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Multi-Response Parameter Optimization of Burnishing Process Through Taguchi Technique

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Abstract - Determination of parametric settings that can simultaneously optimize multiple responses of the roller burnishing process is the main objective of this paper. This study presents the multi-response optimization of roller burnishing parameters using the Taguchi technique. Experiments are designed and conducted based on Taguchi's L9 orthogonal array design. The burnishing process parameters are burnishing speed, burnishing feed rate, number of passes and the responses are surface roughness, hardness and tensile strength. The Taguchi's signal-to-noise (S/N) ratio and analysis of variance (ANOVA) are determined based on their performance characteristics to analyses and evaluate the optimum combination levels of the roller burnishing parameter settings. For multi-response optimization of the burnishing parameters, the WSN ratio method is adopted as it leads to better optimization performance as compared to other methods because it involves lesser computational complexity. The individual optimal combinations for each response were found through the main effect plots obtained after calculating the S/N ratio. The percentage contributions for each response are calculated through analysis of variance, giving insight to the influence they have on the response. The optimal factor-level combination obtained for the multi-response optimization of roller burnishing parameters is obtained as **A3B1C3.**

1.0 INTRODUCTION

Burnishing is a post finishing operation, in which highly polished ball or roller burnishing tools are pressed against pre-machined surfaces to plastically deform peaks into valleys. Today, it has become a beneficiary process among the conventional finishing operations in metal finishing processes in industries because of its many advantages. Burnishing processes are used in manufacturing to improve the size, surface finish, or surface hardness of a workpiece. It is essentially a forming operation that occurs on a small scale. Burnishing is the plastic deformation of a surface due to sliding contact with another object. It smooths the surface and makes it shinier. Burnishing may occur on any sliding surface if the contact stress locally exceeds the yield strength of the material. The phenomenon can occur both unintentionally as a failure mode, and intentionally as part of a manufacturing process. It is a squeezing operation under cold working. Burnishing is also known by various other names such as super finishing process and ballizing process.

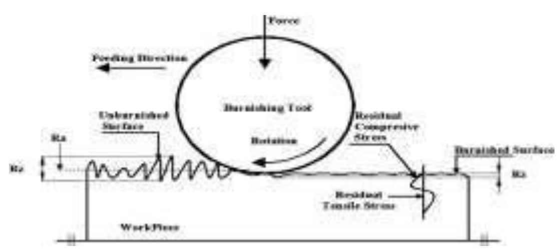


Figure 1.1 Mechanism of burnishing, converting peaks into valleys

Burnishing also occurs on surfaces that conform to each other, such as between two flat plates, but it happens on a microscopic scale. Even the smoothest of surfaces will have imperfections if viewed at a high enough magnification. The imperfections that extend above the general form of a surface are called asperities, and they can plow material on another surface just like the ball dragging along the plate. The combined effect of many of these asperities produce the smeared texture that is associated with burnishing. The effects of burnishing are normally undesirable in mechanical components for a variety of reasons, sometimes simply because its effects are unpredictable. Even light burnishing will significantly alter the surface finish of a part. Initially the finish will be smoother, but with repetitive sliding action, grooves will develop on the surface along the sliding direction. The plastic deformation associated with burnishing will harden the surface and generate compressive residual.

It is observed that the conventional machining methods such as turning and milling leave inherent irregularities on machined surfaces and it becomes necessary to very often resort to a series of finishing operations with high costs. However, conventional finishing processes like grinding, honing and lapping are traditionally used finishing processes, but these methods essentially depend on chip removal to attain the desired surface finish, these machining chips may cause further surface abrasion and geometrical tolerance problems. Accordingly, burnishing process offers an attractive post-machining alternative due to its chip less and relatively simple operations.

