Optimization of Cutting Parameters in Turning of AISI 201 Stainless Steel to Reduce Chip Reduction Coefficient in both Dry and Wet Condition

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Abstract

The most vital phenomenon in machining is optimization, as it defines the continuous improvement in the quality of the material. Cutting fluid becomes, nowadays, an important part of turning because it assists to minimize the mechanical and thermal losses. Minimization of Chip Reduction Coefficient and optimization of the cutting parameters contribute to protect losses of productivity and to reduce the production cost. This work investigates the optimized cutting parameters in dry turning and wet turning of AISI 201 stainless steel work piece using cemented carbide tool and finds the minimum chip reduction coefficient and compares the results of the two conditions. It reveals that the cutting fluid shows a significant effect on the machining and reduces the chip reduction coefficient. Statistical analysis ANOVA shows that Depth of Cut and Spindle speed is the most influential factor in wet and dry turning respectively. It uses Multiple Regressions to predict the output and to find the correlation between parameters. Genetic Algorithm is used to select the optimal values of cutting parameters and find the minimized Chip Reduction Coefficient. The optimized cutting parameters from Genetic Algorithm for both dry and wet turning are spindle speed of 650 rev/min, feed rate of 0.12 mm/rev and depth of cut of 0.4 mm. The minimum chip reduction coefficient for dry turning is 1.067651 and for wet turning is 1.020852.

Keywords
Chip Reduction Coefficient, Cutting Fluid, Genetic Algorithm, Optimization, Wet Turning.

1. Introduction
The purpose of Turning is to create rotational parts by removing extra materials from the performed parts. It is the most important and widely used machining process to shape metals, because the working conditions and environment can be varied. Productivity and expense are the key focus for any company to be profitable. An organization wants to increase the productivity and reduce the manufacturing cost. In turning process, higher values of cutting parameters may improve productivity but it also increases the risk of damage in surface quality and tool life (Sharma et al., 2007). Orthogonal and oblique cutting are the two basic types of cutting using a single point cutting tool. The cutting edge of the tool, in orthogonal cutting, remains normal to the direction of feed and cutting velocity and the direction of chip flow velocity is normal to the cutting edge of the tool (Kaushish, 2013). In most of the machining processes, chips are obtained as: i) Continuous chip, ii) Continuous chip with buildup edge, iii) Discontinuous chips. The chip thickness (a_2) usually becomes larger than the uncut chip thickness (a_1) in machining because of compression of the chip ahead of the tool, frictional resistance to the chip flow and lamellar sliding. Chip reduction coefficient (ξ) is defined as the ratio of the chip thickness after and before cut, as shown in the equation (1).

$$\xi = a_2/a_1 \tag{1}$$

Where, a_1 is the chip thickness before turning is performed and a_2 is the chip thickness after turning. Larger value of Chip Reduction Coefficient (ξ) contributes to more thickening, in other words, more forces or energy is invested to accomplish the machining operation. So it is always essential to reduce a_2 or ξ without sacrificing productivity to minimize the power consumption and amount of energy invested in machining process (Sahoo and Mohanty, 2013). Chip reduction coefficient is, primarily, influenced by process parameters like feed, cutting speed, depth of cut and so on. Machinability is defined as the ability of being machined which depends on the characteristics of the tool-work material. The increasing importance of turning operation is gaining new dimensions in the present industrial era, in which the growing competition calls for all the efforts to be directed towards the economical manufacture of machined parts. More than 20% of the value of manufactured products attributed to the cost of machining in industrialized countries. Hence it is important to monitor the machinability behavior of different materials by changing the machining parameters and working environment to obtain optimal result (Senapati, 2014). The machinability of a material provides an indication of its adaptability to manufacturing by a machining process. Good machinability is defined as an optimal combination of factors such as low cutting forces, good surface finish, low tool tip temperature and low power consumption. Therefore the machining operation is performed with the perfect combination of cutting parameters so that effectiveness, efficiency and overall economy are achieved. Thus, optimization is seen as an effective method for continuous enhancement of production quality in the product. It offers modeling of the relationship between input-output and in-process parameters and deciding the optimum cutting state (Das and Nayak, 2013). Cutting fluids are used extensively to mitigate the detrimental impacts of the heat and friction on both tool and work piece. The cutting fluids generally produces three beneficial results in the process such as heat removal, lubrication on the chip–tool interface and chip removal (Yan et al., 2015). Metal cutting fluids changes the performance of machining operations because of their lubrication, cooling, and chip flushing functions but the use of cutting fluid has become more problematic in terms of both employee health and environmental pollution. Dhar et al. (2006) found significant reduction in tool wear rate and surface roughness by Minimum Quantity Lubrication (MQL) through reduction in the cutting zone temperature and change in the chip–tool and work–tool interaction. The need for an ecologically friendly metal working fluid in machining operations surges because the use of cutting fluids in the machining concerned with environment, health and safety, and manufacturing cost.

