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Surface hardness improvement in surface grinding process using combined Taguchi method and regression analysis

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Abstract
This study has implemented a combined Taguchi method and regression analysis to optimize grinding parameters to enhance the superficial hardness of workpiece. The workpiece material is AISI1045 annealed steel and the process parameters include depth of cut, wheel speed, workpiece speed, cross feed, and mode of dressing. The DOE technique is used to find out the number of experiments by using Taguchi's L27 which includes five parameters (depth of cut, wheel speed, workpiece speed, cross feed, and mode of dressing) at three levels. By applying the mean response and signal to noise ratio (SNR), the best optimal grinding condition has been reached at D3/S3/W2/F2/M1 i.e. depth of cut is 0.03 mm, wheel speed is 32 m/s, workpiece speed is 10 m/min, cross feed is 5 mm/rev, and mode of dressing is fine. Based on the ANOVA, the significance and percentage contribution of each parameter is determined. It has been revealed that depth of cut has maximum contribution on surface hardness. The mathematical model of surface hardness has been developed using regression analysis as a function of the above mentioned independent variables. A confirmation experiment, as final step, has been carried out with 94.5% confidence level to certify optimized result.

Keywords : Surface grinding, Microhardness, Microstructure, Optimization, Taguchi, Regression analysis

1. Introduction

Grinding is a process of material removal in the shape of small chips which are due to the mechanical effects of abrasive particles of grinding wheel. It is basically a finishing process which directly influences dimensional and geometrical accuracy and quality of products. This typical grinding process has an intrinsic potential which can induce an individual hardened surface in products (Brockhoff and Brinksmeier 1999). Under the proper process parameters, obtaining a product with a desired surface hardness can be conditionally possible. Therefore, controlling of process parameters is often considered as one of the fundamental concerns in grinding process by researchers and engineers.

Grinding process researches in which surface hardness of components are enhanced, have been recently more studied. The composite heat flux generated and mechanical loads in grinding is utilized to induce phase transformation in the top layers of products, whereas, the same surface performance of the component could be attainable as implementing other superficial strengthening processes (Zhang, Ge et al. 2009). Hence, the surface hardening of components using grinding can be a cost-effective technique for inducing compressive residual stress as a realistic substitution for the induction hardening or flame hardening process (Venkatachalapathy and Rajmohan 2003).

Basically, existence of tensile residual stress can significantly influence the characteristics of the components: reduced static and dynamic strength, weakened resistance to stress corrosion, etc. (X.X. Yu 1999). In materials with high brittleness, the existence of thermal stress normally causes many micro cracks on the surface of the components, which can also lead to increase the surface roughness (X.X. Yu 1999). It has been represented that the main sources of residual stresses include plastic deformation due to grinding forces and thermal stresses. The former factor leads to compressive residual stress which is often lower than the tensile one due to the later source (X.X. Yu 1999). Therefore, the residual stress remained in the grinded surface is generally tensile one. In order to prevent surface damage and reduce the tensile

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residual stress, several techniques including heat treatment, lapping, and shot peening are recommended. However, there are two important restrictions when these treatments are applied: (a) an additional process is needed; and (b) expensive equipment is required unfortunately. The tensile residual stress can be reduced to an acceptable level or even replaced by compressive residual stress if grinding process can be controlled under a certain condition (Capello and Semeraro 2002, Zhang, Ge et al. 2009). This possibility has been confirmed examining several grinding experiments. Among various methods of grinding process, low stress grinding condition is recommended for components which are subjected to high mechanical stress and corrosive environments. Low stress grinding provides a particular condition in which compressive residual stress can be induced in the surface of products (Bellows 1978). Grind-hardening processes can be considered as a low-stress-grinding process which utilizes the grinding heat for inducing phase transformations in annealed or tempered steels.

In order to understand how the grinding parameters can influence surface hardness, very expensive computer numerical control (CNC) grinding machines and equipment and numerous experiments are needed for the shop floors. Therefore, the optimization methods, as a strong substitution solution for investigating such processes, seems more promising (Fazli Shahri and Mahdavinejad 2018). Recently, they have been increasingly employed by many scientists and several optimization attempts have been done by many researchers to provide optimal condition to improve processes and products. Selection of grinding parameters is traditionally carried out by process planners either on the basis of their experience on the shop floor or with the help of the data handbooks. Optimization of grinding processes is still as one of the most challenging problems because of its high complexity and nonlinearity. It is shown that how back propagation (BP) neural networks can be employed to model and optimize grinding processes, using creep feed grinding of alumina with diamond wheels as an example (Liao and Chen 1994). It has been proposed an improved differential evolution algorithm, named the Taguchi-sliding-based differential evolution algorithm (TSBDEA) (Lee, Hsu et al. 2011). It has been optimized continuous-dress creep-feed grinding process to reduce cycle time and wheel consumption by adaptively adjusting work-speed and dressing need based on grinding models and process power monitoring (Guo, Campomanes et al. 2003). It has been studied an enumeration method to optimize the grinding process parameter. It is used in this approach to select input parameters to achieve an optimal cutting condition (Gupta, Shishodia et al. 2001). It has been presented an optimum strategy permitting burn to appear in the rough grinding stage (cylindrical plunge grinding). In this study, the objective function and constraint functions for the multi-parameter optimum grinding process have been built to minimize production time while ensuring part quality requirements. The non-linear optimum grinding control parameters have been obtained through computer simulation, and the actual grinding process had been controlled by these parameters (Li, Wang et al. 2002). It has been presented a multi-objective optimization model based on the genetic algorithms. In this study, minimum processing time and the optimal carbon efficiency were considered as the optimization objectives. An orthogonal experiment case of the key machining processing was developed to confirm the practicability and feasibility (Deng, Lv et al. 2016).

Although, many researches can be lists that investigate the grinding process to optimize the parameters, there is a lack for optimization of grinding taking five parameters, such as depth of cut, wheel speed, workpiece speed, cross feed, and mode of dressing into account. The former, mode of dressing, is introduced as a new aspect of this study, which is rarely considered by researchers.

