	15139		
B*B	515000		
A*B	2383		
B*C	-18929		

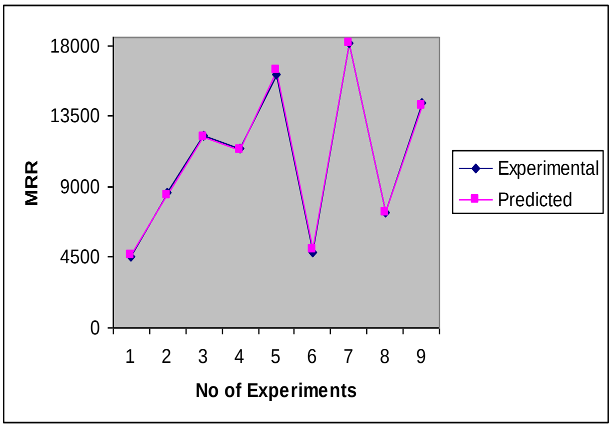

Figure 2: Variations of the Experimental and Predicted Values for MRR

From the table 6.10 it is found that the percentage of error for model values of FWW varies within 4.22%. But their average error is in the acceptable range is shown in Table 6.10 the variations of the experimental and predicted values are shown in Fig 6.3

Table 12: Percentage of Error for FWW

Term	Co-efficient	R^2	Error (%)
Constant	-5.2765	97.4%	4.22%
A	0.011		
B	21.6111		
C	6.1456		
A*A	0.00001		
A*B	0.0127		
A*C	-0.0153		
B*C	-22		

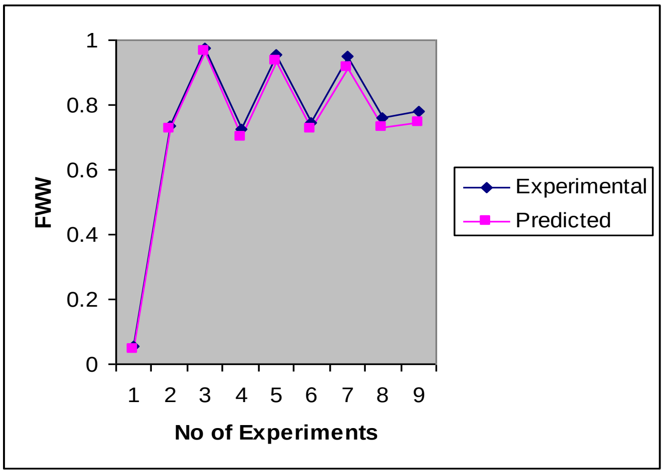

Figure 3: Variations of the Experimental and Predicted Values for FWW

Fitness Function:

The MRR and FWW are considered as the dependent function. Therefore our optimization problem involves multi objective function. The mathematical model of the objective function is given below.

$$MRR = 54870 - 400 * A - 413198 * B + 15139 * C - 515000 * B^2 + 2383 * A * B \quad 189292 * B * C$$

$$FWW = -5.2765 + 0.011 * A - 21.6111 * B + 6.1456 * C + 0.00001 * A^2 - 0.0127 * A * B + 0.0153 * A * C - 22 * B * C$$

$$\text{Fitness function} = (0.6/ (1+MRR)) + (0.4*(FWW))$$

Where,
A –Speed in m/min
B – Feed in mm/rev
C –Depth of cut in mm
MRR–Material removal rate in mm^3/min
FWW –Flank wear width in mm

Discussion of Simulated Annealing:

The simulated annealing method has been effectively applied for minimizing tool wear. In simulated annealing, the initial temperature and no of iterations at particular temperature is important. Initial temperature can be obtained by calculating the average of the function values at a number of random points in the search space. In this work, average function value is in the range of micron, so the initial temperature is chosen as 475. No of iterations at particular temperature is chosen usually 20 to 100. It depends on computing resource and the solution time. From the above discussion, no of iterations at particular temperature is taken as 30. The simulated annealing algorithm is coded in the C++ language.

The results obtained in simulated annealing are shown in table6.1. Flank wear width and Crater wear depth was obtained by substituting the optimum parameter levels in objective function. This parameter levels may give better result than the Taguchi method of optimization.

Table 13: Optimum Level of Process Parameters and Response Variable

Symbol	Process Parameters	Optimum levels	Response Variables	
			MRR (mm^3/min)	FWW (mm)
A	Cutting speed (m/min)	110.032	13912.32	0.716
B	Feed (mm/ rev)	0.21235		
C	Depth of cut (mm)	1.0698		

Conclusion:

An attempt has been made through taguchi method with multiple performance characteristics, to predict the optimum process parameter in turning process. From the result of ANOVA table, it is observed that the depth of cut significantly affects the overall performance characteristics. The confirmation experiment is conducted from the result obtained through Taguchi method for optimum process parameter. Simulated annealing algorithm is implemented in this work, to predict the optimal process parameter. The optimum cutting conditions have been found through a set of trials with simulated annealing. The results obtained through Taguchi method and SA is below

Method	Material removal rate(mm^3/min)	Flank wear width (mm)
Taguchi method	12992.60	0.741
Simulated annealing	13912.32	0.716

From the table shows that SA gives better results when compared to Taguchi method.

The computational experiments may be conducted considering various other parameters like coolant, lubricant etc. By using the above parameters it is possible to obtain results better than the results shown in above table.

References:

1. Hari Singh & Pradeep Kumar, 2004, “Tool wear optimization in turning Operation by Taguchi method”, Indian Journal of Engineering & Material Sciences, vol. 11, 19 – 24.
2. C. Y. Nian, W. H. Yang, Y.S.Tarng, 1999, “Optimization of turning operations with multiple performance characteristics”, Journal of Material Processing and Technology, 95, 90 – 96.
3. Radu Pavel, Keith Sinram, Dana Combs, Michael Dies, loan Marinescu, 2001, “Suface quality and tool wear in Interrupted Hard Turning of 1137 Steel Shafts”, Journal of Material Processing and Technology, 1 – 6.
4. S. K. Choudry, P. Srinivas, 2004, “Tool wear prediction in turning”, Journal of Material Processing and Technology, 153 – 154, 276 – 280.
5. N. S. Mohan, A. Ramachandran, S. M. Kulkarni, 2005, “Optimization of process parameter during drilling of glass-fiber polyster reinforced composite using DOE and ANOVA”, Journal of Material Processing and Technology, 896 – 902.

6. Kirkpatrick. S, Gelatt Jr CD, Vecchi MP, 1983, "Optimization by simulated annealing, Science, 220(4598), 671 – 680.
7. Kalyanmoy deb, 2000, "Optimization for Engineering Design: Algorithms and Examples", Prentice – Hall of India Pvt Limited, New Delhi.
8. Constantino Tsallis, Daniel A. Stariolo, 1996, "Generalized simulated Annealing", Physica A, 233, 395 – 406.
9. Hong yc, Zhiping Lin, 2005, "Speed-up simulated annealing by parallel coordinates", European Journal of Operational Research.
10. K. Babu, N. Baskar, P. Asokan, R. Saravanan, 2004, "Multi – objective optimization of surface grinding operations using memtic algorithm", Proceeding of the National Conference on Modeling and Analysis of Production Systems, 283 – 327.