Analysis of Variance (ANOVA) is widely used in the research of machining. It aims, basically, to apply a statistical method to identify the effect of individual factors and their interactions during machining. Results from ANOVA can determine very limpidly the impact of each factor on the process results. Benlahmidi et al. (2017) performed a statistical analysis of variance (ANOVA) in the analysis of cutting force components in hard turning of AISI H11 steel with the CBN tool and found the cutting force components were influenced principally by depth of cut and work piece hardness. Azizi et al. (2012) also used ANOVA in optimization of machining conditions in hard turning of AISI 52100 steel. Their statistical analysis revealed the feed rate, workpiece hardness and cutting speed have profound impacts in reducing the surface roughness whereas the depth of cut, workpiece hardness, and feed rate have a statistical significance in the cutting force components than the cutting speed. Dirviyam et al. (2014) implied ANOVA in the dry turning of AISI 304 Austenitic Stainless steel using TiC and TiCN coated tungsten carbide cutting tool and revealed that the feed rate is the more significant parameter influencing the surface roughness and cutting force. The cutting speed was identified as the more significant parameter influencing the tool wear. Othogonal array is largely used to design the experiment. Different levels of input variables produce different experimental combination. Davim (2003), Kirby et al. (2006) used orthogonal array to design the experiment while Kaladhar et al. (2012) used full factorial design in the Design of experiment. Linear Regression model is used to find the relationship between their controlled and response parameters. It also clears the correlations between them. Tyagi et al. (2018) used regression analysis in turning to estimate the relationship among variables. Vikram et al. (2012) developed Empirical model for surface roughness by means of nonlinear regression data mining method in MINITAB software while investigating the effect of machining on surface roughness in hard turning process for three different materials in dry conditions and compares with linear optimization.

Various tools and methods can be used in the researches on optimization. Nalbant et al. (2007), Palanikumar (2006) used the Taguchi method to optimize the cutting conditions for surface roughness, Singh & Kumar (2006) used feed force for optimizing while Benlahmidi et al. (2017) and Aggarwal et al. (2008) used Response Surface Methodology (RSM) for optimization. Li et al. (2015) and Zuperl and Cus (2003) used neural network in describing multi objective technique of optimization of cutting conditions. Some authors used Tabu-search Alorithm (sadeghi et al. 2011), a few numbers of authors used Ant colony Algorithm (Pansare and Kavade 2012). Madić et al. used Monte-

Carlo method. Genetic Algorithm is widely used. Subramanian et al. (2013) used genetic algorithm in optimization of cutting parameters for cutting force in shoulder milling of Al7075-T6. Pickering et al. (2016) compared the metaheuristic and linear programming models for optimizing energy supply operation schedule of a hotel. They found proposed operations schedule differs slightly in different methods with few subjectivity in exact operation schedule. They found that metaheuristics favors qualitative subjectivity and Mixed Integer Linear Programming favors quantitative subjectivity. Aktel et al. (2017) compared several metaheuristic algorithms on airport gate assignment problem. Raborn et al. (2020) used a Monte-Carlo simulation study to compare existing implementations of the ant colony optimization, tabu search, and genetic algorithm to select short forms of scales. They concluded that the simulated annealing algorithm showed the best overall performance, while the genetic algorithm created short forms with worse fit. Khosravanian et al. (2018) conducted a comparative analysis to optimize complex 3-D well-path designs with several metaheuristic algorithms. The results suggests that genetic, artificial bee colony and harmony search algorithms can each be successively tuned with control parameters to achieve objectives, while the ant colony algorithm cannot.

