ISLAMIC UNIVERSITY OF TECHNOLOGY (IUT)

MULTI OBJECTIVE OPTIMIZATION OF TURNING PROCESS USING WHALE ALGORITHM

B.Sc. Engineering (Mechanical) THESIS

BY

MAHAMUDUL HASAN TANVIR
STUDENT ID: 141449

AFZAL HUSSAIN
STUDENT ID: 141423

M.M. TOWFIQUR RAHMAN
STUDENT ID: 141406

KHANDOKER ZISHAN
STUDENT ID: 141443

SAKIB ISHRAQ
STUDENT ID: 141420

SUPERVISED BY
DR. MOHAMMAD AHSAN HABIB

A THESIS PRESENTED TO THE DEPARTMENT OF MECHANICAL AND CHEMICAL ENGINEERING, ISLAMIC UNIVERSITY OF TECHNOLOGY DHAKA IN PARTIAL FULFILMENT OF THE REQUIREMENT FOR THE AWARD OF DEGREE FOR

BACHELORS OF SCIENCE (B. Sc.)
IN
MECHANICAL ENGINEERING

Candidate’s Declaration

It is hereby declared that this thesis or any part of it has not been submitted elsewhere for the award of any degree or diploma.

Signature of the Candidate

MAHAMUDUL HASAN TANVIR
Student No.: 141449
Session 2017-2018
Department of Mechanical and Chemical Engineering (MCE)
Islamic University of Technology (IUT), OIC
Board Bazar, Gazipur
Dhaka, Bangladesh.

AFZAL HUSSAIN
Student No.: 141423
Session 2017-2018
Department of Mechanical and Chemical Engineering (MCE)
Islamic University of Technology (IUT), OIC
Board Bazar, Gazipur
Dhaka, Bangladesh.

M.M.TOWFIQUR RAHMAN
Student No.: 141406
Session 2017-2018
Department of Mechanical and Chemical Engineering (MCE)
Islamic University of Technology (IUT), OIC
Board Bazar, Gazipur
Dhaka, Bangladesh.

KHANDOKER ZISHAN
Student No.: 141443
Session 2017-2018
Department of Mechanical and Chemical Engineering (MCE)
Islamic University of Technology (IUT), OIC
Board Bazar, Gazipur
Dhaka, Bangladesh.

SAKIB ISHRAQ
Student No.: 141420
Session 2017-2018
Department of Mechanical and Chemical Engineering (MCE)
Islamic University of Technology (IUT), OIC
Board Bazar, Gazipur
Dhaka, Bangladesh.

Signature of the Supervisor

Dr. Mohammad Ahsan Habib
Assistant Professor
Department of Mechanical & Chemical Engineering (MCE)
Islamic University of Technology (IUT), OIC
Board Bazar, Gazipur
Dhaka, Bangladesh.

Certificate of Approval

The thesis titled "Multi objective Optimization of Turning Process using Whale Algorithm" of Academic Year 2017-2018 has been found as satisfactory and accepted as partial fulfillment of the requirement for the degree of Bachelor of Science in Mechanical Engineering on 04 November, 2018.

BOARD OF EXAMINERS

----

1. **Dr. Mohammad Ahsan Habib**
   Assistant Professor
   Department of Mechanical and Chemical Engineering
   Islamic University of Technology (IUT)
   Board Bazar, Gazipur, Dhaka, Bangladesh.

----

2. **Prof. Dr. Md. Zahid Hossain**
   Professor and Head
   Department of Mechanical and Chemical Engineering
   Islamic University of Technology (IUT)
   Board Bazar, Gazipur, Dhaka, Bangladesh.

Acknowledgements

I would like to begin by saying Alhamdulillah and grateful to Almighty Allah who made it possible for me to finish this project successfully on time. Equally say a big thank to my supervisor Dr. Mohammad Ahsan Habib, Associate Professor, Department of Mechanical and Chemical Engineering, IUT for all his support, ideas about experiments, discussions, time and for explaining so patiently the hard topics and checking this thesis and papers above all his care and concern. These will ever remain in my memory. Thanks to my examiners for their constructive ideas, suggestions and double-checking my work.

Special thanks to all faculties for their support and encouragement throughout the period of my studies.

I will like to say a big thank you to the Head of Department Professor Dr. Zahid Hasan for his continues encouragement and support during the period of my studies. Finally, I will like to express my lasting gratitude to my family members for their patience, support, encouragement, enthusiasm and prayers.

Table of Contents

Abstract

This work is the optimization of machining parameters in steel turning operation. In this study, the experimental work was carried out by turning Stainless Steel 304 by using carbide inserts. There were three main purposes of this study. First was to explain and demonstrate a systemic procedure to collect a combination of data of parameters and then apply when the turning operation is performed. The second was to find the optimal combination by using Optimization Algorithm- WOA and Grey Analysis. The main conclusion drawn from this study is that efficient turning operations can be performed on 304 SS which will save power and time.

.

Chatper 1 Introduction

Current world's manufacturing, undisputedly, is governed mostly by the processes of metal removal. There have been major improvements in the processes at a systematic level that means by generation of the house of models (W. Grzesik n.d.). Experimentation and prototyping results were the data that were required for research in the zone of metal cutting (M. Salio 2006). This meant the researches were very expensive and also time-consuming (Amol Thakare n.d.). But it did not stop the researches in this field and the study have been undergoing for decades due to dependency of the manufacturing sector to understand better at addressing specific problems (M. Salio 2006).

The software DX-7 was used for creating equations among the parameters. This software uses statistical modeling. In statistical modeling, regression analysis is a set of statistical processes for estimating the relationships among variables.

AdvantEdge was used for our simulations. ThirdWave System's AdvantEdge is a machining specific FEM package. It has preprogrammed modules for both 2D and 3D machining operations including turning and milling. AdvantEdge also comes with a workpiece modeler as well as a material property library.

Our Study utilizes SAE 304 SS which is one of the most common stainless steel. The steel contains 0.08% C, 2% Mn, 0.75% Si, 0.045% P, 0.03% S, 20% Cr, 10.5% Ni. It is an austenitic stainless steel. It is less electrically and thermally conductive than carbon steel and is essentially non-magnetic. It has a higher corrosion resistance than regular steel and is widely used because of the ease in which it is formed into various shapes. It has a wide range of applications in many industries.

We used lathe machine for the turning operation and collected all the necessary data. The values were incorporated in the optimization analysis to find the most optimal parameters.

1.1 Optimization Algorithm: WOA and Grey Analysis

For optimization, we considered Whale Optimization Algorithm (WOA) – a recently proposed, nature inspired meta-heuristic optimization algorithm, which mimics the social behavior of humpback whales. The algorithm is first published in *Advances in Engineering Software* by Seyedali Mirjalili and Andrew Lewis in 2016. WOA is tested with 29 mathematical optimization problems and 6 structural design problems in the original paper and results are very instructive, it shows WOA algorithm is competitive enough compared to the state-of-art meta-heuristic algorithms as well as conventional methods.

1.1.1 Whale Optimization Algorithm

WOA algorithm is inspired form special hunting method of humpback, this foraging behavior is called bubble-net feeding method. Humpback whales prefer to hunt close to the surface by recognizing the location of prey and encircling them. This is the first step of the mathematical model of WOA algorithm. This behavior is represented by the following equations:

$$\vec{D} = \left|\vec{C}.\overrightarrow{X_p}(t) - \vec{X}(t)\right|$$

$$\vec{X}(t+1) = \overrightarrow{X_p}(t) - \vec{A}\vec{D}$$

Where t indicates the current iteration, and $\vec{A}$ and $\vec{C}$ are coefficient vectors, $\overrightarrow{X_p}$ is the position vector of the prey, and $\vec{X}$ indicates the position vector of a whale.

The vectors $\vec{A}$ and $\vec{C}$ are calculated as follows:

$$\vec{A} = 2\vec{a}\vec{r_1} - \vec{a}$$

$$\vec{C} = 2.\vec{r_2}$$

Where components of $\vec{a}$ are linearly decreased from 2 to 0 over the course of iterations and $\vec{r_1}, \vec{r_2}$ are random vectors in [0,1].