1.1 CLASSIFICATION OF BURNISHING PROCESS

a) Ball Burnishing: In this process the deformation element is hard ball. The material used for ball are generally alumina carbide ceramic, cemented carbide, silicon nitride ceramic, silicon carbide ceramic, bearing steel. In ball burnishing there is a point contact between ball and work piece. Here the ball acts as tool in deformation of the surfaces layer, for the specified normal force it gives high specific pressure, additional fatigue strength, micro hardness & depth of work hardening layer as compared to roller burnishing.

b) Roller Burnishing: In this cold working process roller burnishing produces a superior surface finish by the pure rotation of hardened rollers over a turned metal surface. Whereas all machined surfaces consist of a sequence of up-downs (peaks-valleys) of irregular height and spacing, the plastic deformation creates a displacement of the material of the peaks which into the valleys. It results into a mirror-like finish with work hardened, wear, corrosion and fatigue resistant surface.

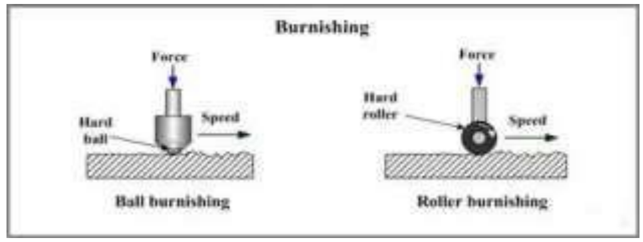


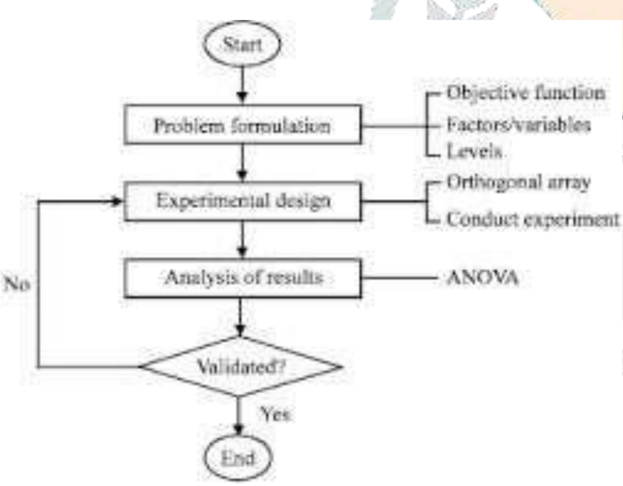
Figure 1.2 Types of burnishing

2.0 LITERATURE SURVEY

Literature review on multi-response optimization methods often require process conditions for two or more response variables that are contradictory. The goal of multi-response optimization is, therefore, to find out the settings of the input variables that can achieve an optimal compromise of the response variables. With this aim, several multi-response optimization methods, mostly response surface methodology-based, were proposed in the statistical literature. These include desirability function approach (Derringer and Suich, 1980; Kim and Lin, 2000), multivariate loss function approach (Pignatelli, 1993; Tsum, 1999), Mahala Nobis distance minimization approach (Khouri and Conlon, 1981), etc. These mathematically rigorous techniques are usually impractical for application by the process engineers who may not have a strong background in mathematics/statistics. Some researchers were also motivated to make use of the techniques of artificial intelligence, like artificial neural network (Hsieh and Tong, 2001), genetic algorithm (Jayapal et al., 2005), etc. for optimization of multi-response processes. The problem with the artificial intelligence-based techniques is that, in these approaches, the parameters can be set optimally, but nothing can be known about the possible relationship between the control factors and responses, and therefore, they do not help the process engineers to acquire sufficient experience during optimization of the concerned process. One serious limitation of Taguchi method is that it focuses on optimization of single response only. Considerable researches have been carried out aiming to establish an objective method for solving multi-response optimization problems using Taguchi method. Some of the proposed approaches in this regard, usually found in the engineering literature, are WSN ratio method (Tai et al., 1992), GRA method (Lin and Lin, 2002), MRSN ratio method (Ramakrishnan and Karuna Moorthy, 2006), utility theory method (Walia et al., 2006) and VIKOR method (Tong et al., 2007). In general, the required process conditions for two or more response variables are contradictory. Therefore, a commonly adopted approach for tackling the multi-response problem is to first define an overall process performance index (PPI) and then to optimize the PPI. In this process, the multi-response problem is transformed into a single response problem, which can be easily solved. Thus, in these approaches, the quality losses or SN ratios of individual responses are first converted into a PPI and then, the factor-level combination that would optimize the PPI is determined examining the level averages on the PPI. All the necessary computations for this purpose can be performed using EXCEL worksheet or Minitab Software. Therefore, these methods are well acceptable to the process engineers.