In this paper, the cutting conditions are optimized and the chip reduction coefficient is minimized in the dry and wet turning of AISI 201 stainless steel using Genetic Algorithm and the variation of the results in the two environmental conditions is compared. No previous author did compare the results of optimization of cutting parameters of AISI 201 stainless steel in such different environmental conditions and very few regarded Chip Reduction Coefficient as a response factor. The correlation between the parameters is obtained by the Regression analysis and the effect of the input parameters to the output is found through ANOVA.

2. Materials and Methods

The work piece material used for the work is AISI 201 stainless steel of Length 294 mm And Diameter 24.97 mm. Cemented carbide cutting tool insert has been used for the experiment. The tool geometry of the cutting tool are: Side Cutting Edge Angle- 68 degree, End Cutting Edge Angle- 68.5 degree, Side Relief Angle- 5 degree, End Relief Angle- 5 degree & Nose Radius- 54 degree. Figure 1 shows the experimental setup in laboratory. Water is used as the Cutting Fluid for making the environment wet. For measuring Chip Reduction Coefficient the experiment was carried out on lathe machine which is made in Sweden and the motor power of Lathe is 3500W. The lathe is an Engine Lathe and it has three jaw chucks.

Figure 1: Experimental Setup

2.1. Design of Experiments

For this work, we have selected three levels of each cutting parameters. The selected cutting parameters and their levels are given in Table 1.

Table 1. Cutting Parameters and their Levels

Cutting parameter	Level 1	Level 2	Level 3
Spindle Speed (rpm)	245	490	650
Feed (mm/rev)	0.12	0.14	0.16
Depth of Cut (mm)	0.2	0.3	0.4

Taguchi L_9 Orthogonal array is used to design the experiment. MINITAB-17 software is used for carrying out Design of Experiment. The experimental design is described in Table 2.

Table 2. Design of Experiment

Para. / Sl.	Spindle Speed, v (rpm)	Feed, f (mm/rev)	Depth of Cut, d (mm)
1	245	0.12	0.2
2	245	0.14	0.3
3	245	0.16	0.4
4	490	0.12	0.3
5	490	0.14	0.4
6	490	0.16	0.2
7	650	0.12	0.4
8	650	0.14	0.2
9	650	0.16	0.3

2.2. Empirical Data

The Chip Reduction Coefficient is calculated using the equation (1). A digital Slide Calipers is used to carry out the calculations. The experimental data is shown below in Table 3.

Table 3. Experimental result for dry turning

Para. / No.	Spindle Speed, v (rpm)	Feed, f (mm/rev)	Depth of Cut, d (mm)	Chip Reduction Coefficient (ξ_{dry})
1	245	0.12	0.2	1.4
2	245	0.14	0.3	1.17
3	245	0.16	0.4	1.25
4	490	0.12	0.3	1.17
5	490	0.14	0.4	1.1
6	490	0.16	0.2	1.3
7	650	0.12	0.4	1.06
8	650	0.14	0.2	1.07
9	650	0.16	0.3	1.1

It is seen from the table 3 that Chip Reduction Coefficient in dry turning is maximum (1.4) in the combination of spindle speed 245 rpm, feed rate 0.12 mm/rev and depth of cut 0.2 mm and the chip reduction coefficient is minimum (1.06) in the combination of spindle speed 650 rpm, feed rate 0.12mm/rev, depth of cut 0.4mm. The experimental results of wet turning are shown in Table 4.