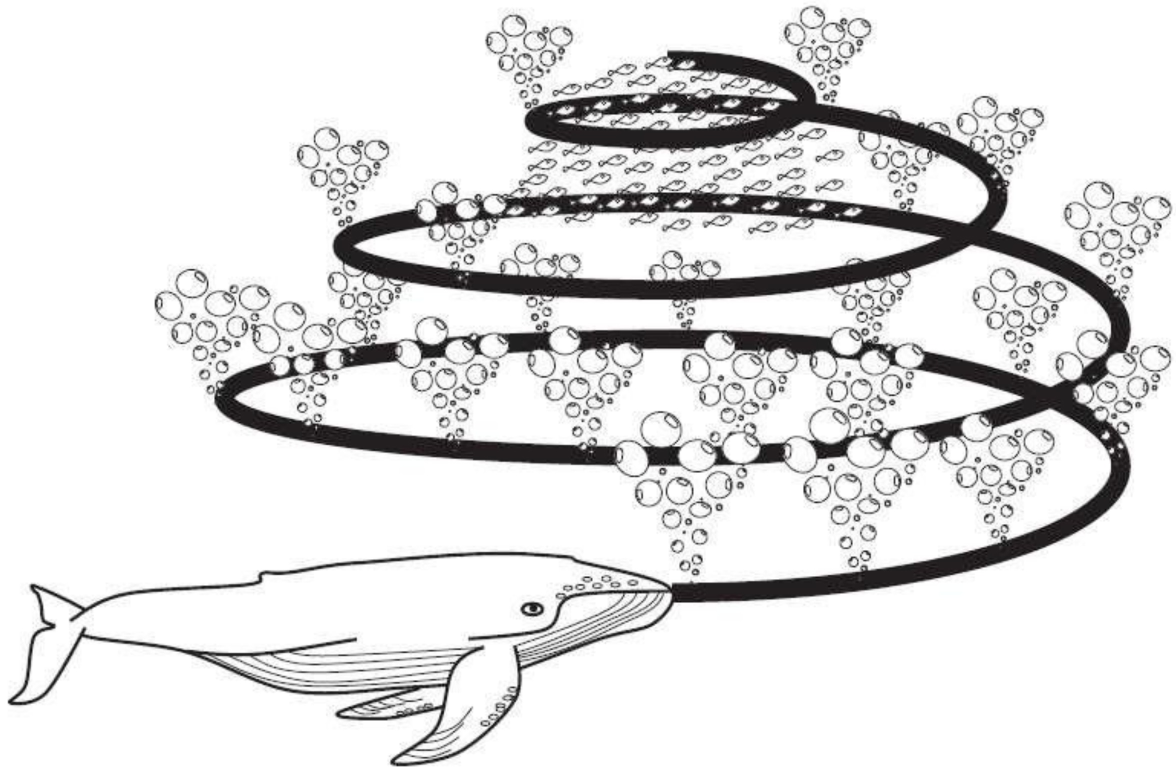


Figure: Bubble-net feeding behavior of humpback whale

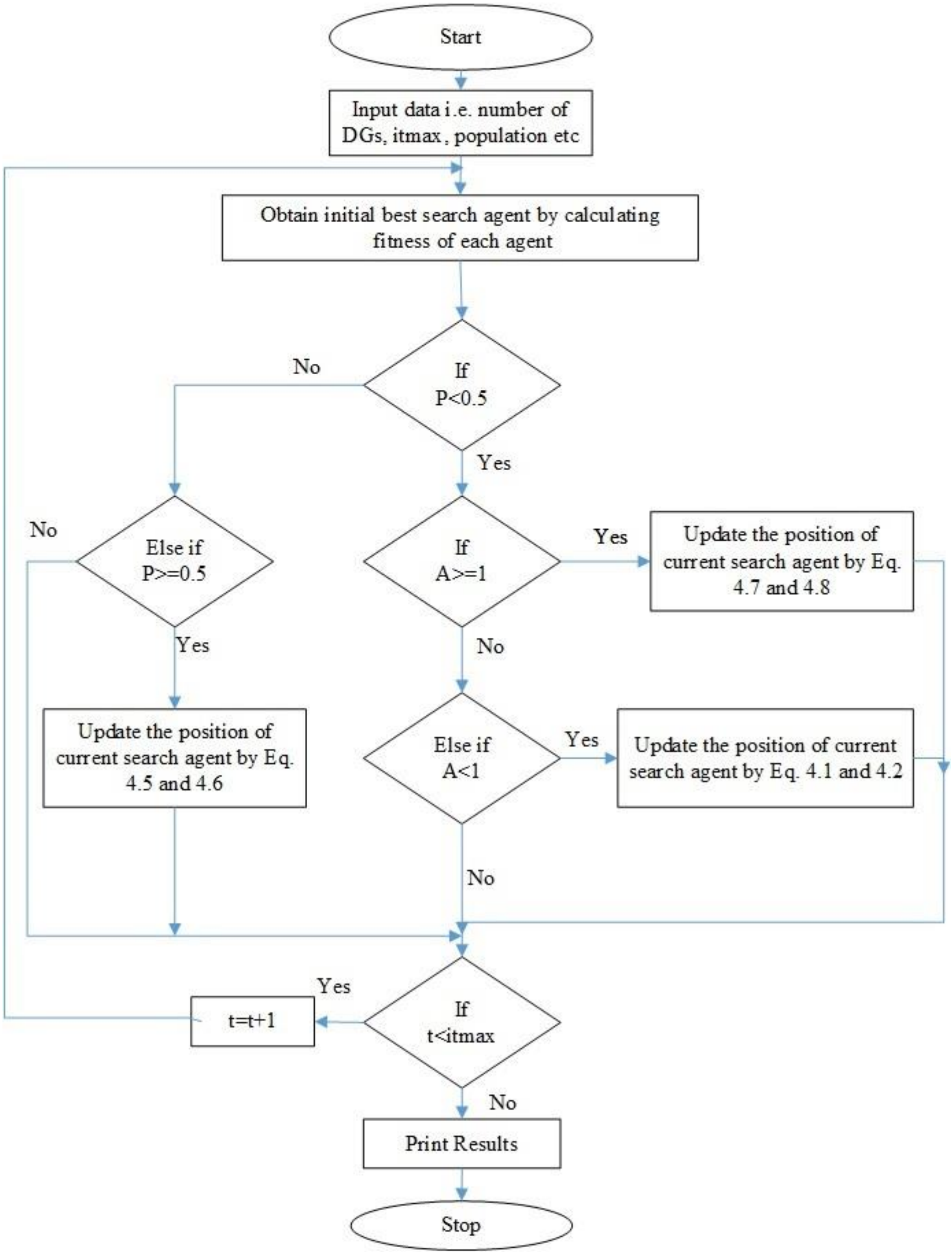
The second step is Bubble-net attacking method (exploitation phase), which consist of two mechanism that runs simultaneously. i) Shrinking encircling mechanism: where the circle shirks in order to get closed to the best position i.e. the prey location, ii) Spiral updating position: where a spiral equation is created between the position of whale and prey to mimic the helix-shaped movement of humpback whales as follows:

$$\vec{X}(t+1) = \overrightarrow{D'} e^{bt} \cos(2\pi t) + \overrightarrow{X^*}(t)$$
$$\vec{D} = \left|\overrightarrow{X^*}(t) - \vec{X}(t)\right|$$

The final step is Search for prey (exploration phase): In many cases optimization algorithm might get fall into local minima or maxima. For this reason, an exploration phase is needed where the humpback whales search for prey randomly outside the search space. The mathematical model is as follows:

$$\vec{D} = \left|\vec{C}\, \overrightarrow{X_{rand}} - \vec{X}\right|$$
$$\vec{X}(t+1) = \overrightarrow{X_{rand}} - \vec{A}.\vec{D}$$

The algorithm can be visualize more clearly using this flowchart:



1.1.2 Grey Relational Analysis

The grey system theory initiated by Deng in 1982 has been proven to be useful for dealing with poor, incomplete, and uncertain information. The grey relational analysis based on the grey system theory can be used to solve the complicated interrelationships among the multiple performance characteristics effectively. In grey relational analysis, black represents having no information system has a level of information between black and white. In other words, in a grey system, some information is known and some information is unknown. In a white system, the relationships among factors in the system are certain; in a grey system, the relationships among factors in the system are uncertain.

1.1.3 Data pre-processing

Data pre-processing is normally required since the range and unit in one data sequence may differ from the others. Data preprocessing is also necessary when the sequence scatter range is too large, or when the directions of the target in the sequences are different. Data pre-processing is a means of transferring the original sequence to a comparable sequence. Depending on the characteristics of a data sequence, there are various methodologies of data pre-processing available for the grey relational analysis. If the target value of original sequence is infinite, then it has a characteristic of the "higher is better". The original sequence can be normalized as follows:

$$x_i^*(k) = \frac{x_i^0(k) - \min x_i^0(k)}{\max x_i^0(k) - \min x_i^0(k)}$$

When the "lower is better" is a characteristic of the original sequence, then the original sequence should be normalized as follows:

$$x_i^*(k) = \frac{\max x_i^0(k) - x_i^0(k)}{\max x_i^0(k) - \min x_i^0(k)}$$

Where i =1 … … … m; k = 1 … … … n; m is the number of experimental data items and n is the number of parameters $x_i^0(k)$ denotes the original sequence $x_i^*(k)$ the sequence after the data pre-processing, max $x_i^0(k)$ the largest value of $x_i^0(k)$, min $x_i^0(k)$ the smallest value of $x_i^0(k)$ and $x_i^*(k)$ is the desired value, which is assumed 1.

1.1.4 Grey relational coefficient

In grey relational analysis, the measure of the relevancy between two systems or two sequences is defined as the grey relational grade. When only one sequence, $x_i^*(k)$, is available as the reference sequence, and all other sequences serve as comparison sequences, it is called a local grey relation measurement. After data pre-processing is carried out, the grey relation coefficient $\xi_o(k)$ for the k^{th} performance characteristics in the i^{th} experiment can be expressed as:

$$\xi_i(k) = \frac{\Delta_{\min} + \zeta\Delta_{\max}}{\Delta_{0i}(k) + \zeta\Delta_{\max}}$$

where, $\Delta_u(k)$ is the deviation sequence of the reference sequence and the comparability sequence.

$$\Delta_{0i}(k) = \left\| x_0^*(k) - x_i^*(k) \right\|$$
$$\Delta_{\min} = \min_{\forall j \in i} \min_{\forall k} \left\| x_0^*(k) - x_j^*(k) \right\|$$
$$\Delta_{\max} = \max_{\forall j \in i} \max_{\forall k} \left\| x_0^*(k) - x_j^*(k) \right\|$$

$x_0^*(k)$ denotes the reference sequence and $x_i^*(k)$ denotes the comparability sequence. ζ is distinguishing or identification coefficient: $\zeta \in [0,1]$ (the value may be adjusted based on the actual system requirements). A value of ζ is the smaller and the distinguished ability is the larger. $\zeta = 0.5$ is generally used.

1.1.5 Grey relational grade

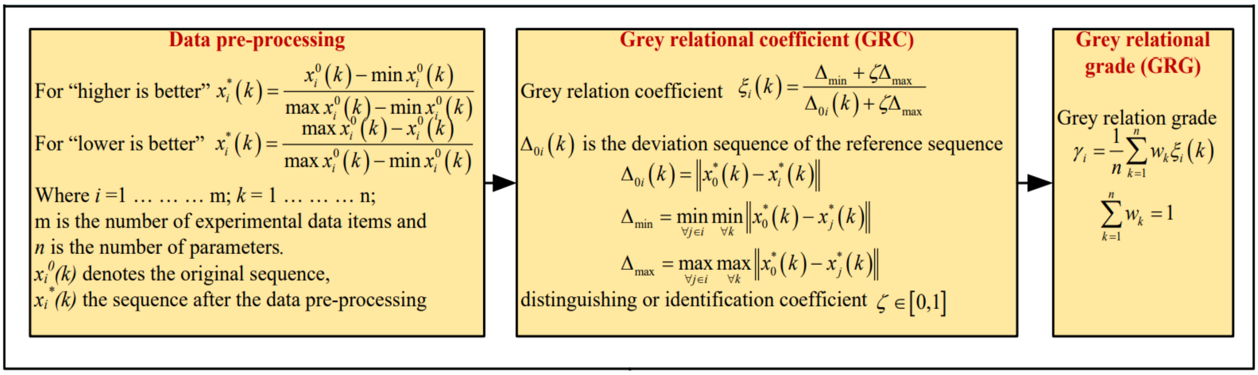
After the grey relational coefficient is derived, it is usual to take the average value of the grey relational coefficients as the grey relational grade. The grey relational grade is defined as follows:

$$\gamma_i = \frac{1}{n}\sum_{k=1}^{n}\xi_i(k)$$

However, in a real engineering system, the importance of various factors to the system varies. In the real condition of unequal weight being carried by the various factors, the grey relational grade in equation above was extended and defined as:

$$\gamma_i = \frac{1}{n}\sum_{k=1}^{n} w_k \xi_i(k) \qquad \sum_{k=1}^{n} w_k = 1$$

Three steps in Gray Analysis is summarized as follows:



Chatper 2 Literature Review

In turning process parameters such as cutting tool geometry and materials, the depth of cut, feed rates, cutting speeds as well as the use of cutting fluids will impact the material removal rates and the machining qualities like the surface roughness, the roundness of circular and dimensional deviations of the product (Kalpakjian and Schmid, 2001)

Yang and Tarng (1998) employed Taguchi method to investigate the cutting characteristics of S45C steel bars using tungsten carbide cutting tools. The optimal cutting parameters of the cutting speed, the feed rate and the depth of cut for turning operations with regard to performance indexes such as tool life and surface roughness are considered.

Davim (2003) investigated the influence of cutting conditions (cutting velocity and feed) and cutting time on turning metal matrix composites. An orthogonal array and the analysis of variance are employed to investigate the cutting characteristics of flank wear (VB), power required (Pm) and surface roughness (Ra).

Manna and Bhattacharyya (2004) took the significant cutting parameters into consideration and used multiple linear regression mathematical models relating the surface roughness height Ra and Rt to the cutting parameters for turning process of Al/SiC-MMC.

Aslan et al. (2007) used an orthogonal array and the analysis of variance (ANOVA) to optimization of cutting parameters in turning hardened AISI 4140 steel (63 HRC) with Al_2O_3 +TiCN mixed ceramic tool. The flank wear (VB) and surface roughness (Ra) had investigated a process optimization to determine optimal values of cutting parameters, such as cutting speed, feed rate and depth of cut.

Nalbant et al. (2007) used Taguchi method to find the optimal cutting parameters for surface roughness in turning operations of AISI 1030 steel bars using TiN coated tools. Three cutting parameters, namely, insert radius, feed rate, and depth of cut, are optimized with considerations of surface roughness, and so on.

However, very few studies have been conducted to investigate roundness under different turning parameter. Additionally, cutting fluids properly applied (Kalpakjian and Schmid, 2001; EI Baradie, 1996), can increase productivity and reduce costs by choosing higher cutting speeds, higher feed rates and greater depths of cut. Effective application of cutting fluids can also increase tool life, decrease surface roughness, increase dimensional accuracy and decrease the amount of power consumed. The water-soluble (Water-miscible) cutting fluids are primarily used for high speed machining operations because they have better cooling capabilities (EI Baradie, 1996).

Recently, Deng (1989) proposed a Grey relational analysis. The Grey relational analysis is a method for measuring the degree of approximation among the sequences using a Grey relational grade. Theories of the Grey relational analysis have attracted considerable interest among researchers. Some other researchers have also examined the optimization of process parameters. For example, Huang and Lin (2002) applied the Grey relational analysis to design the die-sinking EDM machining parameters. Fung et al. (2003) studied the Grey relational analysis to obtain the optimal parameters of the injection molding process for mechanical properties of yield stress and elongation in polycarbonate/acrylonitrilebutadiene- styrene (PC/ABS) composites. Shen et al. (2004) studied

different polymers (such as PP, PC, PS, POM) with various process parameters of the microgear. The simulation used the Taguchi method and the Grey relational analysis were
provided.

Aggarwal et al. (2008) apply a response surface methodology and Taguchi's technique for optimizing power consumption in CNC turning of AISI P-20 tool steel. The effect of the cutting speed, feed rate, depth of cut, nose radius, and cutting environment (dry, wet, and cryogenic) has been experimentally tested. It has been determined that the cryogenic coolant is the most significant factor for minimum power consumption, followed by the cutting speed and the depth of cut. The effect of feed rate and nose radius were found to be insignificant compared to other factors.
Very similar results for the effect of cutting speed, feed rate, depth of cut, and nose radius on the minimization of power consumption have been achieved during the turning of Al alloy, SiC particle composites by applying a response surface methodology (Bhushan, 2013).

In machining processes, the most commonly used optimization criterions are material removal rate (MRR), surface roughness (SR), cutting force, tool life and power consumption, which has been used from the beginning of the researches in this branch to some of the most recent works (Goparsamy et al., 2009).

However, single objective approaches have a limited value to fix the optimal cutting parameters, where several different and contradictory objectives must be simultaneously optimized. Hence, multi-objective approaches which consider several different and contradictory objectives have been reported in cutting parameters optimization.