In this study, the effects of surface dry-grinding parameters on surface hardness of AISI1045 steel are investigated. A Taguchi based optimization method, as a statistical technique is employed to design the experiments in an orthogonal array L27 and maximize the surface hardness results. After designing the experiments, grinding process setup, preparation of the materials and heat treatment procedures, recording the surface hardness, and details of metallorgraphical studies are provided. Surface hardness values are evaluated by metallographic observations and micro-hardness measurements. After performing the experiments, signal-to-noise (S/N) ratios are deduced from the Taguchi technique to measure the quality characteristics with emphasis on variation and analyzes the experimental data. In the following, a regression analysis is also utilized to predict a linear correlation for the objective function, surface hardness, by using the statistical tool Mini Tab. Furthermore, an estimation of the error variance and evaluation of statistical significance of the obtained model equation using ANOVA are performed. Finally, a confirmation experiment is conducted to verify the optimal grinding parameters obtained from the parameter design. As a result, the combination of Taguchi's method and regression analysis in this study, leads to superior parameter values for surface grinding process.

2. Experimental procedure

2.1 Preparation of Samples (Heat treatment procedure)

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The material used in this study was AISI1045 steel, with the chemical composition given in Table 1 (Wegst 1998), which was ground with determined operating parameters in the absence of coolant within the dry-grinding condition. In fact, no cooling fluid has been used in this study. The reason for considering the dry-grinding is attributed to this fact that the surface hardness criteria has been rarely investigated in the literature.

The workpieces were cut in the dimensions $40 \times 30 \times 10 mm^3$ and all of the samples were subjected to annealing heat treatment. They were kept in the furnace for 1h and 30min at 860°C, in order to achieve a ferrite-pearlitic structure. Subsequently, for cooling of samples, they were left in the furnace to reach to the room temperature (Wegst 1998). Since, a particular crystallographic orientation of microstructural phases may affect the hardness values, the procedure of hardness measurement was performed based on Vickers hardness in a specific traverse section of the workpiece (O. Zurita 2003).

Table 1. Nominal chemical composition and mechanical properties of AISI1045 Steel (wt.%) (Wegst 1998)

C	Si	Fe	Mn	P	S	Cr
0.43-0.50	0.25	98.51 - 98.98	0.60-0.90	≤ 0.04	≤ 0.05	≤ 0.2

Modulus of elasticity	Density	Thermal expansion(20ºC)	Specific heat capacity	Tensile strength	Poisson's Ratio	Thermal conductivity	Yield strength
201 GPa	$7.872*10^3 kg/m^3$	$15.1*10\text{-}6\ ºC^{-1}$	486J/(kg*K)	585 MPa	0.290	50.9W/(m*K)	505 MPa

2.2 Grinding process

A BLOHM horizontal spindle surface grinding machine (6.5 kW), with a A60L5V10 wheel (250mm × 25mm×76.2 mm size) was employed for grinding experiments. Figure 1 illustrates the experimental setups for this study.

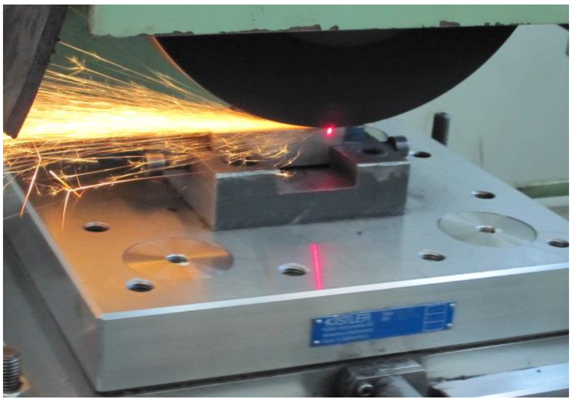

Fig 1. Experimental setups

2.3 Preparation of metallographical samples

In order to more precisely investigate the results, the microstructures of the samples were analyzed metallographically. The samples were cut perpendicular to the grinding plane. The metallographic assessments were performed according to ASTM E3-80 standard, metallographic equipment, Nitral 4% and an attack time 15s (Tottle 1984).

2.4 Measurement of surface micro-hardness

In order to study variation of surface hardness values, a Vickers micro-hardness sweep (Buheler-4046 tester) was employed in a cross section of the workpiece. The applied force for micro-hardness measurement was 100gf for 15s. The

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indentations were made with a 0.5 mm distance in the cross section of the workpieces, covering the entire surface (i.e., from one side to the other side of the workpiece). Three different indentations were made for each distance to get an average micro-hardness value. The average was calculated by neglecting the values that are significantly outside the range demarcated by the other measures. If the hardness values were obtained out of range, the indentations were continued until a representative amount achieved.

3. Design of Experiment Based on Taguchi method

Basically, DOE methods are categorized into three techniques, i.e., full factorial experiment, fractional (or partial) factorial experiment, and one-at-a-time experiment (Ross 1988). If m parameters are to be tested with L levels, a straightforward full-factorial design requires $\mathrm{L^m} = \mathrm{Level^{factor}}$. Had conventional experimental analysis been followed, 3^5=243 trials would have been necessary to yield the same information. In order to dissolve this problem to satisfy the economical aspects of experiments, Taguchi demonstrated that the number of runs can be drastically decreased based on a degrees-of-freedom approach as below:

$$N = 1 + \sum_{i=1}^{NV}(L_i - 1) \tag{1}$$

where NV is number of independent variables, and L is number of bound levels, and N is total number of experiments required. Eq. (1) shows 243 experiments of above example is reduced to only 27 repetitions. Based on Eq. (1), the Taguchi method offers the use of orthogonal arrays, a pre-manipulated combinatorial design tables, which contains the shortest possible matrix of discrete and independent variable combinations (Taguchi and Taguchi 1987). The researchers can easily adopt the most adequate orthogonal array is abbreviated as L_N, where the L refers to the number of levels and N indicates the number of trials that needs to be run for a given experiment, according to number of parameters and input levels. The current study suggests five controllable input parameters (factors) in surface grinding process, as shown in Table 2, namely depth of cut, wheel speed, workpiece speed, cross feed, and mode of dressing were considered with three different levels to evaluate the process in terms of surface hardness. In this study, L_{27} (3^5) Taguchi method indicates using a twenty-seven trial orthogonal array to examine the power of five factors at three levels. Thus, each parameter can be analyzed at three levels. Applying this orthogonal array (L_{27}), gives minimum number of experiments needed for the predictors. It means that Taguchi method can significantly reduce the amount of cost and time consumed for performing all the experiments, decrease the effects of noise factors, eliminate different results that may be obtained from three designs of the same experiment, determine interaction between different process parameters and specify the optimum experimental conditions.