Table 4. Experimental result for wet turning

Para. / No.	Spindle Speed, v (rpm)	Feed, f (mm/rev)	Depth of Cut, d (mm)	Chip Reduction Coefficient (ξ_{wet})
1	245	0.12	0.2	1.3
2	245	0.14	0.3	1.1
3	245	0.16	0.4	1.2
4	490	0.12	0.3	1.1
5	490	0.14	0.4	1.125
6	490	0.16	0.2	1.125
7	650	0.12	0.4	1.04
8	650	0.14	0.2	1.1
9	650	0.16	0.3	1.13

From the table 4, the maximum (1.3) chip reduction coefficient in wet turning is in the combination of spindle speed 245 rpm, feed rate 0.12 mm/rev and depth of cut 0.2 mm and the chip reduction coefficient is minimum (1.04) in the combination of spindle speed 650 rpm, feed rate 0.12 mm/rev, depth of cut 0.4mm.

2.3. Analysis of Variance (ANOVA)

Analysis of Variance (ANOVA) provides a statistical method to identify the effect of individual factors. The result of ANOVA for Chip Reduction Coefficient, from MINITAB-17 is tabulated in the following Tables. This analysis is carried for a 5% significance level i.e. for a 95% confidence level.

Table 5. ANOVA data table for Chip Reduction Coefficient (ξ_{dry}) in dry turning

Source	Degree of Freedom (DoF)	Sum of Square (SS)	Mean Square (MS)	F-value	P-Value	Percentage (%) contribution
Model	3	0.06637	0.022123	5.27	0.052	23.86
v	1	0.03900	0.038995	9.29	0.028	42.07
f	1	0.01654	0.016537	3.94	0.104	18.84
d	1	0.01084	0.010837	2.58	0.169	12.69
Error	5	0.02099	0.004197			2.52
Total	8	0.08736				

Table 5 shows the percentage contribution of each cutting parameter to the total variation, indicating their degree of influence on the Chip Reduction Coefficient (ξ_{dry}) in dry turning. It can be seen from table 5 that Spindle speed is the most influential parameter followed by feed rate and depth of cut. It also depicts that the cutting parameters (feed rate, speed and spindle speed) between the chosen levels contribute 97.48% of the total variation in the Chip Reduction Coefficient. Results of ANOVA for wet turning is shown below in the table 6:

Table 6. ANOVA data table for Chip Reduction Coefficient (ξ_{wet}) in wet turning

Source	Degree of Freedom (DoF)	Sum of Square (SS)	Mean Square (MS)	F- value	P-Value	Percentage (%) contribution
Model	3	0.056493	0.018831	2.34	0.191	22.58
v	1	0.005410	0.008061	0.67	0.450	10.66
f	1	0.004267	0.004267	0.53	0.500	7.48
d	1	0.046817	0.046817	5.81	0.061	56.14
Error	5	0.040307	0.005410			2.11
Total	8	0.096800				

Table 6 shows the analysis of variance with arithmetic average of Chip Reduction Coefficient (ξ_{wet}) in wet turning. It shows the percentage contribution of each cutting parameter to the Chip Reduction Coefficient. Depth of cut (56.14%) is the most dominant parameter followed by spindle speed, whereas the influence of feed is negligible. It can be seen that the cutting parameters (feed rate, speed and spindle speed) influences 97.89% of the total variation in the Chip Reduction Coefficient for wet turning.

2.4. Linear Regression Model

The Empirical results are used to obtain the mathematical relationship between cutting parameters (speed, feed, depth of cut). The coefficient of mathematical Models is computed using method of general linear regression. The linear regression equation of Chip Reduction Coefficient obtained from MINITAB-17 for dry turning is shown in equation (2):

$$\xi_{dry} = 1.820 - 0.000395 * v - 2.62 * f - 0.425 * d \quad (2)$$

The Regression Equation of Chip Reduction Coefficient for wet Turning is represented in equation (3):

$$\xi_{wet} = 1.313 - 0.000147 * v + 1.33 * f - 0.883 * d \quad (3)$$

Predicted value for Chip Reduction Coefficient
The optimal level of cutting parameter Spindle Speed = 650, Feed = 0.12, Depth of Cut = 0.4. So the predicted Chip Reduction Coefficient (Regression Model) according to equation (2) for dry turning is:
$\xi_{dry} = 1.820 - 0.000395 * 650 - 2.62 * 0.16 - 0.425 * 0.3 = 1.079$