Significant work has been done to optimize cutting parameters based on machining science and economic considerations. A comprehensive literature review of optimization techniques in metal machining processes has been provided by Mukherjee and Ray (2006).

In a turning operation, it is an important task to select cutting parameters for achieving high cutting performance. Usually, the desired cutting parameters are determined based on experience or by use of a handbook. However, this does not ensure that the selected cutting parameters have optimal or near optimal cutting performance for a particular machine and environment. To select the cutting parameters properly, several mathematical models [1–6] based on statistical regression techniques or neural computing have been constructed to establish the relationship between the cutting performance and the cutting parameters. Then, an objective function with constraints is formulated to solve the optimal cutting parameters using optimization techniques. Therefore, considerable knowledge and experience are required for using this modern approach.

Furthermore, a large number of cutting experiments has to be performed and analyzed in order to build the mathematical models. Thus the required model buildings is very costly in terms of time and materials. In this paper, an alternative approach based on the Taguchi method [7–9] is used to determine the desired cutting parameters more efficiency.

Basically, the Taguchi method is a powerful tool for the design of high quality systems. It provides a simple,efficient and systematic approach to optimize designs

for performance, quality, and cost. The methodology is valuable when the design parameters are qualitative and discrete. Taguchi parameter design can optimize the performance characteristics through the settings of design parameters and reduce the sensitivity of the system performance to sources of variation. In recent years, the rapid growth of interest in the Taguchi method has led to numerous applications of the method in a world-wide range of industries and nations [10].

In the following, the Taguchi method is introduced first. The experimental details of using the Taguchi method to determine and analyze the optimal cutting parameters are described next. The optimal cutting parameters with regard to performance indexes such as tool life and surface roughness are considered.

Hauschild et al. (2005) report suggests that the deficiency in the evaluation of the life cycle and the process involved in product's manufacturing to provide substantial consumption amounts of energy and other resources and, as a result, have a measurable impact on the environment.

Reducing the energy consumption of machine tools can significantly improve the environmental performance of manufacturing systems. To achieve this, monitoring of energy consumption patterns in the systems is required. It is vital in these studies to correlate energy usage with the operations being performed in the manufacturing system. However, this can be challenging due to complexity of manufacturing systems and the vast number of data sources. Event stream processing techniques are applied to automate the monitoring and analysis of energy consumption in manufacturing systems (Vijayaraghavan and Dornfeld, 2010).

The aim of the work reported by Hanafi and Khamlichi (2012), is to outlines the application of gray relational theory and Taguchi optimization methodology in order to optimize the cutting parameters for PolyEther Ether Keytone reinforced with 30% of carbon fibers. The material is turned by using TiN coated tools under dry conditions. The objective of optimization is to achieve simultaneously the minimum power consumption and the best surface quality. This involves in practice reducing the environmental footprint related to such manufacturing process while providing enhanced functional performance in terms of surface integrity of machined parts. The obtained results have indicated that cutting speed and depth of cut are the most influential parameters. The optimal setting of machining parameters achieving sustainability target in terms of minimum surface roughness and minimum cutting power was determined.

The aim of the work reported in Huseyin Cetin et al. (2011), was to evaluate the performances of six CFs, four different VBCFs from sunflower and canola oils with different ratios of extreme pressure (EP) additives, and two commercial types of CFs (semi-syntheticand mineral) for reducing of surface roughness, and cutting and feed forces during turning of AISI 304L austenitic stainless steel with carbide insert tool. Taguchi's mixed level parameter design (L18) is used for the experimental design. Cutting fluid, spindle speed, feed rate and depth of cut are considered as machining parameters. Regression analyses are applied to predict surface roughness, and cutting and feed forces. ANOVA is used to determine effects of the machining parameters and CFs on surface roughness, cutting and feed forces. In turning of AISI 304L, effects of feed rate and depth of cut are found to be more effective than CFs and spindle speed on reducing forces and improving the surface finish. Performances of VBCFs and commercial CFs are also compared and results generally show that sunflower and canola based CFs perform better than the others.

Cemal Cakir et al. [1] described a procedure to calculate the machining conditions for turning operation with minimum production cost as the objective function. The authors determined production time and cost for different work piece and tool material for the same input data. Meng et al. [2] described a machining theory to calculate optimum cutting condition in turning for minimizing cost or maximizing production rate. Lee et al. [3] developed a self-organizing adaptive modeling technique to find the relationship between cutting speed, feed, depth of cut and surface roughness, cutting force, and tool life. Uros Zuperl et al. [9] developed neural network to describe the multi-objective optimization of cutting conditions for machining. Franci Cus et al. [10] proposed Genetic algorithm for the determination of cutting parameters to reduce production cost and time. Experimental result shows that proposed Genetic algorithm is effective and efficient for solving optimization problem. Ezugwu et al. [12] developed a model for the analysis and prediction of the relationship between cutting and process parameters during high speed turning of nickel-based Inconel 718 alloy. Ramon et al. [14] used Genetic algorithm for optimizing cutting parameters and made a remark on the advantages of multi-objective optimization approach over single objective function. Al-Ahmari [16] developed empirical model for tool life, surface roughness and cutting force for turning operations. Data mining techniques such as response surface methodology and neural network are used to develop the machinability model.

The selection of optimal cutting parameters, like the number of passes, depth of cut for each pass, feed and speed, is a very important issue for every machining processes. In workshop practice, cutting parameters are selected from machining databases or specialized handbooks,
but the range given in this sources are actually starting values, and are not the optimal values (Dereli et al., 2001). Optimization of cutting parameters is usually a difficult work (Kumar and Kumar, 2000), where the following aspects are required: knowledge of machining; empirical equations relating the tool life, forces, power, surface finish, etc., to develop realistic constrains; specification of machine tool capabilities; development of an effective optimization criterion; and knowledge of mathematical and numerical optimization techniques (So¨ nmez et al., 1999).
In any optimization procedure, it is a crucial aspect to identify the output of chief importance, the so-called optimization objective or optimization criterion. In manufacturing processes, the most commonly used optimization criterion is specific cost, which has been used by many authors, from the beginning of the researches in this branch (Taylor, 1907) to some of the most recent works (Liang et al., 2001; Wang et al., 2002;Saravanan et al., 2003; Cus and Balic, 2003; Amiolemhen and Ibhadode, 2004).
Sometimes, other criteria like machining time (Chuaet al., 1991), material removal rate (Ko and Kim, 1998; Chien and Tsai, 2003) or tool life (Molinari and Nouari, 2002) have been used too. However, these single objective approaches have a limited value to fix the optimal cutting

conditions, due to the complex nature of the machining processes, where several different and contradictory objectives must be simultaneously optimized. Some multi-objective approaches have been reported in cutting parameters optimization (Lee and Tarng, 2000; Zuperl and Cus, 2003; Cus and Balic, 2003), but mainly they use a priori techniques, where the decision maker combines the different objectives into a scalar cost function. This actually makes the multi-objective problem, single-objective prior to optimization (Van Veldhuizen and Lamont, 2000).

On the other hand, in the a posteriori techniques, the decision maker is presented with a set of non-dominated optimal candidate solutions and chooses from that set. These solutions are optimal in the wide sense that no other solution in the search space are superior to them when all optimization objectives are simultaneously considered (Abbass et al., 2001). They are also known as Pareto-optimal solutions. Comparing citations by technique, in the last years, evidences the popularity of a posteriori techniques (Van Veldhuizen and Lamont, 2000). In dealing with multiobjective optimization problems, classical optimization methods (weighted sum methods, goal programming, min–max methods, etc.) are not efficient, because they cannot find multiple solutions in a single run, thereby requiring them to be applied as many times as the
number of desired Pareto-optimal solutions.

On the contrary, studies on evolutionary algorithms have shown that these methods can be efficiently used to eliminate most of the above-mentioned difficulties of classical methods (Soodamani and Liu, 2000). In this paper, a multi-objective optimization method, based on a posteriori techniques and using genetic algorithms, is proposed to obtain the optimal parameters in turning processes.

Cemal Cakir et al. [1] described a procedure to calculate the machining conditions for turning operation with minimum production cost as the objective function. The authors determined production time and cost for different work piece and tool material for the same input data. Meng et al [2] described a machining theory to calculate optimum cutting condition in turning for minimizing cost or maximizing production rate. Lee et al. [3] developed a self-organizing adaptive modeling technique to find the relationship between cutting speed, feed, depth of cut and surface roughness, cutting force, and tool life. Uros Zuperl et al. [9] developed neural network to describe the multi-objective optimization of cutting conditions for machining. Franci Cus et al. [10] proposed Genetic algorithm for the determination of cutting parameters to reduce production cost and time. Experimental result shows that proposed Genetic algorithm is effective and efficient for solving optimization problem. Ezugwu et al. [12] developed a model for the analysis and prediction of the relationship between cutting and process parameters during high speed turning of nickel-based Inconel 718 alloy. Ramon et al. [14] used Genetic algorithm for optimizing cutting parameters and made a remark on the advantages of multi-objective optimization approach over single objective function. Al-Ahmari [16] developed empirical model for tool life, surface roughness, and cutting force for turning operations. Data mining techniques such as response surface methodology and neural network are used to develop the machinability model.

Chatper 3 Methodology and Development of Experimental Setup

3.1 INTRODUCTION

The objective of this chapter is to determine the optimum parameters for turning process of 304 stainless steel through multiple objective optimization. For this optimization process, multiple parameters are taken into account such as heat rate, surface roughness and peak tool temperature. The multiple objective optimization process is based on single objective optimization and grey analysis.

There can be several combinations of parameters to conduct a turning operation on 304 SS. But to gain minimal chatter or corrosion of the cutting tool, an optimum set of parameters can be really helpful and elongates the lifespan of the cutting tool.

To optimize the turning process, combination sets of cutting speed and the depth of cuts are fixed and experiments and simulations are done accordingly.

The experiments were done with High Speed Steel or HSS. These are carbide tipped inserts that are used for the turning operation. Using the same parameters, the simulations were done through a software called AdvantEdge that is an FEA product to understand metal cutting process and the

Work piece	Dimensions (mm)
Diameter	25
Length	5

results were compared to find the parameters that are most suitable to optimize the turning process and are directly related to the job process.

Design of Experiment:

Experimental Plan:

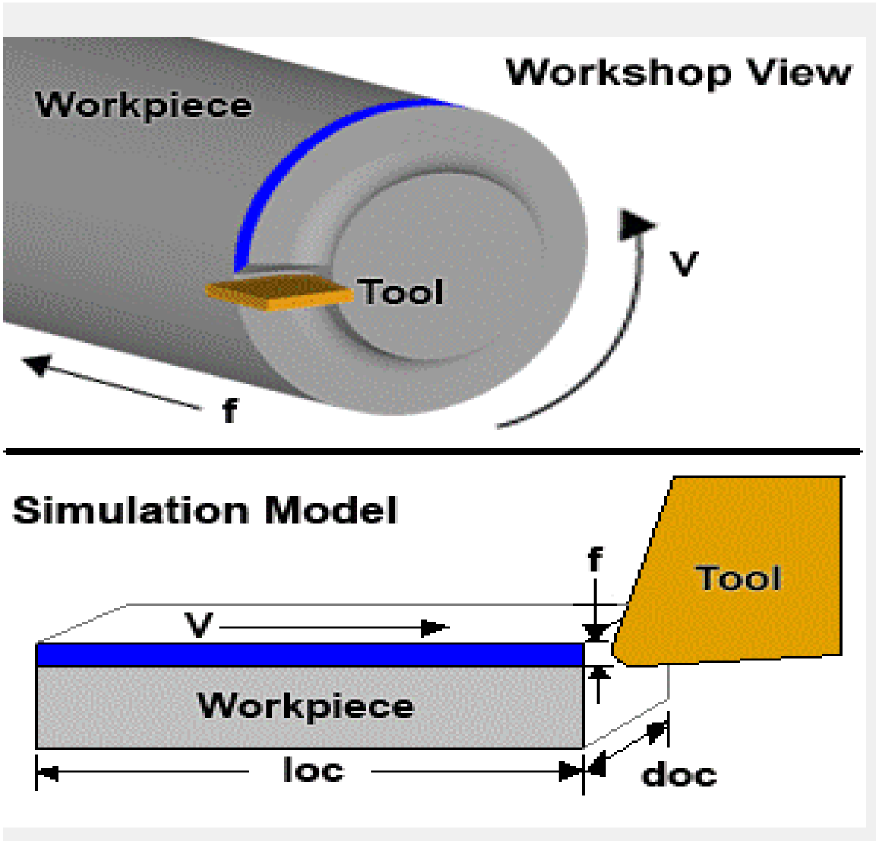


Figure: Experimental job piece and cutting tool model

Work piece Composition and Dimension:

Components	**Weight (%)**
C	0.03
Cr	19.0
Mn	2.0
Ni	10.0
P	0.045
S	0.03
Si	0.75

Tool Parameters:

\

Parameters	Dimensions
Cutting Edge Radius	0.2 (mm)
Rake Angle	10 (Degree)
Relief Angle	10 (Degree)

Table: Parameters used for cutting tool

Experimental design is widely used to control the effects of parameters in many processes. The usage of experimental designs reduces the number of experiments, usage time and material resources. Moreover, the analysis performed based on the results is realized with ease and the errors done in the experiments can bi minimized. Statistical method measures the effects of change in operating variables and their mutual interactions on process through experimental design way. The three steused are numerical approach using the software AdvantEdge, experimentation done in turning machine with controlled parameters and optimizing the whole process in case of parameters.