2.1 TAGUCHI DESIGN METHOD

The procedure of Taguchi design method is illustrated as follows:



2.2 ORTHOGONAL ARRAYS

Taguchi has developed a system of tabulated designs (arrays) that allow for the maximum number of main effects to be estimated in an unbiased (orthogonal) manner, with a minimum number of runs in the experiment. Orthogonal arrays are used to systematically vary and test the different levels of each of the control factors. Commonly used OAs includes the L4, L9, L12, L18, and L27. The columns in the OA indicate the factor and its corresponding levels, and each row in the OA constitutes an experimental run which is performed at the given factor settings. Typically, either 2 or 3 levels are chosen for each factor. Selecting the number of levels and quantities properly constitutes the bulk of the effort in planning robust design experiments. If there is an experiment having 3 factors which have three values, then total number of experiments is 27. Then results of all experiment will give 100% accurate results. In comparison to above method the Taguchi orthogonal array make list of nine experiments in a particular order which cover all factors. Those nine experiments will give 99.96% accurate results. By using this method, number of experiments are reduced to 9 instead of 27 with almost same accuracy.

Table 2.1 Standard type of S/N ratios

Signal to Noise ratio	Use when the goal is to	S/N Ratio Formula
Larger is better	Maximize the response	S/N = -10xlog10(Sum $(1/Y^2)/n$)
Nominal is best	Standard deviations only	S/N = -10xlog10(S^2)
Nominal is best	Standard deviations only	S/N = 10xlog10(Ybar^2/ S^2)
Smaller is better	Minimize the response	S/N = -10xlog10(Sum $(Y^2)/n$)

There are three standard types of S/N ratios depending on the desired performance response.

- Larger-the-better: This term is applied to problems where maximization of the quality characteristic of interest is sought and thus is referred to as the larger-the better type problem.
- Smaller-the-better: This termed is used for a problem where minimization of the characteristic is intended.
- Nominal-the-best: A nominal-the-best type of problem is one where minimization of the mean squared error around a specific target value is desired. Adjusting the mean on target by any means renders the problem to a constrained optimization problem.

3.0 EXPERIMENTAL

Burnishing process parameters, Speed always refers to the spindle and the work piece. When it is stated in revolutions per minute (rpm) it tells their rotating speed. But the important feature for a particular Boring operation is the surface speed, or the speed at which the work piece material is moving past the cutting tool. It is simply the product of the rotating speed timing the circumference of the work piece before the cut is started? It is expressed in meter per minute (m/min), and it refers only to the work piece. Every different diameter on a work piece will have a different cutting speed, even though the rotating speed remains the same. v = πDN/1000 mm/min. Feed rate is defined as tool's distance travelled during one spindle revolution. Basically, Feed rate is the velocity at which the tool is fed, that is, advanced against the workpiece. Feed rate and cutting speed are mostly determined by the material that is being machined. In addition, the deepness of the cut, size and condition of the lathe, and rigidity of the lathe should still be considered. Number of passes is defined as the number of times a tool passes completely during machining that determines the amount of time a job has been under that machining process on the basis of the number of times the cutting tool has passed.

Three experimental factors and three levels for each factorare considered. So, L9 orthogonal array is taken and the experimental combinations are shown in table below.