The optimal level of cutting parameter Spindle Speed = 650 rpm, Feed = 0.12 mm/rev, Depth of Cut = 0.4 mm. So the predicted Chip Reduction Coefficient (Regression Model) according to equation (3) for wet turning is:
$\xi_{wet} = 1.31- 0.000147 * 650 + 1.33 * 0.12 -0.883 * 0 .4 = 1.021$

2.5. Genetic Algorithm

An optimization algorithm is a process that is executed in an iterative manner by comparing various solutions until the optimum or satisfactory solution is achieved. After comparing a few design solutions, accepting the best solution is the way of achieving optimization in many industrial designing activities. Genetic Algorithm is used here to optimize machining parameters. The selection of optimal cutting parameters like feed, depth of cut and cutting speed is very important for every machining process. So in this paper we have found the best combination of cutting parameters (feed, speed, and depth of cut) to get optimal chip reduction coefficient.
To optimize the cutting parameters using Genetic Algorithm, the fitness function for the Chip Reduction Coefficient is taken as the constrained optimization problem. From the observed Data for Chip Reduction Coefficient, the response function has been determined using regression Model and fitness function is defined in the equation (2) for dry turning and equation (3) for wet turning:

$$\text{Minimize } \xi_{dry} = 1.820 - 0.000395 * v - 2.62 * f - 0.425 * d$$
$$\text{Subject to,}$$
$$245 \text{ rpm} \leq v \leq 650 \text{ rpm}$$
$$0.12 \text{ mm/rev} \leq f \leq 0.16 \text{ mm/rev}$$
$$0.2 \text{ mm} \leq d \leq 0.4 \text{ mm}$$
$$x_l(i) \leq x(i) \leq x_u(i)$$

$$\text{Minimize } \xi_{wet} = 1.313 - 0.000147 * v + 1.33 * f - 0.883 * d$$
$$\text{Subject to,}$$
$$245 \text{ rpm} \leq v \leq 650 \text{ rpm}$$
$$0.12 \text{ mm/rev} \leq f \leq 0.16 \text{ mm/rev}$$
$$0.2 \text{ mm} \leq d \leq 0.4 \text{ mm}$$
$$x_l(i) \leq x(i) \leq x_u(i)$$

Where, $x_l(i)$ and $x_u(i)$ are the lower and the upper bounds of process variable x(i). x(1), x(2) and x(3) are the cutting speed, feed and depth of cut respectively. With a view to optimizing the cutting parameters using GAs, to obtain optimal solution, following parameters have been selected with less computational effort.
Population Size = 50
Maximum Number of Generation = 1000
Total String Length = 50
Crossover Probability (Pc) = 0.9
Mutation Probability (Pm) = 0.01
Primarily, a collection of 50 random pairs of the coefficient are generated, dismissing the unstable cases. These 50 pairs of coefficient are converted into binary codes to construct the as “old-pop”. From this grouped population and, equal numbers of new populations are generated by using the usual GA operators. A particular probability of each operator is set keeping the mutational probability small enough. The crossover probability (0.9) and mutation probability (0.01) are taken. Two strings of population are selected for either mutation or crossover using the roulette wheel technique. As the technique specifies, a random number between 0 and 1 is multiplied, for selection, with the sum of fitness of all “old-pop” strings. When this value is greater than or equal to the cumulative fitness of the i^{th} string, this string is selected from the “old-pop”. In this manner, two strings (mate-1 and mate-2) are selected

to the mating pool. Out of these mates, two strings (child-1 and child-2) are created using the GA operators. This procedure is continued until 50 new population strings are formed. Out of 100 strings (the original 50 and newly created 50), the most-fit 50 population strings are retained. These strings are replaced into the "old-pop" to represent the second generation "old-pop". In this method, 1000 generations are continued until the convergence of the algorithm into the unique fit solution. The binary data in the solution is encoded to include the optimal parameters for the machining.