3.2 Experimentation:

In order to determine the optimum parameters, the three parameters cutting speed, depth of cut and feed were kept fixed and changed at regular interval to conduct the turning process.

To form the cutting tool, at first sawing process were done. Then to form the cutting tool, grinding process were done to get the proper rake angle and relief angle. To form the cutting tool properly, expert supervision was ensured.

The cutting speeds were altered within five values that were permitted by the turning machine.

S. No.	Input		
	Cutting Speed (m/s)	Feed (mm/min)	Depth of Cut (mm)
1	11.00	0.18	0.4
2	28.27	0.18	0.4
3	11.00	0.36	0.4
4	28.27	0.36	0.4
5	11.00	0.18	0.8
6	28.27	0.18	0.8
7	11.00	0.36	0.8
8	28.27	0.36	0.8
9	7.42	0.27	0.6
10	31.85	0.27	0.6
11	19.64	0.14	0.6
12	19.64	0.4	0.6
13	19.64	0.27	0.32
14	19.64	0.27	0.88
15	19.64	0.27	0.6
16	19.64	0.27	0.6

17	19.64	0.27	0.6
18	19.64	0.27	0.6
19	19.64	0.27	0.6
20	19.64	0.27	0.6

Table : Parameters used in the turning operation

The depth of cut and feed were changed within ranged values and the intermediary differences were generated by using DX7. The software uses normal distribution to generate the values from the given sets of values.

Using the generated depth of cuts, feeds and the permitted cutting speeds the turning operations were initiated. The job piece was set within the lathe chuck and the spindle was set to rotate at the given speed. The job piece that is made of 304 stainless steel was to turn by the carbide tipped cutting tool made from High Speed Steel or HSS. After the turning process, the surface roughness was measured using the surface roughness measuring machine and were tabulated.

The coolant that was used in the experiment was a composition of 10% chrysan, C225 soluble oil. The temperature that the coolant was used was 20 degree Celsius. The heat transfer co-efficient of the coolant was 9933 W/m^2.k. (reference)

Figure : Surface Roughness Measurement Machine

3.3 Simulation Process

AdvantEdge is the Premier Finite Element Analysis (FEA) product used to understand the metal cutting process. AdvantEdge features a full suite for analysis including chip formation, temperatures and stresses and forces on the tool and workpiece. The software has a validation process and material models built into the program. Specifically for metal cutting, this allows the user to make confident decisions without physical testing.

The sole purpose for numerical analysis is to reduce the physical testing and limit the error to a minimal curb. The numerical analysis was done with the AdvantEdge software that simulates the turning process according to the given parameters and conditions.

The parameters used in these simulations were set as per the chart formulated from the software DX7. Using the sets of values, set by the software, the simulations were run and changed accordingly.

Work-piece Geometry

Step 1: Setting the process type and selecting the defining dimension (figure)

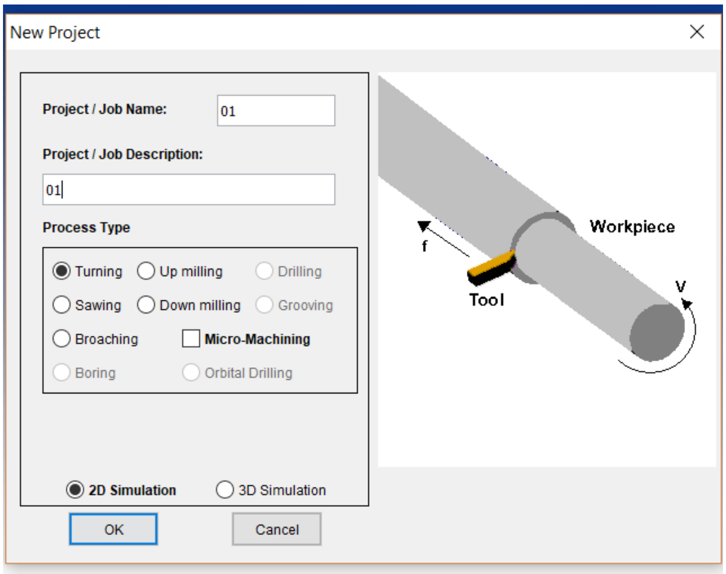


Figure: Process selection

Step 2: Setting the turning process parameter (figure)\

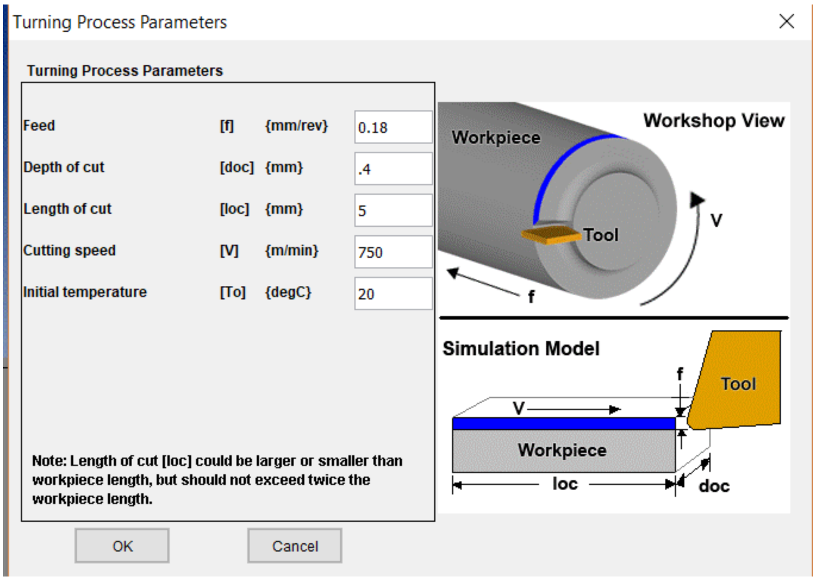


Figure : Importing turning process parameters

Step 3: Setting the turning tool parameters

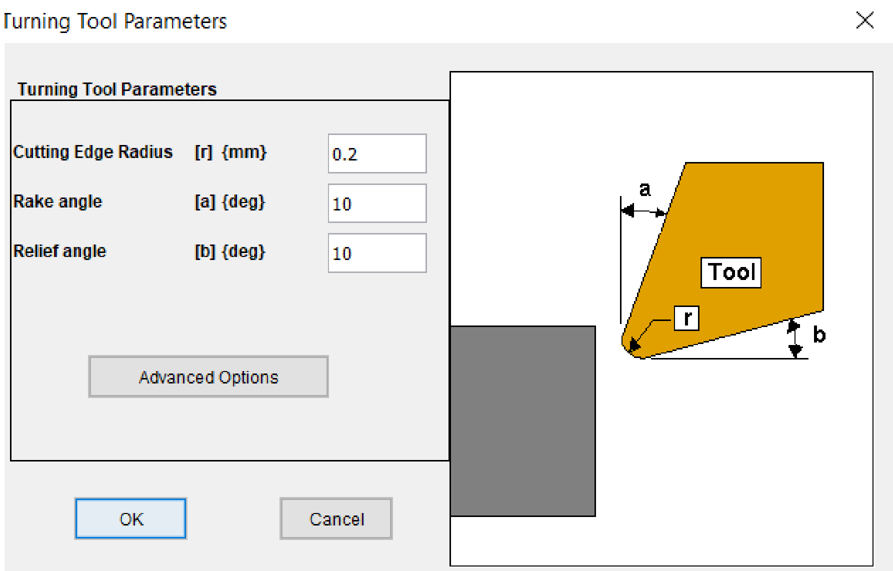


Figure : Parameter input for cutting tool

Step 4: Appointing the work piece dimensions (figure)

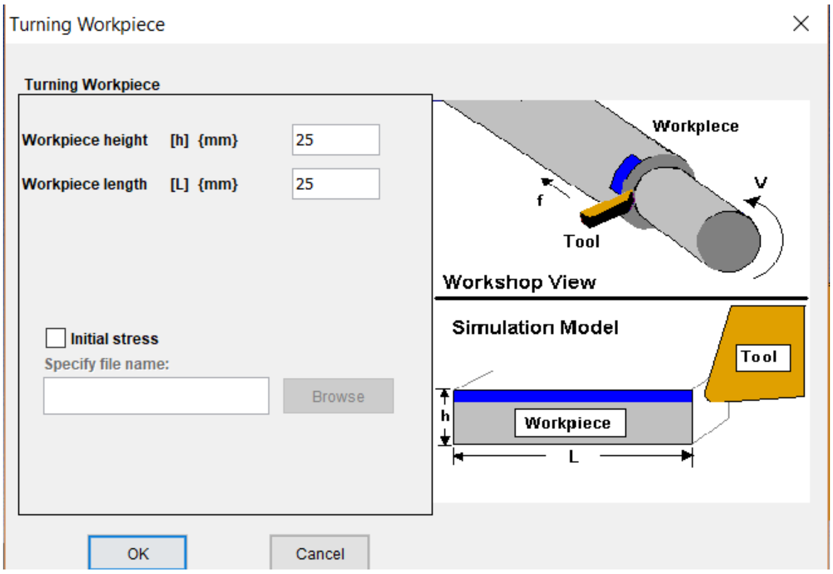


Figure : Dimension input for work piece

Step 5: Choosing the cutting tool material (figure)

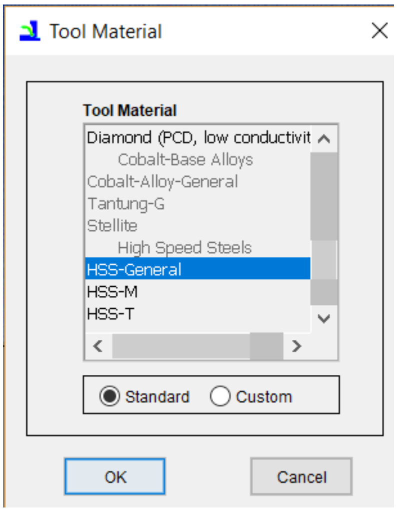


Figure : Determination of tool material

Step 6: Selecting the material for work piece

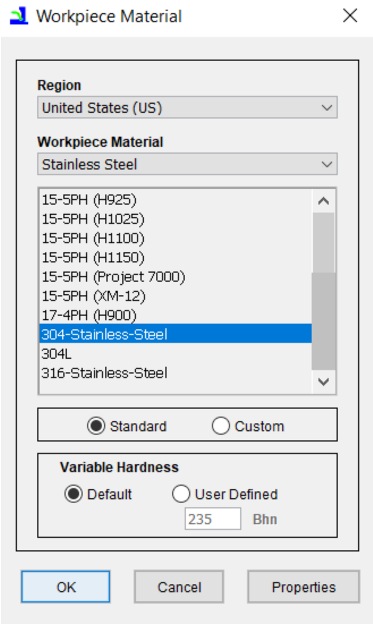


Figure: Selection of job piece material

Step 7: Selection of coolant for the operation and defining its properties (figure)

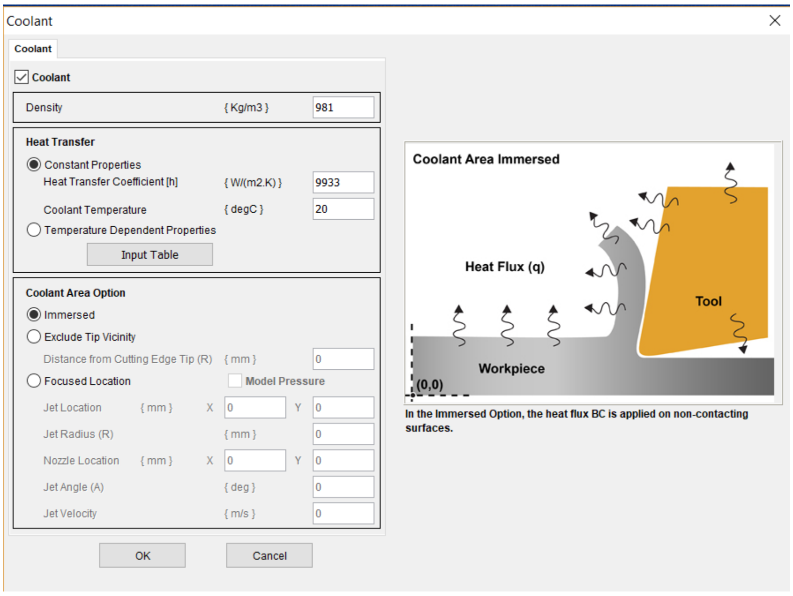


Figure: Coolant properties

Step 8: Initiation of simulation and selecting the properties (figure)