Table 3.1 Process Parameters for Burnishing

CODE	PARAMETER	LEVELS L1	L2	L3
A	SPEED	720	1080	1440
B	FEED	0.5	1.0	1.5
C	NUMBER OF PASSES	1	2	3

3.1 EXPERIMENTAL SETUP AND JOB SPECIFICATIONS

Figure 3.1 ø14mm x 200mm mild steel round bars

Figure 3.2 Centre Lathe Machine

3.2 OBTAINING RESPONSES

The responses are obtained after the burnishing process is complete using the following testing apparatus, as per the requirement of the analysis and optimization of the parameters.

Table. 3 Conditions of burnishing

Machine Tool	Centre lathe Machine
Work-piece	Mild steel
Dimensions/Size	Ø 14mm x 200mm
Cutting tool	Single roller burnishing tool
Cutting Velocity	720, 1080, 1440
Feed rate	0.5, 1, 1.5
Number of Passes	1, 2, 3
Lubrication	No

Trials	Tensile strength N/mm^2
1	0.585
2	0.315
3	0.603
4	0.396
5	0.639
6	0.612
7	0.639
8	0.612
9	0.621

Table 3.2 Tensile strength calculated from UTM

Table 3.3 Surface roughness calculated with surface rroughness testing apparatus

Trials	Surface roughness (µm)
1	1.65
2	2.0
3	3.9
4	2.23
5	3.7
6	3.2
7	1.0
8	2.3
9	4.10

Table 3.4 Hardness calculated from Brinell's hardness test

Trials	Hardness (N/mm^2)
1	153.53
2	153.53
3	162.11
4	168.58
5	177.27
6	153.53
7	168.58
8	186.91
9	162.11

3.3 STATISTICAL ANALYSIS AND OPTIMIZATION

Table 3.5 Basic L9 orthogonal array design

Trial	LEVEL		
	L1	L2	L3
1	*1*	*1*	*1*
2	*1*	*2*	*2*
3	*1*	*3*	*3*
4	*2*	*1*	*2*
5	*2*	*2*	*3*
6	*2*	*3*	*1*
7	*3*	*1*	*3*
8	*3*	*2*	*1*
9	*3*	*3*	*2*

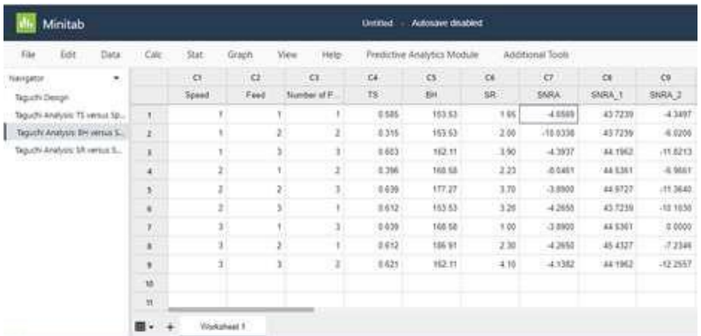
The analysis begins with using a statistical analysis software called Minitab. The Taguchi design is created by determining the design parameters in the software. A robust design of parameters is obtained according to Taguchi's design of experiments. The L9 orthogonal array is chosen for the control factors because it is the most efficient orthogonal design to accommodate the three factors at three levels.

3.4 ANALYZE TAGUCHI DESIGN

After the Taguchi design is created, the next step is to analyze the design. The analysis of Taguchi design is to obtain the S/N ratios of the responses with respect to the design parameters. The S/N ratio for tensile strength and hardness demands for the LTB type criterion whereas for surface roughness, STB type of criterion is viable. Since, tensile strength and hardness are essentially required to be large and surface roughness to be smaller. The S/N ratio values are calculated with the formula and verified using the Minitab software.