Table 2. The effective factors on surface hardening and corresponding values which selected for dry-grinding tests empirically

Input Parameters		Units	Lable	Lower Level	Medium Level	Upper Level
				1	2	3
Depth of cut	a_e	mm	D	0.01	0.02	0.03
Wheel speed	v_c	m/s	S	20	25	32
Workpiece speed	v_w	m/min	W	5	10	15
Cross feed	S	mm/rev	F	1	5	10
Mode of dressing		-	M	Fine (1)	Medium (2)	Coarse (3)

(1) 0.010 mm depth, 75 mm/min cross-feed, two passes with one spark-out pass
(2) 0.020 mm depth, 150 mm/min cross-feed, two passes with no spark-out pass
(3) 0.030 mm depth, 300 mm/min cross-feed, two passes with no spark-out pass

4. Regression Method

Generally, the relationship between independent and dependent variables can be determined by regression analysis. In other words, regression analysis as one of the oldest but the most popular methodologies, is usually used to estimate dependent variables as a function of independent variables and also predict new observations. Typically, regression technique employs the least squares method by minimizing the sum of the squared residuals (Draper, Smith et al. 1966). This approach provides the advantage of investigating the relative importance of a number of predictor variables for their relationship with a response variable.

5. Results and Discussion

5.1 Analysis and calculation of Signal-to-Noise Ratio for surface hardness of AISI1045

In order to evaluate the influence of factors on a response, Taguchi's method utilizes the statistical methods of performance called means and signal-to-noise ratio (logarithmic functions of desired output to serve as objective function), for optimization to measure the deviation of quality characteristics from the desired values. Here, this ratio is that of H_{avg} (signal) to the standard deviation of surface hardness (noise). The level with the ratio "larger the better" was used for maximizing the surface hardness. For the "larger the better" characteristics (i.e. high H_{avg}), the S/N ratio is defined by Eq. (2)

$$\eta = (S/N)_i = -10\, log \frac{1}{n} \left(\sum_{j=1}^{n} \frac{1}{{Y_{ij}}^2}\right) \tag{2}$$

where, η is the S/N ratio for the larger-the-better case, 'i' is the serial number of a trial; 'Y_{ij}' is the measured value of quality characteristic for the i^{th} trial and j^{th}; 'n' is the number of repetitions for the experimental combination. Therefore, the S/N ratio is applied to ascertain the factor level that has an important variance and predict the combination of optimized grinding parameters.

One of the aim of this paper is to optimize the fabrication parameters for surface grinding with the highest surface hardness. Accordingly, the present work assigned depth of cut (factor D), wheel speed (factor S), workpiece speed (factor W), cross feed (factor F), and mode of dressing (factor M), whose respective levels were 0.01-0.03 mm, 20-32 m/s, 5-15 m/min, 1-10 mm/rev and Fine-Coarse of the adopted L27 (3^5) orthogonal array (Table 3); also, the S/N ratios were computed for each of these 27 trials. Table 3 shows the experimental layout for input grinding parameters using L27 orthogonal array and the levels associated with them. Table 3 also illustrates the H_{avg} values and S/N ratio for each experimental trial. First, the mean S/N ratio of each factor at a certain level was calculated. Hence, the mean S/N ratio for factor D at levels 1, 2 and 3 were calculated by averaging out the S/N ratios for the experiments 1-9, 10-18 and 19-27, respectively. The mean S/N ratio for every level of the other factors (S, W, F and M) was calculated in the same manner. The average values of means and S/N ratios of different parameters at various levels are given in the response table (Table 4), which demonstrates the average of the selected mean and S/N ratio for each level of the factors. According to range analysis from S/N, the effects of each parameter were ranked based on delta statistics as follows: factor D, factor S, factor M, factor W, and factor F (Table 4).

Table 3. Experimental results of L_{27} (3^5) for average surface hardness and their corresponding S/N ratios.

Experiment no.	Factors and their levels					Surface Micro-hardness for repeated tests				Calculated S/N ratio
	D	S	W	F	M	Reading 1	Reading 2	Reading 3	Mean (H_{avg})	S/N ratio for H_{avg}
1	1	1	1	1	1	174	170	172	172.0	44.7106
2	1	1	1	1	2	179	179	177	178.3	45.0247
3	1	1	1	1	3	175	177	174	175.3	44.8773
4	1	2	2	2	1	184	183	181	182.7	45.2332
5	1	2	2	2	2	186	183	185	184.7	45.3278
6	1	2	2	2	3	190	195	192	192.3	45.6811
7	1	3	3	3	1	195	194	193	194.0	45.7560
8	1	3	3	3	2	194	192	196	194.0	45.7560
9	1	3	3	3	3	190	188	191	189.7	45.5598
10	2	1	2	3	1	205	206	207	206.0	46.2773
11	2	1	2	3	2	202	204	206	204.0	46.1926
12	2	1	2	3	3	200	202	198	200.0	46.0206
13	2	2	3	1	1	211	208	211	210.0	46.4444
14	2	2	3	1	2	208	207	205	206.7	46.3054
15	2	2	3	1	3	204	205	208	205.7	46.2633
16	2	3	1	2	1	230	235	233	232.7	47.3347

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17	2	3	1	2	2	216	218	220	218.0	46.7691
18	2	3	1	2	3	218	220	216	218.0	46.7691
19	3	1	3	2	1	261	264	269	264.7	48.4540
20	3	1	3	2	2	258	259	255	257.3	48.2099
21	3	1	3	2	3	249	246	244	246.3	47.8305
22	3	2	1	3	1	277	276	279	277.3	48.8600
23	3	2	1	3	2	265	261	264	263.3	48.4101
24	3	2	1	3	3	259	255	258	257.3	48.2099
25	3	3	2	1	1	286	287	286	286.3	49.1374
26	3	3	2	1	2	280	283	281	281.3	48.9844
27	3	3	2	1	3	276	277	275	276.0	48.8182

Table 4. Response table for surface hardness (means and mean S/N ratio)

Level	Means of surface hardness (Vickers)					Mean S/N ratio				
	D	S	W	F	M	D	S	W	F	M
1	184.8	211.6	221.4	221.3	225.1	45.33	46.40	46.77	46.73	46.91
2	211.2	220.0	223.7	221.9	220.9	46.49	46.75	46.85	46.85	46.78
3	267.8	232.2	218.7	220.6	217.9	48.55	47.21	46.73	46.78	46.67
Delta	83.0	20.7	5.0	1.2	7.2	3.22	0.81	0.12	0.12	0.24
Rank	1	2	4	5	3	1	2	4	5	3