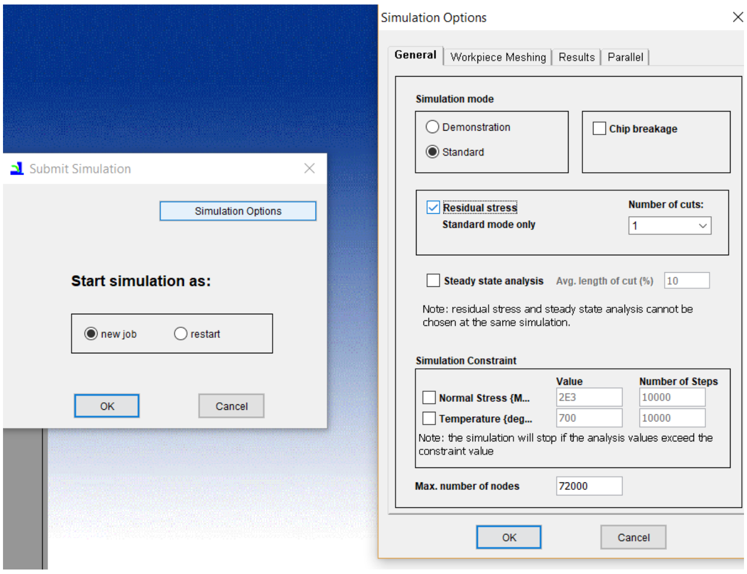


Figure: Imitation of simulation

Step 9: Obtaining result using Techplot (figure)

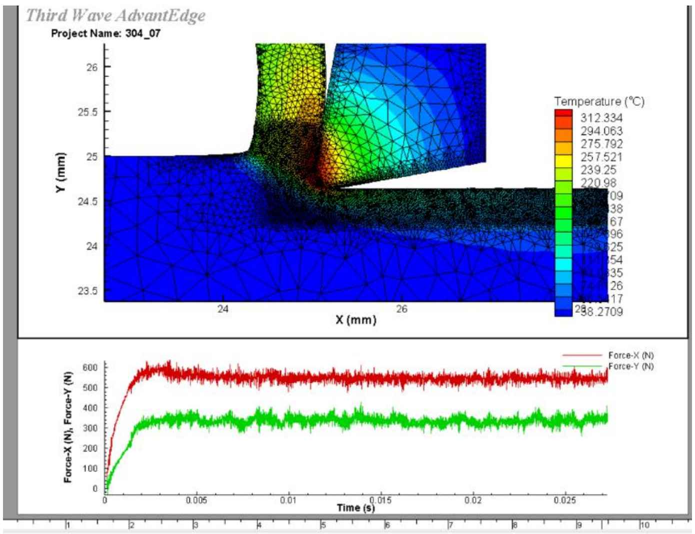


Figure: Visual representation of Techplot

3.3.1 Mesh Generation

All the parameters and conditions were prefixed and controlled. The meshes for the simulation were auto generated.

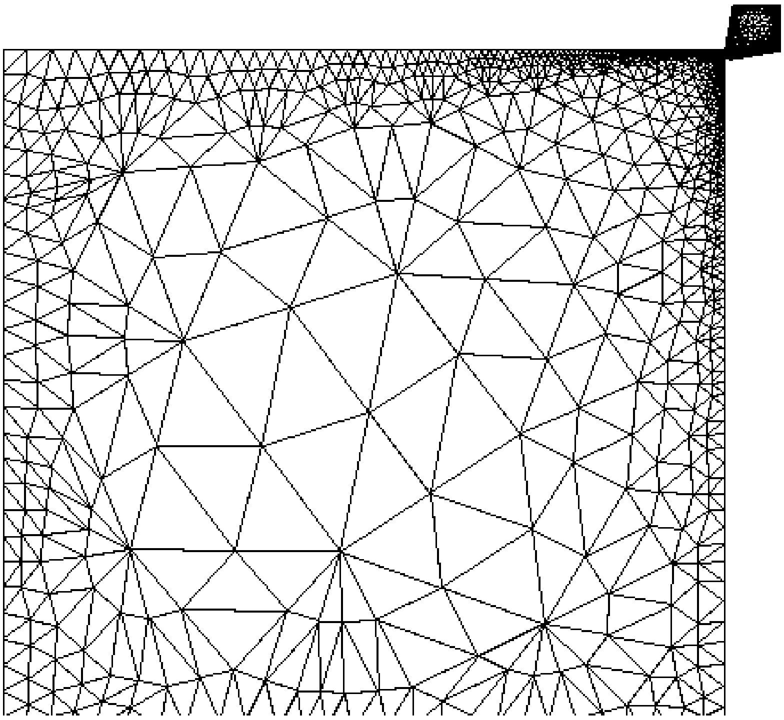


Figure: Mesh type

The mesh values were set automatically according to the parameters that the users defined.

The mesh had the following values:

Mesh Refine = 2

Mesh Coarse = 6

Mesh type: Dynamic

3.4 Surface Roughness Visualization

3.4.1 SEM Images

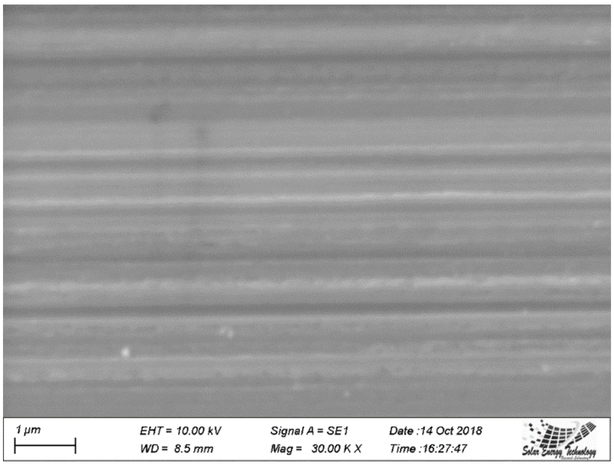
A **scanning electron microscope** (**SEM**) is a type of electron microscope that produces images of a sample by scanning the surface with a focused beam of electrons. To get a better idea on the parameter surface roughness, a number of SEM images have been captured at the BCSIR. The work pieces, that were taken SEM image of were 4mm in width and 3 mm in height.

Parameters used to prepare the specimen:

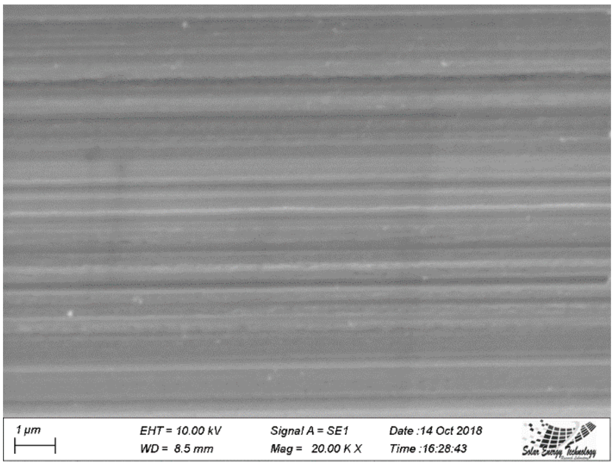
Cutting Speed: 7.42

Depth of Cut: 0.32

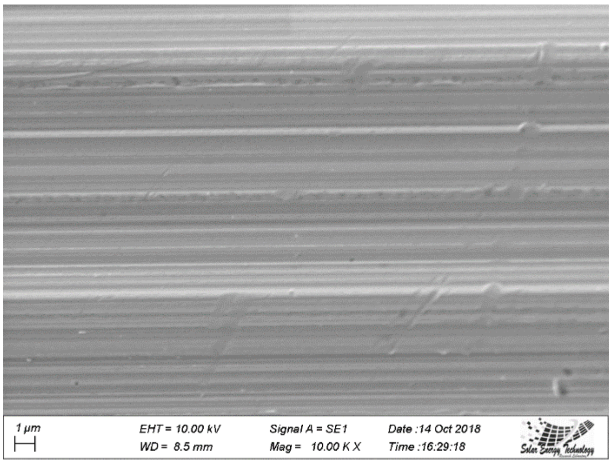
Feed Rate: 0.14

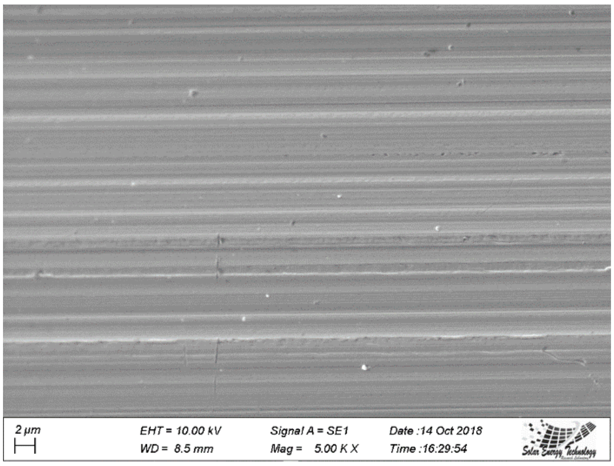


(a)



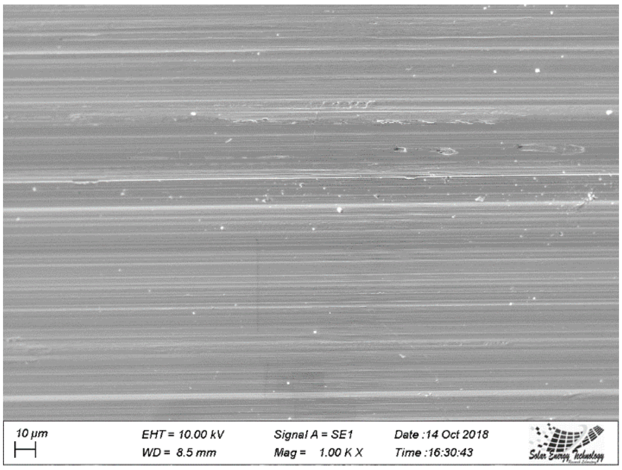
(b)

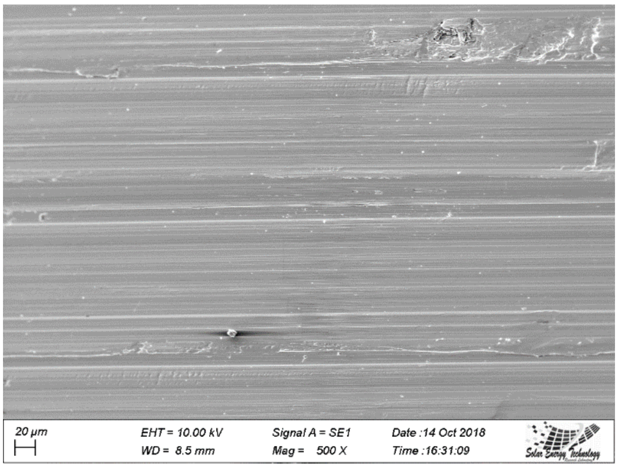

1 µm
EHT = 10.00 kV
WD = 8.5 mm
Signal A = SE1
Mag = 10.00 K X
Date :14 Oct 2018
Time :16:29:18


2 µm
EHT = 10.00 kV
WD = 8.5 mm
Signal A = SE1
Mag = 5.00 K X
Date :14 Oct 2018
Time :16:29:54

(c)

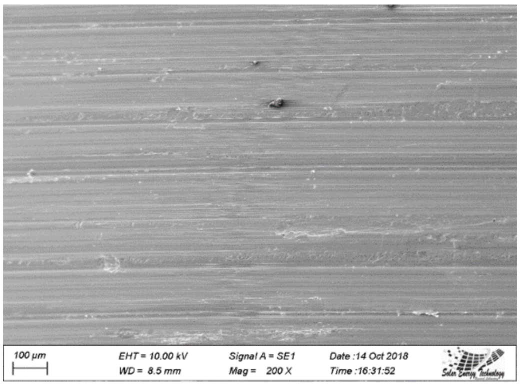
(d)