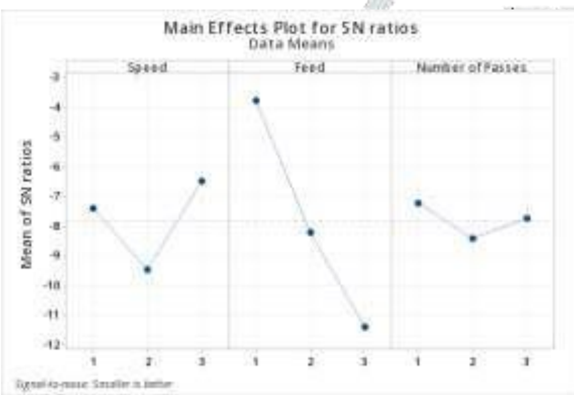
Table 3.5 S/N ratio calculations

S.no	SR	TS	BH	SNRA1	SNRA2	SNRA3
1	1.65	0.585	153.53	-4.3497	-4.6569	43.7239
2	2.00	0.315	153.53	-6.0206	-10.0338	43.7239
3	3.90	0.603	162.11	-11.8213	-4.3937	44.1962
4	2.23	0.396	168.58	-6.9661	-8.0461	44.5361
5	3.70	0.639	177.27	-11.3640	-3.8900	44.9727
6	3.20	0.612	153.53	-10.1030	-4.2650	43.7239
7	1.00	0.639	168.58	0.0000	-3.8900	44.5361
8	2.30	0.612	186.91	-7.2346	-4.2650	45.4327
9	4.10	0.621	162.11	-12.2557	-4.1382	44.1962



	C1 Speed	C2 Feed	C3 Number of P...	C4 TS	C5 BH	C6 SR	C7 SNRA	C8 SNRA_1	C9 SNRA_2
1	1	1	1	0.585	153.53	1.65	-4.6569	43.7239	-4.3497
2	1	2	2	0.315	153.53	2.00	-10.0338	43.7239	-6.0206
3	1	3	3	0.603	162.11	3.90	-4.3937	44.1962	-11.8213
4	2	1	2	0.396	160.58	2.23	-8.0461	44.5361	-6.9661
5	2	2	3	0.639	177.27	3.70	-3.8900	44.9727	-11.3640
6	2	3	1	0.612	153.53	3.20	-4.2650	43.7239	-10.1030
7	3	1	3	0.639	160.58	1.00	-3.8900	44.5361	0.0000
8	3	2	1	0.612	186.91	2.30	-4.2650	45.4327	-7.2346
9	3	3	2	0.621	162.11	4.10	-4.1382	44.1962	-12.2557
10									
11									

Figure 3.3 S/N ratios verified using Minitab 21 Software



Graph 3.1 Main effect plot for Surface roughness

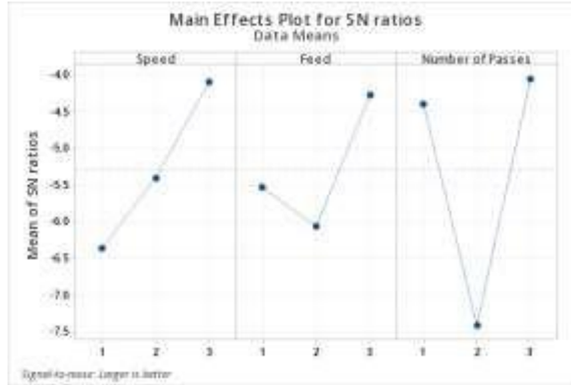
The optimal combination obtained for minimizing the surface roughness is 3rd level of speed (1440 RPM), 1st level of feed (0.5 mm/min) and 1st level of number of passes (1 pass) i.e., A3B1C1.

Table 3.8 Response table for surface roughness

Response Table for Signal to Noise Ratios

Smaller is better

Level	Speed	Feed	Number of Passes
1	-7.397	-3.772	-7.229
2	-9.478	-8.206	-8.414
3	-6.497	-11.393	-7.728
Delta	2.981	7.621	1.185
Rank	2	1	3