5.2 Evaluation of ANOVA

Basically, the analysis of variance (ANOVA) is used for the S/N ratios and the means for the response functions being investigated. Each linear model analysis provides the coefficients for each factor at the low level, their p-values and an ANOVA table. The results are employed to determine whether the factors are significantly related to the response data and the main significant effects and interactions of various controllable factors. The order of the coefficients by absolute value indicates the relative importance of each factor to the response. The Seq SS (sequential sums of squares) and Adj SS (adjusted sums of squares) in the ANOVA table also indicate the relative importance of each factor. The factor with the highest coefficient and biggest sum of squares indicates the largest impact. These results go back the factor ranks in the response tables. The most important outputs from an ANOVA analysis categorized in a table includes the sources of variation, their degrees of freedom (DF), and the adjusted mean squares (MS). The ANOVA table also lists the Fischer's F distribution (F-value), p-values, and their % contributions. F and p values are used in statistical significance testing to find out the confidence on the response. It means that they are employed whether the predictors (factors) are significantly related to the response. The details of ANOVA table can be arranged as below calculation:

- Source of variation shows from the factor, the interaction and the error. The total is a sum of all the sources.
- DF indicates the difference between the number of variables in the population and the number of independent observations in the sample, in this study, since the number of levels for each factor are three, number of sources of variation (five factors) minus three (DF=2).
- SS refers to sum of squares between factor and the sum of squares within error. It calculates the square of deviation from the grand mean.
- MS is calculated by dividing the sum of squares (SS) by the respective degrees of freedom (DF).
- F computed by dividing the factor mean square (MS) by the residual mean square (MS error); the factor is significant at chosen α level (α is a threshold value used to judge whether a test statistic is statistically significant) when the calculated value of F-ratio is higher than the critical F (tabulated value of F-ratio).
- P used to determine whether a factor is significant; typically compare against a desired α value. Other words, it is a measure of statistical significance that rejects the null hypothesis when the p-value is less than the significance level ($p < 0.05$).
- % contribution of each sources of variation (factor), ρ, can be between 0 and 100. ρ value of 100 demonstrates ideal fit and value of 0 shows no predictive power at all. ρ can be founded by follows Eq. (3)

(Taguchi 1986):

$$\rho = \frac{SS_d}{SS_T} \tag{3}$$

where, SS_d is the sum of squared deviations and SS_T is the total sum of squared deviations. The total sum of squared deviations in Y (output parameter), SS_T, is also calculated using Eqs. (4) and (5):

$$SS_T = SS_d + SS_e \tag{4}$$

$$SS_e = \sum_{i=1}^{n_i}(\eta_i - \eta_n)^2 \tag{5}$$

where, SS_e is the sum of squared error, n_i determines the total number of observations in the orthogonal array and η_i represents the average of the observed values (the mean S/N ratio) for the ith experiment.

5.2.1 ANOVA for S/N ratio of surface hardness

Table 5 represents that the factor ‘D’ (Depth of cut) indicates the highest sum of square value and has also the largest impact on the surface hardness followed by wheel speed, mode of dressing, workpiece speed, and cross feed. The order of impact of factors as seen in the Table 5 is as follows: D, S, M, W and F. The results confirmed that factor ‘D’ is the most significant factor, affecting maximum surface hardness, among the five under consideration, and the parameter ‘F’ becomes lowest significant in predicting the surface hardness. It is clear that, as the depth of cut rises (10-30μm), the H_{avg} increases. Each of the parameter under study possesses 2 degrees of freedom and there are 26 degrees of freedom for the total set of factors.

Table 5. ANOVA table for SN ratios for surface hardness.

Source	DF	Seq SS	Adj SS	Adj MS	F	P	Contribution (%)
Depth of cut	2	47.8996	47.8996	23.9498	583.76	0	92.25
Wheel speed	2	2.9718	2.9718	1.4859	36.22	0	5.72
Workpiece speed	2	0.0686	0.0686	0.0343	0.84	0.452	0.13
Cross feed	2	0.0602	0.0602	0.0301	0.73	0.496	0.12
Mode of dressing	2	0.2651	0.2651	0.1325	3.23	0.066	0.51
Residual Error	16	0.6564	0.6564	0.041			1.26
Total	26	51.9216					100.00

5.2.2 Linear model analysis of S/N for surface hardness

The linear model analysis based on Taguchi technique for the surface hardness carried out with the larger-the-better approach for the S/N ratios. The S/N ratios against D, S, M, W, and F gives the main effects plot for S/N ratios as in Fig.2 which shows the plot of the level average response (main effects) for S/N ratios in estimating the surface hardness. The S/N ratio for the surface hardness is maintained as ‘larger-the-better’ and the graph needs to read for each factor which indicates the highest value for the chosen S/N ratio. From this figure it can be figured out the relative consequence of each effect. A parameter, which will not lead to a significant effect on the response, will result in a line with relative horizontal slope. On the contrary, if a factor impressively affects the response, it will lead to a largest slope line in the main effect plot. It is observed from the Main effects plots for Fig. 2 that the surface hardness of AISI1045 increases with the increase of depth of cut and wheel speed. But the surface hardness of AISI1045 decreases as the mode of dressing changes from fine to coarse.

With the ANOVA and S/N, the optimal combination of the grinding parameters can be predicted as depth of cut is 0.03 mm, wheel speed is 32 m/s, workpiece speed is 10 m/min, cross feed is 5 mm/rev, and mode of dressing is fine. It can also be observed that surface hardness is higher for the parameters with highest mean of S/N ratios. Hence, based on the S/N ratio analysis, the optimal combination of D3/S3/W2/F2/M1 parameters are recommended, which provide the highest surface hardness. Here for instance, S3 indicates 3th level in the factor S is recognized. The S/N Ratio and H_{avg} are predicted as 49.2215 and 285.593 respectively by Taguchi analysis for the main effects of increasing H_{avg}. It must be noticed that above this combination of factorial levels (D3/S3/W2/F2/M1), the H_{avg} significantly decreases.