10 µm
EHT = 10.00 kV
WD = 8.5 mm
Signal A = SE1
Mag = 1.00 K X
Date :14 Oct 2018
Time :16:30:43


20 µm
EHT = 10.00 kV
WD = 8.5 mm
Signal A = SE1
Mag = 500 X
Date :14 Oct 2018
Time :16:31:09

(e)

(f)



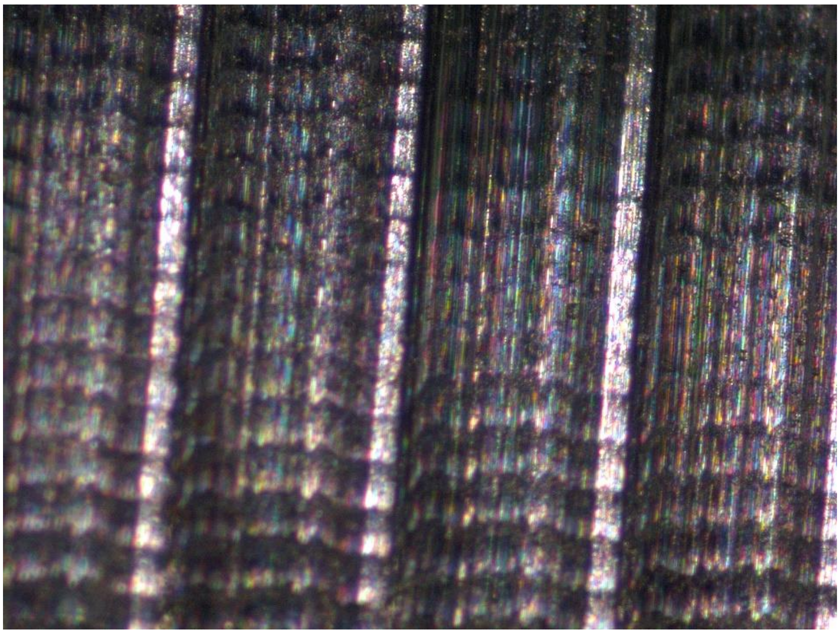
(g)

Figure: SEM Images (a) Magnified 30,000 times, (b) Magnified 20,000 times, (c) Magnified 10,000 times, (d) Magnified 5,000 times, (e) Magnified 1,000 times, (f) Magnified 500 times, (g) Magnifie4.1d 200 times

3.4.2 Optical Microscopic Images

The optical microscope, often referred to as the light microscope, is a type of microscope that uses visible light and a system of lenses to magnify images of small subjects. Basic optical microscopes can be very simple, although many complex designs aim to improve resolution and sample contrast.

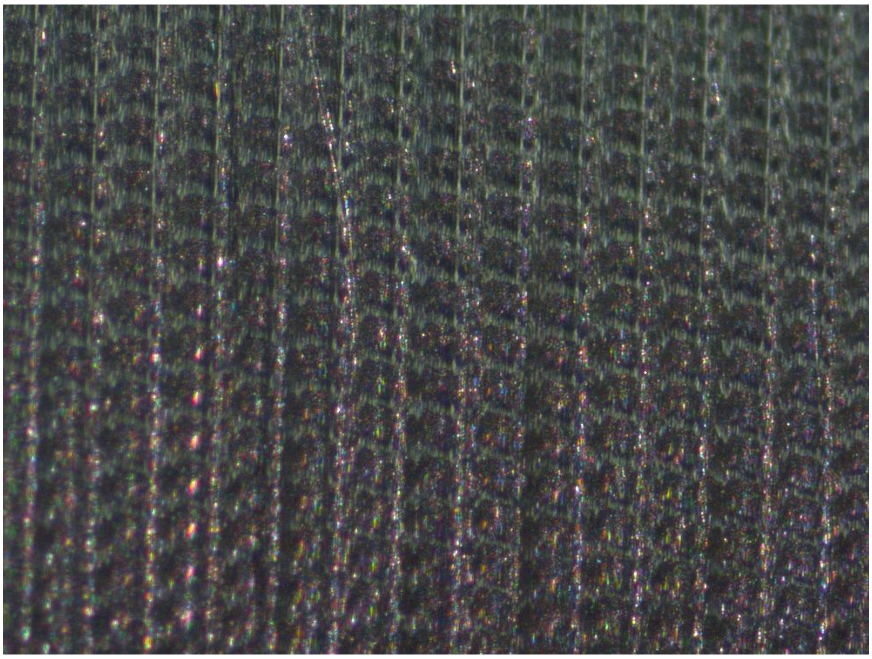
The image from an optical microscope can be captured by normal, photosensitive cameras to generate a micrograph. Purely digital microscopes were used which use a CCD camera to examine the sample, showing the resulting image directly on a computer screen without the need for eyepieces.



Specimen Parameter:

Cutting speed-11 m/s, feed-0.18 mm/min, depth of cut-0.4mm

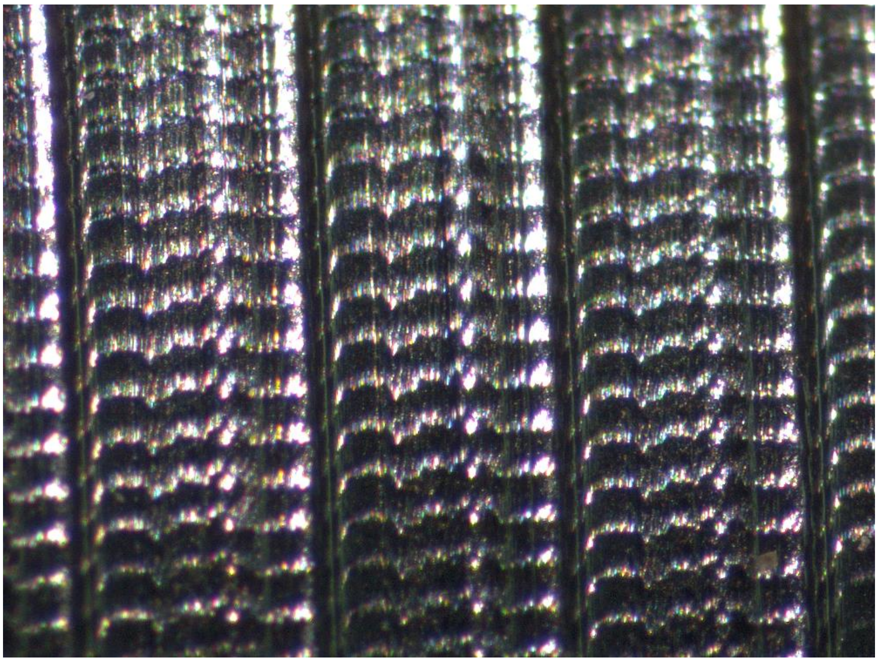
(a)



Specimen Parameter:

Cutting speed-28.27 m/s, feed-0.18 mm/min, depth of cut-0.4mm

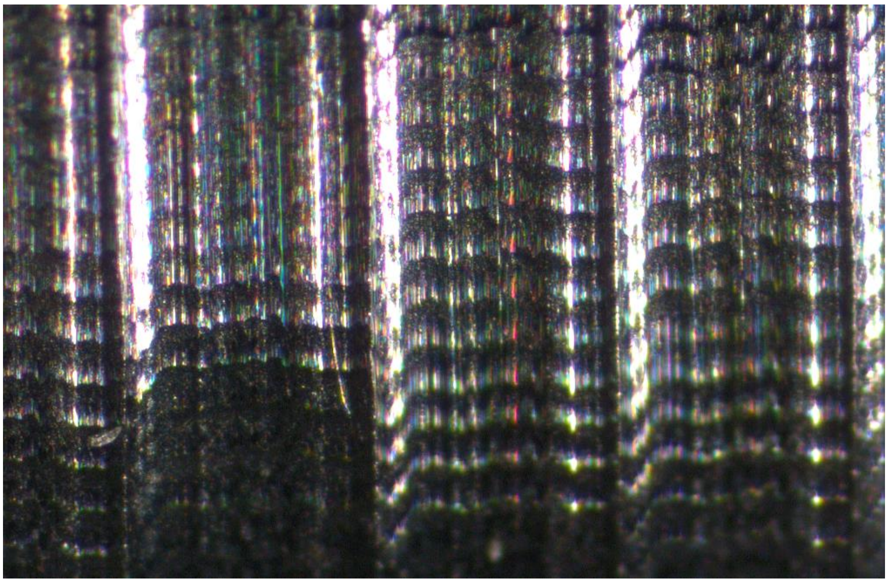
(b)



(c)

Specimen Parameter:

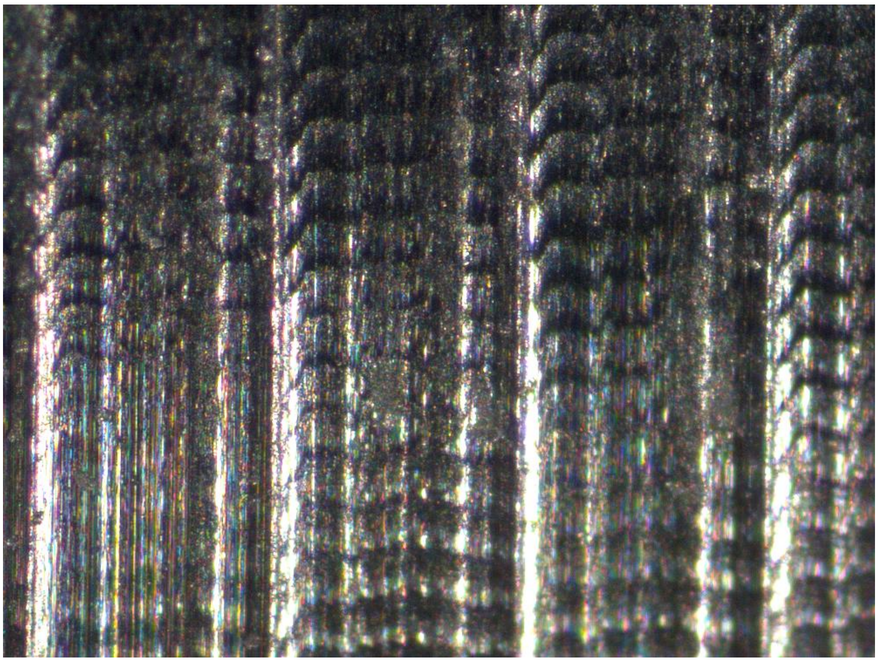
Cutting speed-11 m/s, feed-0.36 mm/min, depth of cut-0.4mm



(d)

Specimen Parameter:

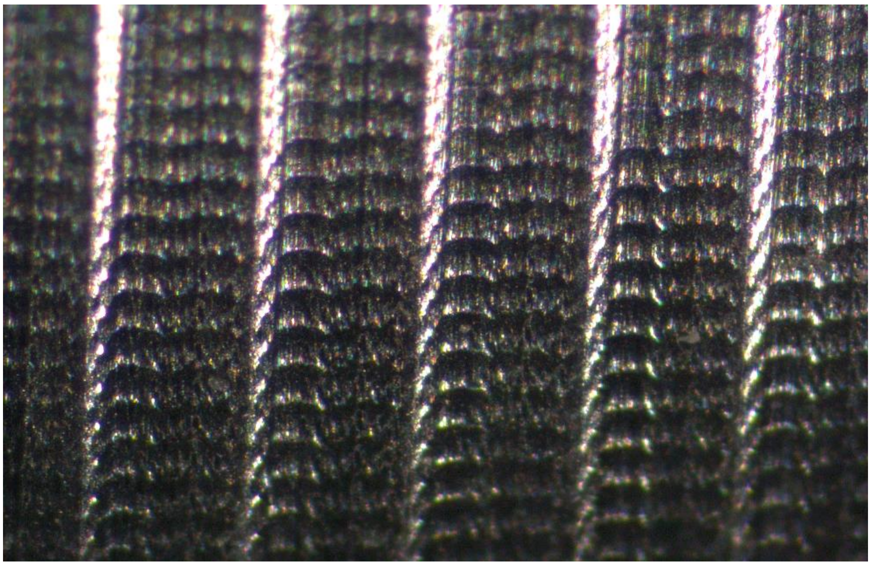
Cutting speed-28.27 m/s, feed-0.36 mm/min, depth of cut-0.4mm



Specimen Parameter:

Cutting speed-11 m/s, feed-0.18 mm/min, depth of cut-0.8mm

(e)



Specimen Parameter:

Cutting speed-11 m/s, feed-0.36 mm/min, depth of cut-0.8mm

(f)

Figure: Optical Microscopic Images of specimens machined under various parameters.