Graph 3.9 Main effect plot for tensile strength

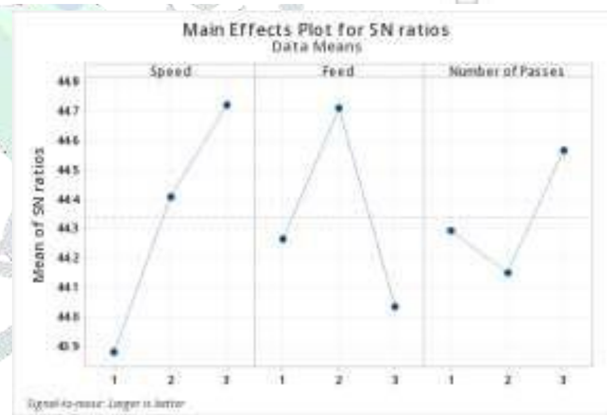
The optimal combination obtained for retaining the maximum tensile strength is 3rd level of speed (1440 RPM), 3rd level of feed (1.5 mm/min) and 3rd level of number of passes (3 passes) i.e., A3B3C3.

Table 3.9 Response table for tensile strength

Response Table for Signal to Noise Ratios

Larger is better

Level	Speed	Feed	Number of Passes
1	-6.361	-5.531	-4.396
2	-5.400	-6.063	-7.406
3	-4.098	-4.266	-4.058
Delta	2.264	1.797	3.348
Rank	2	3	1



Graph 3.3 Main effect plot for hardness

The optimal combination obtained for retaining the maximum hardness is 3rd level of speed (1440 RPM), 2nd level of feed (1.0 mm/min) and 3rd level of number of passes (3 passes) i.e., $A_3B_2C_3$

Table 3.10 Response table for hardness

Response Table for Signal to Noise Ratios

Larger is better

Level	Speed	Feed	Number of Passes
1	43.88	44.27	44.29
2	44.41	44.71	44.15
3	44.72	44.04	44.57
Delta	0.84	0.67	0.42
Rank	1	2	3

3.5 ANALYSIS OF VARIANCE

ANOVA is a statistical technique which provides important conclusions based on analysis of the experimental data. This technique is very useful for revealing the level of significance of the influence of factors or interaction between factors on a particular response. Basically, it is used to determine the individual interactions of all of the control factors in the test design. This analysis was carried out on a 5% significance level and a 95% confidence level. The significance of control factors in ANOVA is determined by comparing the F values of each control factor. The last column of the table shows the percentage value of each parameter contribution which indicates the degree of influence on the process performance. The final ANOVA results for surface roughness, hardness and tensile strength are illustrated below:

Table 3.11 Speed v SR

Analysis of Variance

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
Speed	2	0.6124	6.44%	0.6124	0.3062	0.21	0.819
Error	6	8.8956	93.56%	8.8956	1.4826		
Total	8	9.5080	100.00%				

Table 3.12 Feed v SR

Analysis of Variance

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
Feed	2	6.657	70.02%	6.657	3.3287	7.01	0.027
Error	6	2.851	29.98%	2.851	0.4751		
Total	8	9.508	100.00%				

Table 3.13 Number of passes v SR

Analysis of Variance

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
Number of Passes	2	0.3964	4.17%	0.3964	0.1982	0.13	0.880
Error	6	9.1116	95.83%	9.1116	1.5186		
Total	8	9.5080	100.00%				

Table 3.14 Speed v TS

Analysis of Variance

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
Speed	2	0.02306	20.78%	0.02306	0.01153	0.79	0.497
Error	6	0.08791	79.22%	0.08791	0.01465		
Total	8	0.11097	100.00%				

Table 3.15 Feed v TS

Analysis of Variance

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
Feed	2	0.01361	12.26%	0.01361	0.006804	0.42	0.673
Error	6	0.09736	87.74%	0.09736	0.016227		
Total	8	0.11097	100.00%				

Table 3.16 Number of passes vs TS

Analysis of Variance

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
Number of Passes	2	0.05935	53.48%	0.05935	0.029673	3.45	0.101
Error	6	0.05162	46.52%	0.05162	0.008604		
Total	8	0.11097	100.00%				

Table 3.17 Speed v BH

Analysis of Variance

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
Speed	2	398.9	37.37%	398.9	199.4	1.79	0.246
Error	6	668.6	62.63%	668.6	111.4		
Total	8	1067.5	100.00%				