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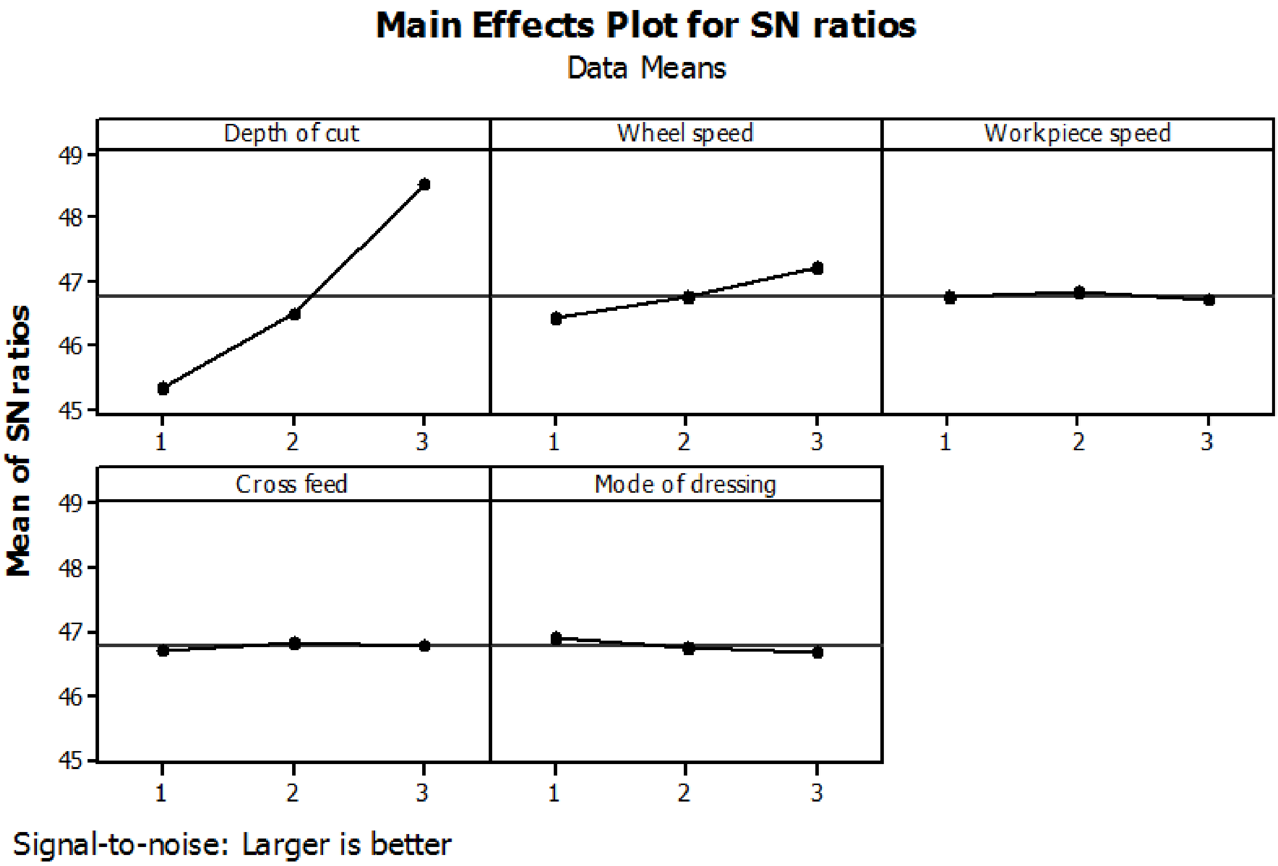

Fig 2. Main effects plot for SN ratios for surface hardness

5.2.3 Linear model analysis of means for surface hardness

The ANOVA for means for estimating the surface hardness value is shown in Table 6 and Fig.3 depicts the main effects plot for means. The sum square value for means also verifies the order of significance of the parameters as observed in the S/N ratios similar to the analysis for S/N ratios. From Table 6, it can be observed that the Workpiece speed, Cross feed, and Mode of dressing have a higher value of p (>0.05) representing that those factors are insignificant. Similarly, p-value for the factors D (Depth of cut) and S (Wheel speed) are 0.000, which indicates that the factors D and S have the most significant influence on the surface hardness. However, the remaining factors W, F, and M were found to be statistically insignificant as their % contributions are negligible. In addition to the above, the % contributions of the factors D, S, W, F, and M to the S/N ratio were also calculated as 92.25, 5.72, 0.13, 0.12, and 0.51, respectively (Table 5).

Table 6. ANOVA table for means surface hardness.

Source	DF	Seq SS	Adj SS	Adj MS	F-value	P-value	Contribution (%)
Depth of cut	2	32360.5	32360.5	16180.3	569.67	0	92.16
Wheel speed	2	1943.4	1943.4	971.7	34.21	0	5.53
Workpiece speed	2	112.7	112.7	56.3	1.98	0.17	0.32
Cross feed	2	6.7	6.7	3.4	0.12	0.889	0.02
Mode of dressing	2	237	237	118.5	4.17	0.035	0.67
Residual Error	16	454.4	454.4	28.4			1.29
Total	26	35114.7					100.00