Chatper 4 Results

Table: AdvantEdge software has been used to generate the values in this table. The maximum value from the simulations has been taken.

Experimental					
Roughness	**Peal Tool Temperature (C)**	**Heat Rate(W/mm3)**	**Power**	**Force X**	**Force Y**
2.2	307	1018	32.5	179	143
2	420	2617	83	176	150.2
2.5	338	509	53.5	293	174
2.3	465	1308	135	286	180
2.25	300	1018	65.5	358	285
2.05	420	2618	164	348	288
2.6	335	509	107.2	582	350
2.4	466	1309	271	575.5	367
2.55	277	457	43.9	357	248
2.2	460	1966	185	349	250
2.1	362	2337	19.8	60.8	55.7
2.7	420	818	155	474	280
2.3	390	1212	62	188	132
2.55	389	1212	170	517	365
2.45	382	1212	115.5	353	249
2.46	382	1212	115.5	353	249
2.46	382	1212	115.5	353	249
2.45	382	1212	115.5	353	249
2.46	382	1212	115.5	353	249
2.45	382	1212	115.5	353	249

Table: Using DX-7 and the values from the simulations, a regression equation was generated and the values were generated from the equation.

Emperical					
Roughness	**Peal Tool Temperature (C)**	**Heat Rate(W/mm3)**	**Power**	**Force X**	**Force Y**
2.20	304.7	1006.6	30.1	166.2	133.2
1.99	422.8	2663.9	76.8	163.5	139.9
2.52	336.4	497.5	49.5	272.1	162.1
2.31	466.7	1316.4	125.0	265.6	167.7
2.28	299.2	1006.4	60.6	332.5	265.5
2.06	422.3	2664.9	151.8	323.2	268.3
2.66	333.1	497.5	99.2	540.5	326.1
2.44	470.0	1317.1	250.9	534.5	341.9
2.49	281.2	478.7	51.2	413.9	285.8
2.18	452.3	1896.2	215.9	404.6	288.1
2.10	361.7	2311.4	23.0	70.1	63.8
2.62	419.7	835.2	179.7	546.2	320.8
2.31	390.7	1218.2	72.6	218.6	152.5
2.46	387.6	1218.5	199.0	601.2	421.8
2.47	382.1	1210.0	109.8	336.4	237.7
2.47	382.1	1210.0	109.8	336.4	237.7
2.47	382.1	1210.0	109.8	336.4	237.7
2.47	382.1	1210.0	109.8	336.4	237.7
2.47	382.1	1210.0	109.8	336.4	237.7
2.01	275.5	921.1	7.0	55.8	49.1

.

Table: Normalized data set

Data preprocessing values					
Roughness	**Peal Tool Temperature (C)**	**Heat Rate(W/mm3)**	**Power**	**Force X**	**Force Y**
0.4868	0.1615	0.2037	0.0363	0.1053	0.1363
0.2668	0.6437	0.7032	0.1098	0.1028	0.1462
0.8264	0.2911	0.0503	0.0669	0.1977	0.1792
0.6036	0.8228	0.2971	0.1855	0.1920	0.1875
0.5703	0.1390	0.2037	0.0843	0.2504	0.3328
0.3482	0.6417	0.7035	0.2277	0.2423	0.3369
0.9699	0.2773	0.0503	0.1450	0.4321	0.4227
0.7420	0.8361	0.2973	0.3835	0.4268	0.4462
0.7911	0.0657	0.0447	0.0695	0.3215	0.3628
0.4702	0.7639	0.4719	0.3284	0.3134	0.3663
0.3841	0.3940	0.5970	0.0251	0.0213	0.0332
0.9258	0.6308	0.1521	0.2715	0.4370	0.4148
0.6007	0.5124	0.2675	0.1031	0.1510	0.1650
0.7600	0.5000	0.2676	0.3018	0.4850	0.5649
0.7688	0.4775	0.2650	0.1617	0.2538	0.2915
0.7688	0.4775	0.2650	0.1617	0.2538	0.2915
0.7688	0.4775	0.2650	0.1617	0.2538	0.2915
0.7688	0.4775	0.2650	0.1617	0.2538	0.2915
0.7688	0.4775	0.2650	0.1617	0.2538	0.2915
0.2931	0.0424	0.1780	0.0000	0.0089	0.0114

Table: Normalized Data have been subtracted by 1

Deviation sequences					
Roughness	Peal Tool Temperature (C)	Heat Rate(W/mm3)	Power	Force X	Force Y
0.5132	0.8385	0.7963	0.9637	0.8947	0.8637
0.7332	0.3563	0.2968	0.8902	0.8972	0.8538
0.1736	0.7089	0.9497	0.9331	0.8023	0.8208
0.3964	0.1772	0.7029	0.8145	0.8080	0.8125
0.4297	0.8610	0.7963	0.9157	0.7496	0.6672
0.6518	0.3583	0.2965	0.7723	0.7577	0.6631
0.0301	0.7227	0.9497	0.8550	0.5679	0.5773
0.2580	0.1639	0.7027	0.6165	0.5732	0.5538
0.2089	0.9343	0.9553	0.9305	0.6785	0.6372
0.5298	0.2361	0.5281	0.6716	0.6866	0.6337
0.6159	0.6060	0.4030	0.9749	0.9787	0.9668
0.0742	0.3692	0.8479	0.7285	0.5630	0.5852
0.3993	0.4876	0.7325	0.8969	0.8490	0.8350
0.2400	0.5000	0.7324	0.6982	0.5150	0.4351
0.2312	0.5225	0.7350	0.8383	0.7462	0.7085
0.2312	0.5225	0.7350	0.8383	0.7462	0.7085
0.2312	0.5225	0.7350	0.8383	0.7462	0.7085
0.2312	0.5225	0.7350	0.8383	0.7462	0.7085
0.2312	0.5225	0.7350	0.8383	0.7462	0.7085
0.7069	0.9576	0.8220	1.0000	0.9911	0.9886

Table: Using the Gray Coefficient formula, we have calculated the grade for each set of parameters.

Grey relational coefficient						
Roughness	Peal Tool Temperature (C)	Heat Rate(W/mm3)	Power	Force X	Force Y	Grade
0.4509	0.4878	0.6077	0.7628	0.7269	0.6844	0.5873
0.3607	0.7696	0.9996	0.8032	0.7256	0.6894	0.6642
0.7344	0.5411	0.5424	0.7791	0.7786	0.7067	0.6871
0.5199	0.9796	0.6557	0.8494	0.7752	0.7112	0.7360
0.4982	0.4797	0.6077	0.7887	0.8116	0.8002	0.6251
0.3895	0.7677	1.0000	0.8776	0.8063	0.8030	0.7069
1.0000	0.5349	0.5424	0.8240	0.9502	0.8673	0.8078
0.6351	1.0000	0.6559	1.0000	0.9455	0.8868	0.8393
0.6894	0.4548	0.5402	0.7805	0.8607	0.8214	0.6761
0.4425	0.8990	0.7697	0.9530	0.8548	0.8239	0.7480
0.4038	0.5924	0.8790	0.7570	0.6854	0.6361	0.6111
0.8999	0.7578	0.5840	0.9089	0.9546	0.8610	0.8433
0.5179	0.6650	0.6397	0.7993	0.7516	0.6992	0.6573
0.6540	0.6565	0.6398	0.9319	1.0000	1.0000	0.7779
0.6636	0.6418	0.6384	0.8343	0.8138	0.7727	0.7168
0.6636	0.6418	0.6384	0.8343	0.8138	0.7727	0.7168
0.6636	0.6418	0.6384	0.8343	0.8138	0.7727	0.7168
0.6636	0.6418	0.6384	0.8343	0.8138	0.7727	0.7168
0.6636	0.6418	0.6384	0.8343	0.8138	0.7727	0.7168
0.3696	0.4474	0.5956	0.7444	0.6797	0.6268	0.5394

4.1.1 Effects of cutting parameters on Roughness

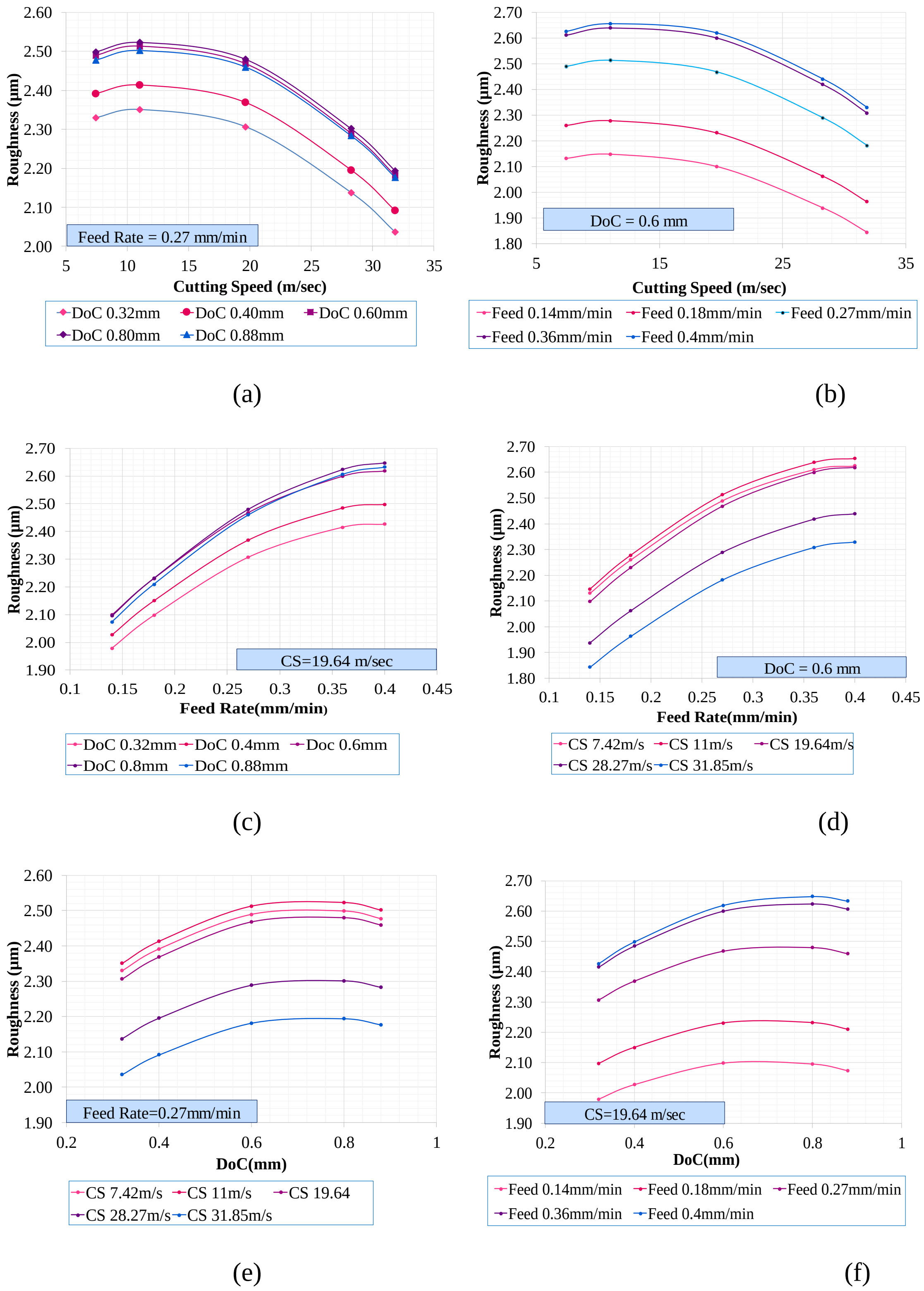
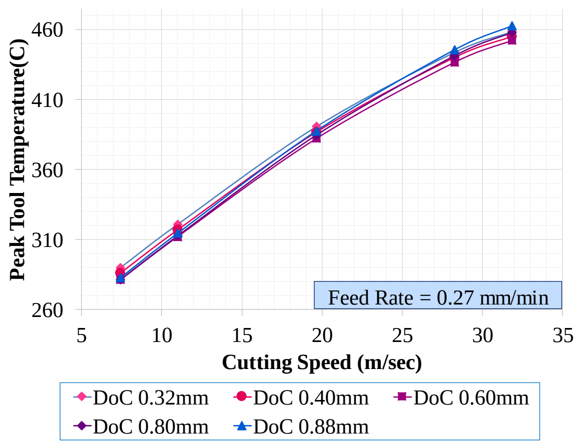
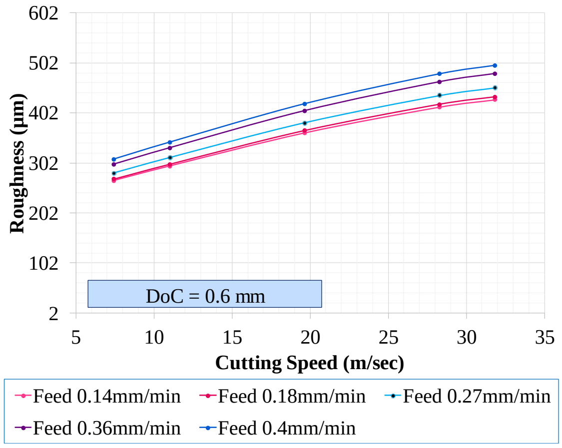