Table 3.18 Feed v BH

Analysis of Variance

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
Feed	2	277.1	25.96%	277.1	138.6	1.05	0.406
Error	6	790.3	74.04%	790.3	131.7		
Total	8	1067.5	100.00%				

Table 3.19 Number of passes v BH

Analysis of Variance

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
Number of Passes	2	94.93	8.89%	94.93	47.47	0.29	0.756
Error	6	972.54	91.11%	972.54	162.09		
Total	8	1067.47	100.00%				

3.6 WSN Ratio Method

The WSN ratio i.e., weighted signal to noise ratio is calculated in order to obtain optimal process condition. The basic approach for solving a multi-response optimization problem involves conversion of multi-responses into PPI and estimation of factor effects of PPI and then determining the optimal factor-level combination that can optimize the PPI value. But, since many research papers and scientific studies have concluded that the WSN ratio method out of all other four methods i.e., GRA, MRSN, VIKOR and the utility approach, gives the best optimal factor level combination, only WSN ratio is deliberately calculated, another reason being its less computational complexity

The scaled SN ratio values of each response are obtained for all the trials. The scaled SN ratio value ($S\eta_{ij}$) for j_{th} response in i_{th} trial is computed using the following equation:

$$S\eta_{ij} = \frac{\eta_{ij} - \eta_j^{\min}}{\eta_j^{\max} - \eta_j^{\min}}$$

where $S\eta_{ij}$ = scaled SN ratio for j_{th} ($j = 1, 2, \ldots, p$) response in i_{th} trial, $\eta j^{\min} = \min\{\eta_{1j}, \eta_{2j} \ldots, \eta_{mj}\}$ and

$\eta j^{\max} =. \max\{\eta_{1j}, \eta_{2j} \ldots, \eta_{mj}\}$

Table 3.20 WSN ratios

Trial	*Factor A*	*Factor B*	*Factor C*	*SNRA1 (SR)*	*SNRA2 (TS)*	*SNRA3 (BH)*	*WSN ratio*
1	1	1	1	-4.3497	-4.6569	43.7239	**0.5061**
2	1	2	2	-6.0206	-10.0338	43.7239	**0.1693**
3	1	3	3	-11.8213	-4.3937	44.1962	**0.4058**
4	2	1	2	-6.9661	-8.0461	44.5361	**0.4097**
5	2	2	3	-11.3640	-3.8900	44.9727	**0.6005**
6	2	3	1	-10.1030	-4.2650	43.7239	**0.3711**
7	3	1	3	0.0000	-3.8900	44.5361	**0.8242**
8	3	2	1	-7.2346	-4.2650	45.4327	**0.7820**
9	3	3	2	-12.2557	-4.1382	44.1962	**0.4118**

The WSN ratio was computed from the following formula:

$$WSN_i = \sum_{j=1}^{p}(W_j \times S\eta_{ij})$$

where $S\eta_{ij}$ = scaled SN ratio for j_{th} (j = 1, 2, …, p) response in i_{th} trial,

$\eta j^{min} = \min\{\eta_{1j}, \eta_{2j}, \ldots, \eta_{mj}\}$ and $\eta j^{max} = \max\{\eta_{1j}, \eta_{2j}, \ldots, \eta_{mj}\}$

The scaled SN ratio values of each response for all the trials is obtained. The scaled SN ratio value ($S\eta_{ij}$) for j_{th} response in i_{th} trial is computed using the above equation. The WSN ratio value for *ith* trial is computed as follows as follows:

$$WSN_i = \sum_{j=1}^{p}(W_j \times S\eta_{ij})$$

where W_j is the assigned weight for j_{th} response and $\sum_{j=1}^{p} W_j = 1.$

In the formula above, the sum of weights assigned is for the computation of WSN ratio is 1. Hence, in our study the weights were assigned equally to all the three ratios. The weights were assigned as 0.33 respectively. The WSN ratios are calculated and are tabulated in table 21. The level averages are obtained by calculating the average of the WSN ratio values with respect to each level and its factor. The arithmetic average is used to calculate the factor effects on WSN and then the optimal factor-level combination is decided by higher-the-better factor effects. This finally permits us to achieve an optimal factor-level combination that optimizes the multiple responses.