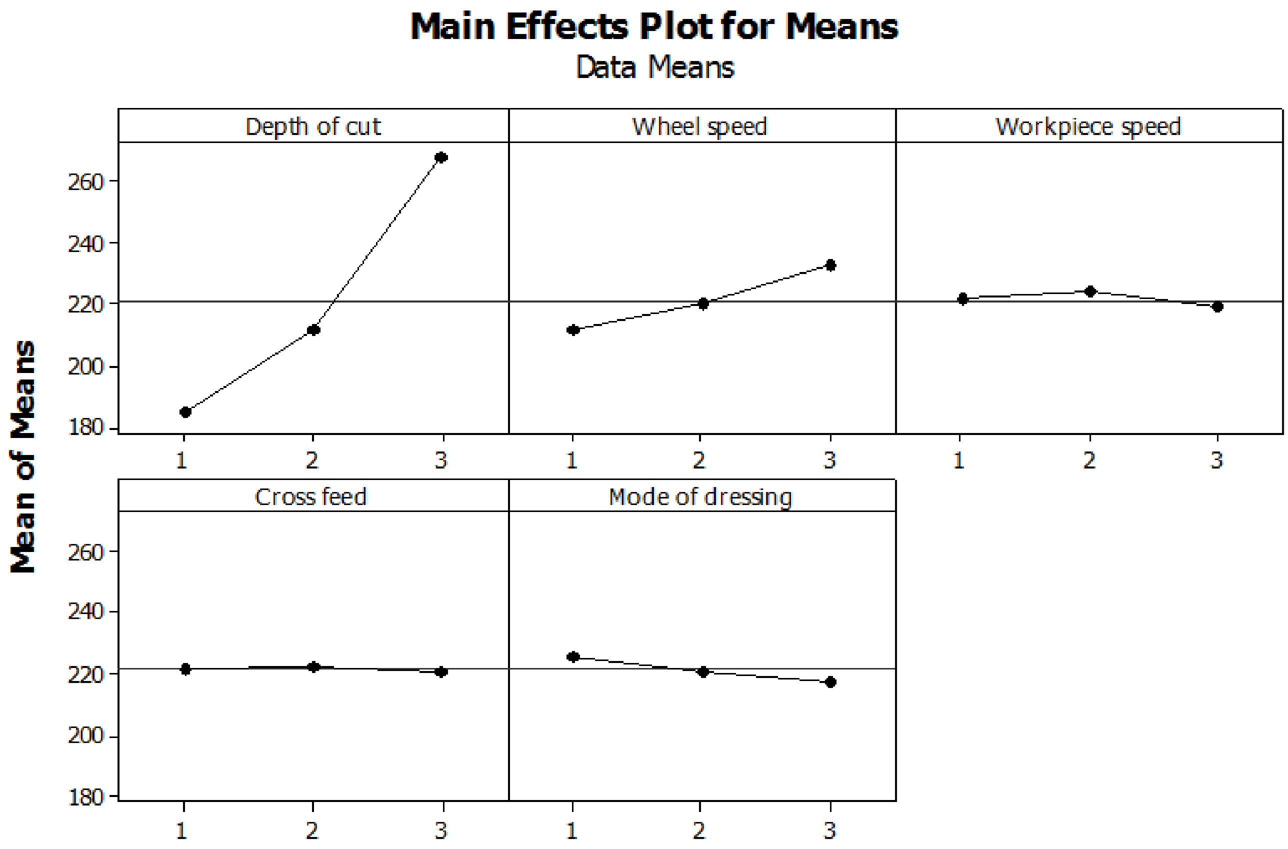

Fig 3. Main effects plot for means of signal-to-noise ratio for surface hardness

5.2.4 Response characteristics of S/N ratios and means for surface hardness

As mentioned, the response table (Table 4) represents that the S/N ratios and means for each level of all parameters. The table lists ranks based on Delta statistics, which compares the relative magnitude of effects. The Delta statistic is the highest minus the lowest average for each factor. Minitab software ascertains ranks based on Delta values; rank 1 to the highest Delta value, rank 2 to the second highest, and so forth. The level averages in the response table are provided to characterize which level of each parameter results in the best result. Figure 4 depicts the residual plots for surface hardness in a four-in-one block arrangement. The normal probability plot and the fitted value against the residuals represent that anomalies were observed only at certain datasets. Following, 'histogram of residuals', 'normal probability plot', 'residual fit', and 'residual order' are described through comparing the present results obtained.

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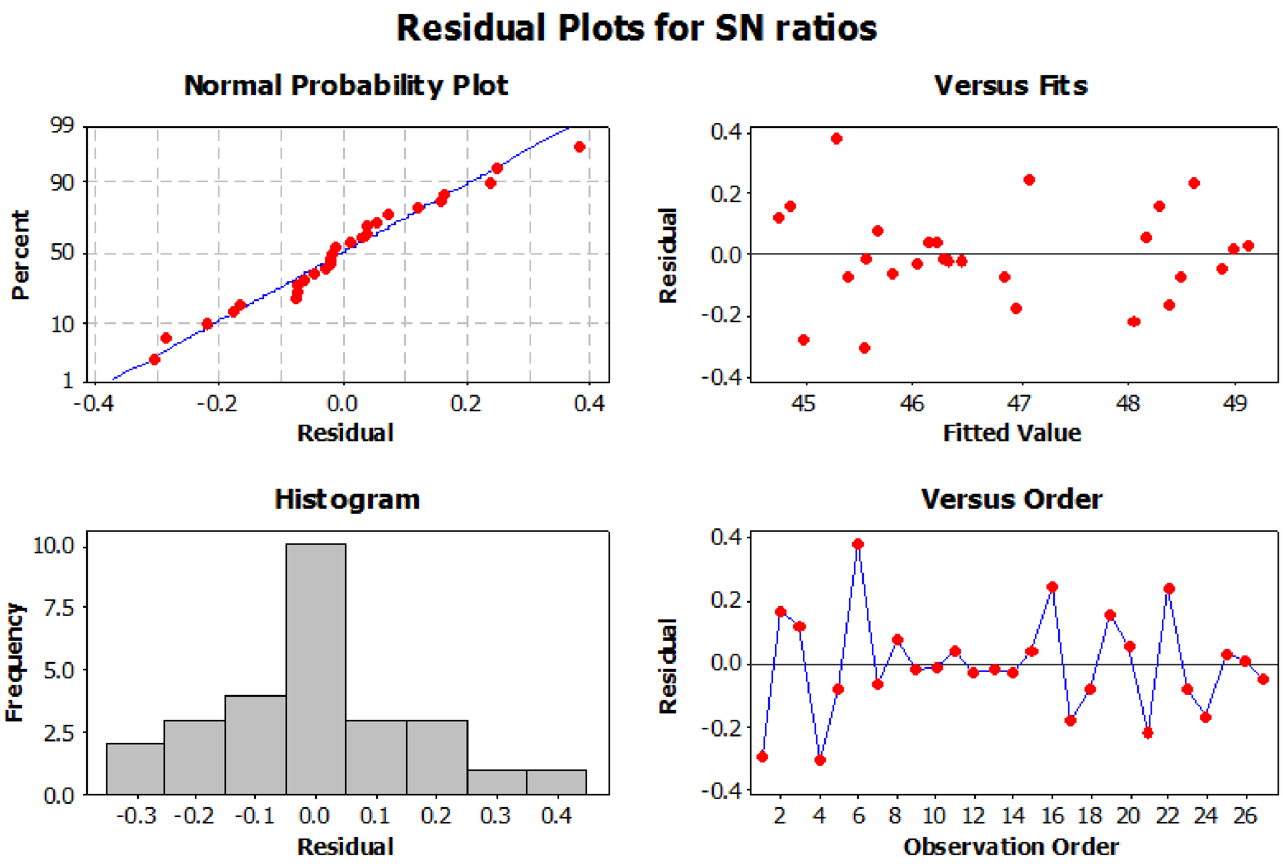