3. Results and Discussion

The optimum parameters from Genetic Algorithm is obtained by using MATLAB 2017 software. The outcome of the calculations and formulation for the optimization by the Regression Model (predicted) and Genetic Algorithm are described and compared in the Table 7 and Table 8. The comparison between the predicted results from regression analysis and the final optimized value from Genetic Algorithm for dry turning is described in Table 7. It is seen that the optimum value of Chip Reduction Coefficient is little lower than the predicted value of it. In the meantime, the optimum cutting conditions are same as the predicted value.

Table 7. Comparison between the predicted and optimal values in dry turning

	Regression Analysis (Predicted)	Genetic Algorithm
Chip Reduction Coefficient (ξ_{dry})	1.079	1.067651
Best Combination (cutting speed, feed, depth of cut)	650 rpm, 0.12 mm/rev, 0.4mm	650 rpm, 0.12 mm/rev, 0.4mm

Table 8 describes the comparison between the predicted results and the optimum value for wet turning. It is observed that the optimized value from Genetic Algorithm is almost same as the predicted value of Chip Reduction Coefficient in the Regression Analysis.

Table 8. Comparison between the predicted and optimal values in wet turning

	Regression Analysis (Predicted)	Genetic Algorithm
Chip Reduction Coefficient (ξ_{wet})	1.021	1.020852
Best Combination (cutting speed, feed, depth of cut)	650 rpm, 0.12 mm/rev, 0.4mm	650 rpm, 0.12 mm/rev, 0.4mm

The optimum results from Genetic Algorithm for different environmental conditions are compared below in the Table 9. It can be told that that the optimum value of Chip Reduction Coefficient in wet turning is less than dry turning, whereas the optimum values of cutting parameters remain same. It can be concluded that the cutting fluid has a remarkable effect on Chip Reduction Coefficient and reduces it.

Table 9. Comparison of optimum values between dry and wet condition

	Dry Turning (ξ_{dry})	Wet Turning (ξ_{wet})
Chip Reduction Coefficient	1.067651	1.020852
Best Combination	650 rpm, 0.12 mm/rev, 0.4mm	650 rpm, 0.12 mm/rev, 0.4mm

4. Conclusion

In this experiment, cutting parameters are optimized in both dry and wet turning of AISI 201 stainless steel in order to reduce the Chip Reduction Coefficient and compare the results. A Taguchi L_9 orthogonal array is used to set up the experimental design. ANOVA analysis is used to investigate the effect of cutting parameters in turning. It is observed that Spindle speed is most influential factor in dry turning followed by feed rate and depth of cut is the last. In wet turning, Depth of Cut is most influential factor followed by spindle speed and feed rate. Regression Analysis is carried out to predict a model of minimizing the Chip Reduction Coefficient. Genetic Algorithm (GA) is performed to optimize the cutting parameters and minimize the Chip Reduction Coefficient. 650 rpm of spindle speed, 0.12 mm/rev of feed rate, 0.4 mm of depth of cut are the optimized cutting parameters for both dry and wet turning. The values of minimum Chip Reduction Coefficient are 1.067651 and 1.020852 for dry turning and wet turning respectively while the predicted values are 1.079 and 1.021 respectively. The minimum value of Chip Reduction Coefficient obtained from GA is higher for the dry turning.

As future work, nose radius, tool tip temperature etc. can be taken into account as the input parameters and surface roughness, surface temperature, cutting force, tool wear etc. can be considered as the response parameters. Different level of cutting parameters can also be taken. The experiment can be carried out with different types of cutting fluids (water based, oil based or water-oil mixed and so on).

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Biographies

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