Table 3.21 Level averages of WSN

FACTOR	*WSN*		
	Level 1	*Level 2*	*Level 3*
A	0.3604	0.4604	**0.6726**
B	***0.58***	0.5172	0.3962
C	0.5530	0.3302	**0.6101**

4. RESULTS AND DISCUSSIONS

This study envisages the fact that roller burnishing process has multiple performance measures which are affected by several process parameters. The multiple response optimization of roller burnishing process through Taguchi technique is achieved through WSN ratio in order to compute the optimal factor-level combination. But before that, individual optimal combinations for the three responses were gathered to optimize the parametric settings. Also, the factors affecting the responses along with the contributions of their influence were studied and established using the analysis of variance on the Minitab 21 Software. Firstly, the optimal combination obtained for minimizing the surface roughness was 3rd level of speed (1440 RPM), 1st level of feed (0.5 mm/min) and 1st level of number of passes (1 pass) i.e., A3B1C1. The optimal combination obtained for retaining the maximum tensile strength was 3rd level of speed (1440 RPM), 3rd level of feed (1.5 mm/min) and 3rd level of number of passes (3 passes) i.e., A3B3C3. The optimal combination obtained for retaining the maximum hardness was 3rd level of speed (1440 RPM), 2nd level of feed (1.0 mm/min) and 3rd level of number of passes (3 passes) i.e., A3B2C3. This was determined by studying the main effect plots of the S/N ratios of each response.

5. CONCLUSION AND FUTURE SCOPE OF WORK

This study concludes the optimization of multiple responses using the WSN ratio method, giving us an optimal factor level combination of the parameter settings of the roller burnishing process, which is better, easier and less complex to compute as compared to the other methods. This is achieved using the robust design method i.e., Taguchi method developed by Genichi Taguchi. Apart from the main objective, single responses were also optimized by studying the main effect plots of the s/n ratios that were required for the computation of WSN ratio. ANOVA helped obtain the factors along with their contributions and the influence they had on the quality characteristics of the mild steel specimen. This study of optimization may help in better manufacturing and machining of goods and products for consumers, in hindsight, offering better ways to improve and maintain the quality of goods and maintain the quality of the machines producing such goods. Optimization of parameters such as time consumption, power consumption and machining conditions such as friction and lubrication, controlled environment set ups and use of non-conventional methodologies for alternate materials opens up future scope of work for further study and understanding of optimization of roller burnishing parameters. Results of such studies will open the gates to better manufacturing and production increasing accuracy, precision, retention of good quality characteristics.

REFERENCES

1. Mohd Shais Khan, Safia, Mohammed Ibrahim Khan (2019) 'Experimental Investigation of Mild Steel Components by Roller Burnishing Process and its Mechanical Properties by Taguchi Method' *International Research Journal of Engineering and Technology (IRJET),* Volume: 06 Issue: 02.

2. Chakravorty, R., Gauri, S.K. and Chakraborty, S. (2013) 'A study on the multi-response optimisation of EDM processes', *Int. J. Machining and Machinability of Materials*, Vol. 13, No. 1, pp.91–109.

3. Phadke, M.S. (1989) Quality Engineering Using Robust Design, Prentice Hall, Englewood Cliffs,New Jersey.

4. Derringer, G. and Suich, R. (1980) 'Simultaneous optimization of several response variables', Journal Quality Technology, Vol. 12,No. 4, pp.214–219.

5. Khuri, A.I. and Conlon, M. (1981) 'Simultaneous optimization of multiple responses represented by polynomial regression functions', Technometrics, Vol. 23, No. 4, pp.363– 375.

6. Walia, R.S., Shan, H.S. and Kumar, P.(2006) 'Multi-response optimization of CAFAAFM process through Taguchi method and utility concept', Materials and Manufacturing Processes,Vol. 21, No. 8, pp.907–914.

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