Fig 4. Residual plots for Surface Hardness in a four-in-one block arrangement

- *Normal probability plot of residuals:* Basically, if the residuals are normally distributed, the points on the plot should create a straight line. The normality assumption may be invalid if the points in this plot from the present data depart from a straight line. The plot may display curvature in the tails when the data are less 50 observations. As a results, when the number of observations reduces, the probability plot may indicate substantial variation and nonlinearity even if the residuals are normally distributed.
- *Residuals versus fitted values:* This plot represents a random pattern of residuals on both sides of zero point. It can be considered as an outlier if a point lies away from the majority of points. It should be noted that there should not be any determinable pattern in this plot. A predominance of either negative or positive residuals, a series of increasing or decreasing points, a pattern such as decreasing residuals with decreasing fits are some roots of errors that are not random.
- *Histogram of residuals:* Histogram presents some advantageous characteristics of the data, such as: unusual values in the data and typical values, shape and spread or variation. Long tails in the plot is sign of skewness in the data. One bar which is far from the others illustrates that this point may be outlier. Because the appearance of the histogram changes relating to the number of intervals applied to categorize the data, the goodness-of-fit tests and normal probability plot are used to evaluate the normality of the residuals.
- *Residuals versus observation order:* This is a plot of all residuals in the order that the data was gathered and can be applied to understand non-random error, especially of time-related effects. A negative and positive correlations are respectively specified by rapid changes in the signs of consecutive residuals and a clustering of residuals with the same sign.

5.3 Regression Model

In the current study, surface hardness, is taken as response (output) while depth of cut, wheel speed, workpiece speed, cross feed, and mode of dressing are considered as independent (input) variables. Assuming no interaction between input parameters, after performing all experiments and obtaining all output parameters, the regression model can be explicitly

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formulated involving the independent variables. The experimental results for average surface hardness can be migrated to a linear regression model equation as shown in Eq. (6):

$$Surface\ Hardness = 128 + 41.5\ \ a_e + 10.3\,S - 1.33\ \ v_c\ \ - 0.33\,S - 3.61\,M \tag{6}$$

Equation 6 specifies regression model obtained for surface hardness of AISI1045. The positive and negative sign of each factor in equation indicates the respectively increase and decrease of response with increase of the related variable.

The regression results as in Table 7 indicate that the predictors D, S, and M are significant because of their low p-values. The R-square (coefficient of determination) which is representative for efficiency of correlated model, was found to be 94.5%. The closer the R-square value to 1.00, the effective the model is and represents the highest proportion of total variability in the response variable. The R-Sq(adj) which is 93.2%, specifies the amount of variation in the regression equation, and the R-Sq(pred) which is 91.35%, determines how accurate the regression equation predicts the response value. As the value of both R-Sq(adj) and R-Sq(pred) are very high (greater than 91%), and they are also so close to the value of R-Sq, it is confirmed that the design models fit the new experimental data very fine. The studentized deleted residual of an observation in Minitab software is found by dividing deleted residual of an observation by an estimate of its standard deviation. Because the raw residuals may be poor indicators of outliers due to their non-constant variance, the studentizing residuals are helpful. Tables 8 and 9 illustrate how that ANOVA for surface hardness based on the regression equation developed and the sequential sum square table for surface hardness. The regression equation for surface hardness had five degrees of freedom. Table 9 indicates the ranking of the source for the developed equation which correlates very well with the numerical estimates. The sources D, S and M are three most significant parameters comparing with others.

Table 7. Regression analysis table for surface hardness

Predictor	Coef	SE Coef	T	P
Constant	128.15	10.26	12.5	0
Depth of cut	41.5	2.256	18.4	0
Wheel speed	10.333	2.256	4.58	0
Workpiece speed	-1.333	2.256	-0.59	0.561
Cross feed	-0.333	2.256	-0.15	0.884
Mode of dressing	-3.611	2.256	-1.6	0.124

S = 9.57059 R-Sq = 94.5% R-Sq(adj) = 93.2% R-Sq(pred) = 91.35%

Table 8. Analysis of variance of surface hardness

Source	DF	SS	MS	F	P
Regression	5	33191.2	6638.2	72.47	0
Residual Error	21	1923.5	91.6		
Total	26	35114.7			

Table 9. Sequential sum square table for surface hardness

Predictor	DF	Seq SS
Depth of cut	1	31000.5
Wheel speed	1	1922.0
Workpiece speed	1	32.0
Cross feed	1	2.0
Mode of dressing	1	2347

5.4 Confirmatory experiment

After the optimal condition of the surface grinding parameters has been chosen, a confirmatory test is needed to be run to predict the quality characteristics using optimal level parameters. As it mentioned, the optimal combination levels of the surface grinding parameters were determined (D3/S3/W2/F2/M1) using the Taguchi method. Table 10 compares the results obtained from the combination of factors achieved from the Taguchi method with the actual results obtained from experiments. According to the verification results, a good agreement between the observed and estimated results can be inferred. In other words, the experimental results confirm the ability of the Taguchi method for prediction of H_{avg} in response to various combinations of levels and factors.

Table 10. Confirmation run for the optimum level condition

	Optimal grinding parameters	
	Predicted	Experimental
Level	$D_3/S_3/W_2/F_2/M_1$	$D_3/S_3/W_2/F_2/M_1$
Average surface hardness	285.593	286.667
S/N ratio for Surface hardness	49.2215	

5.5 Metallographic and hardness analysis

For the evaluated conditions, metallographical analysis of the hardness values leaded to some considering results. Although, occurrence of some changes in microstructure of the samples was prospected, these changes before and after the process were not significant, even for those samples subjected to excessive heat. The surface micro-hardness was recorded three times before and after grinding process for optimum level condition. As illustrated in Table 11, a considerable increase can be observed in average micro-hardness values.

Table 11. The measured values of Vickers micro-hardness before (State A) and after (State B) process for optimum level condition

	First Vickers Value	Second Vickers Value	Third Vickers Value	Average Vickers Value	Equivalevt Brinell Hardness	Equivalevt Rockwell Hardness	
						HRB	HRC
State A	179	183	187	183	172	87	-
State B	288	287	285	286.667	273	-	28

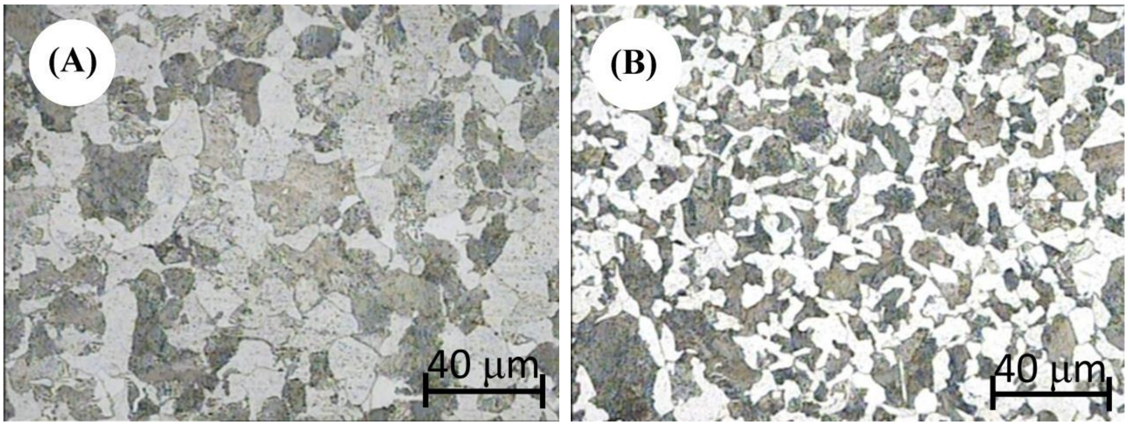

Fig 5. The optical micrographs of polished surface of samples illustrating Ferrite and Perlite in AISI1045 steel, (A) before grinding process, (B) after grinding process for optimum level condition

The residual stress as a representative of hardness is originally induced by the following sources:

- Martensitic transformation below the surface
- Plastic flow of material on the surface and the adjacent zones as a result of thermal stresses which are caused by heat generation during grinding operation
- Plastic deformation at the workpiece surface due to the forces of abrasive grits (Barbacki, Kawalec et al. 2003, Balart, Bouzina et al. 2004).

Plastic deformation beneath the surface is actually generated by characteristics of grinding, such as grit size, process parameters, and material properties (Poggie and Wert 1991). As AISI1045 steel used in this study, has low hardenability due to low percentage of carbon, and the material removal condition were not excessive in contact zone, it seems too hard to reach a martensitic microstructure. In other word, cooling rate in the experiments is not sufficient to make this transformation possible. Figure 5 illustrates the ferritic-pearlitic microstructure of the samples under optimum level

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condition. This type of microstructure is related to annealing heat treatment before grinding process. As it can be observed from Fig. 5 B, the grinding process has produced a fine and equiaxed grain-structure. Accordingly, hardness enhancement which is tabulated in Table 11, can be considered as a result of the finer microstructure. As Fig. 6 shows, the measured micro-hardness values demonstrated a significant increase. This increase can be also as a result of plastic deformation near the contact zone. Higher values of grinding parameters intensify material removal condition and consequently cutting force. These results are consistent with previous investigations (O. Zurita 2003).

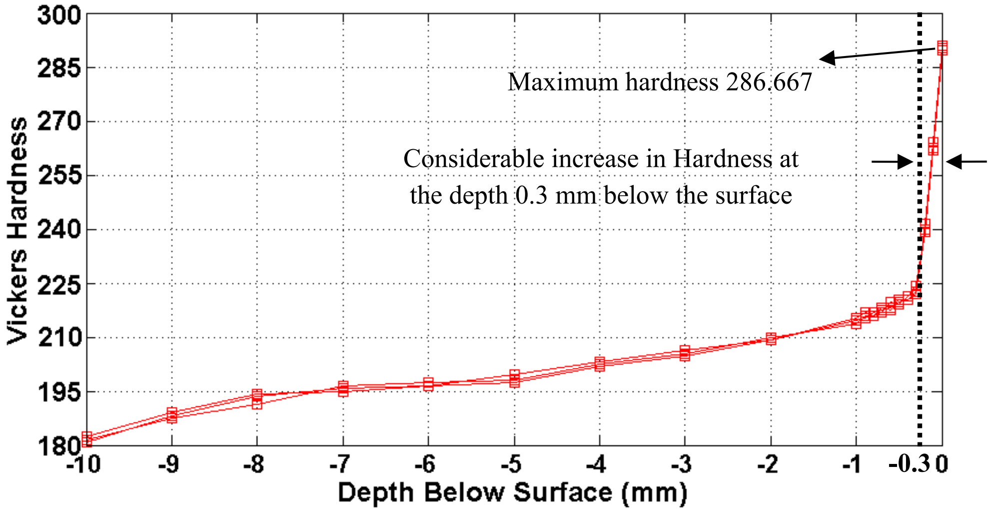

Fig 6. The graph of micro-hardness below the surface under optimized condition obtained by experiment

Figure 6 shows the measured micro-hardness values in cross section of the workpiece. The micro-hardness values beneath the surface is higher than the depth and it reached to the maximum value 286.667 HV right at the top surface of the workpiece. The cross section of workpiece was discretized in 1 mm and three hardness values were averaged for each 1 mm. For the last 1 mm layer of workpiece, the procedure of hardness measurement was repeated in every 0.1mm distance.

6. Conclusions

This study demonstrated that by employing the Taguchi method, the optimal levels of grinding parameters for improving the surface hardness as a quality characteristic could be obtained. Simultaneously, regression analysis was employed to predict and identify the most significant parameters to maximize the surface hardness. The ANOVA analysis indicated that the depth of cut, wheel speed, and mode of dressing had the most significant impact on the average and standard deviation of surface hardness of the ground parts.

Considering the outputs of the optimization procedure, overall observations and results related to the hardness, the following conclusions can be made:

1- If depth of cut and wheel speed are selected with high levels, the surface hardness will be increased.

2- Mode of dressing introduced as an effective parameter on surface hardening, which should not be neglected.

3- By employing the optimal conditions concluded by the Taguchi method, the surface hardness reached maximum, thus, the needs for hardening procedures can be eliminated in production lines.

4- Mathematical equation obtained from regression analysis provided a reasonable confidence level, as if, it can be successfully employed for other similar investigations.

5-Despite the optimization outputs are ended up the parameters that produce surface hardness, the surface roughness as another concerning aspects in grinding operation should not be neglected. Hence, a comprehensive study which includes both hardness and roughness as objectives is recommended to carry out to optimize the grinding process.

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