Figure: Roughness versus (a) & (b)cutting speed, (c) & (d)feed rate, (e) & (f)depth of cut

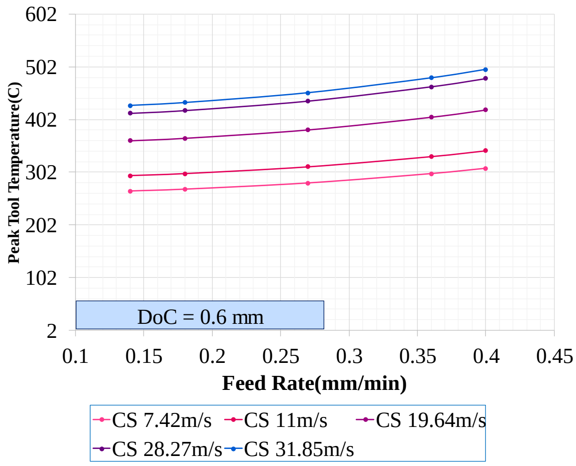
4.1.2 Effects of cutting parameters on Peak Tool Temperature



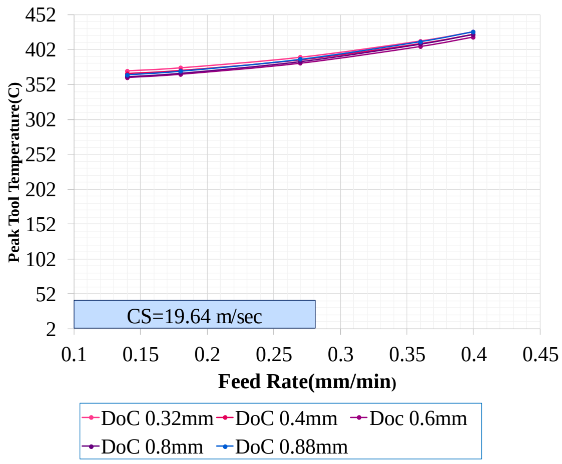
(a)



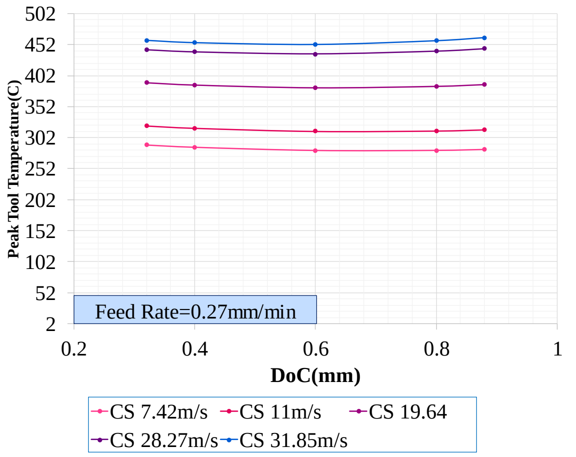
(b)



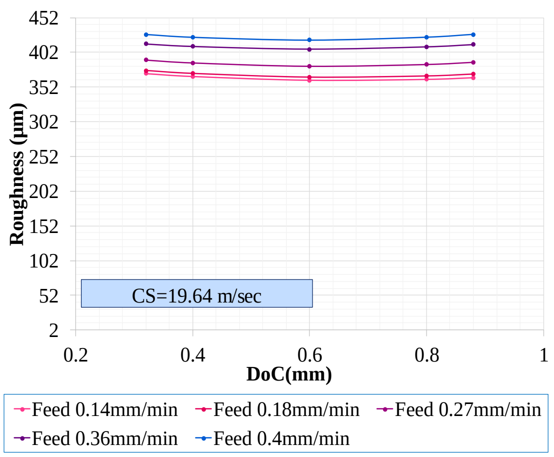
(c)



(d)



(e)



(f)

Figure: Peak Tool Temperature versus (a) & (b) cutting speed, (c) & (d) feed rate, (e) & (f) depth of cut

4.1.3 Effects of cutting parameters on Heat Rate

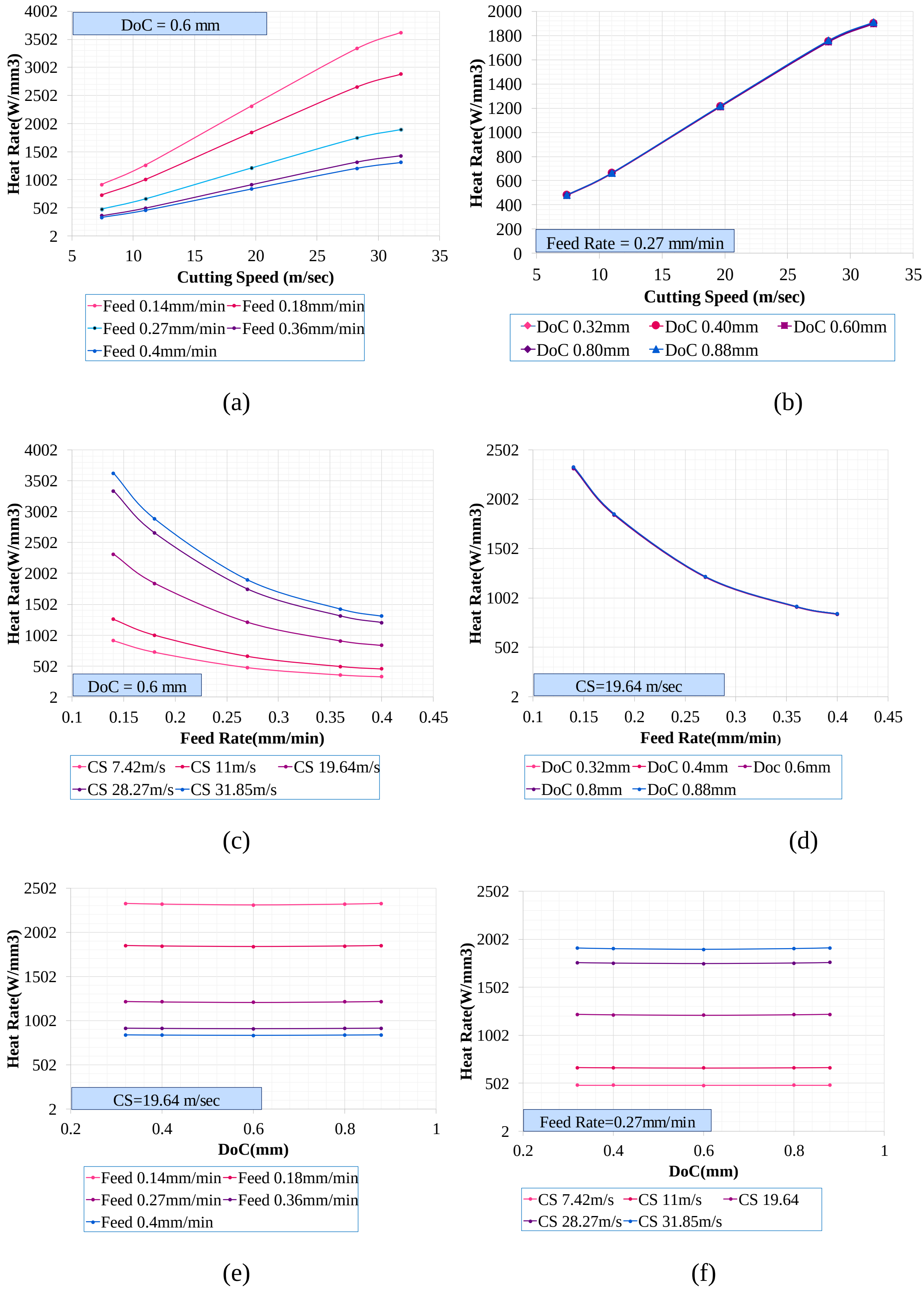


Figure: Heat Rate versus (a) & (b) cutting speed, (c) & (d) feed rate, (e) & (f) depth of cut

4.1.4 Effects of cutting parameters on Power

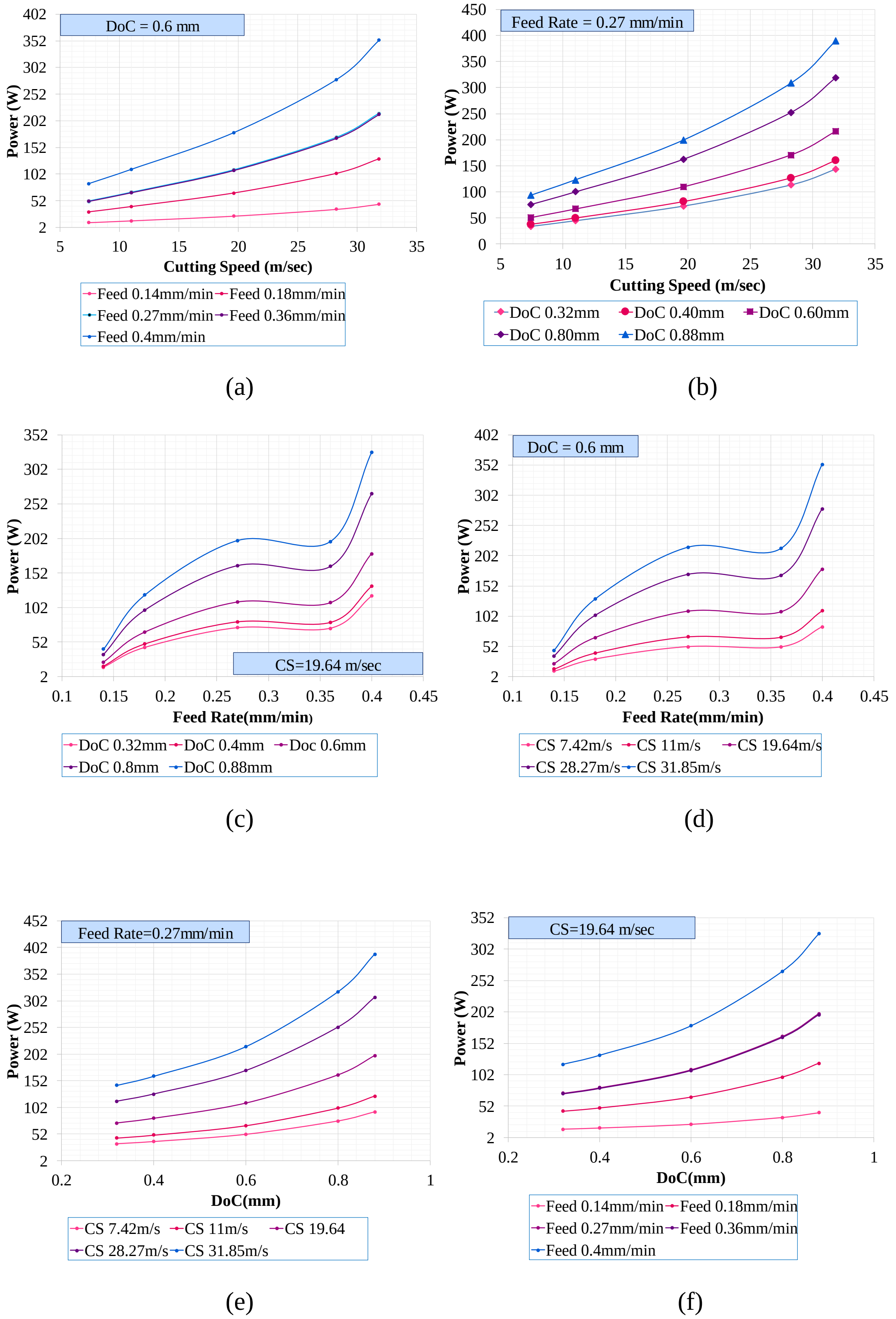


Figure: Power versus (a) & (b) cutting speed, (c) & (d) feed rate, (e) & (f) depth of cut

4.1.5 Effects of cutting parameters on Force X

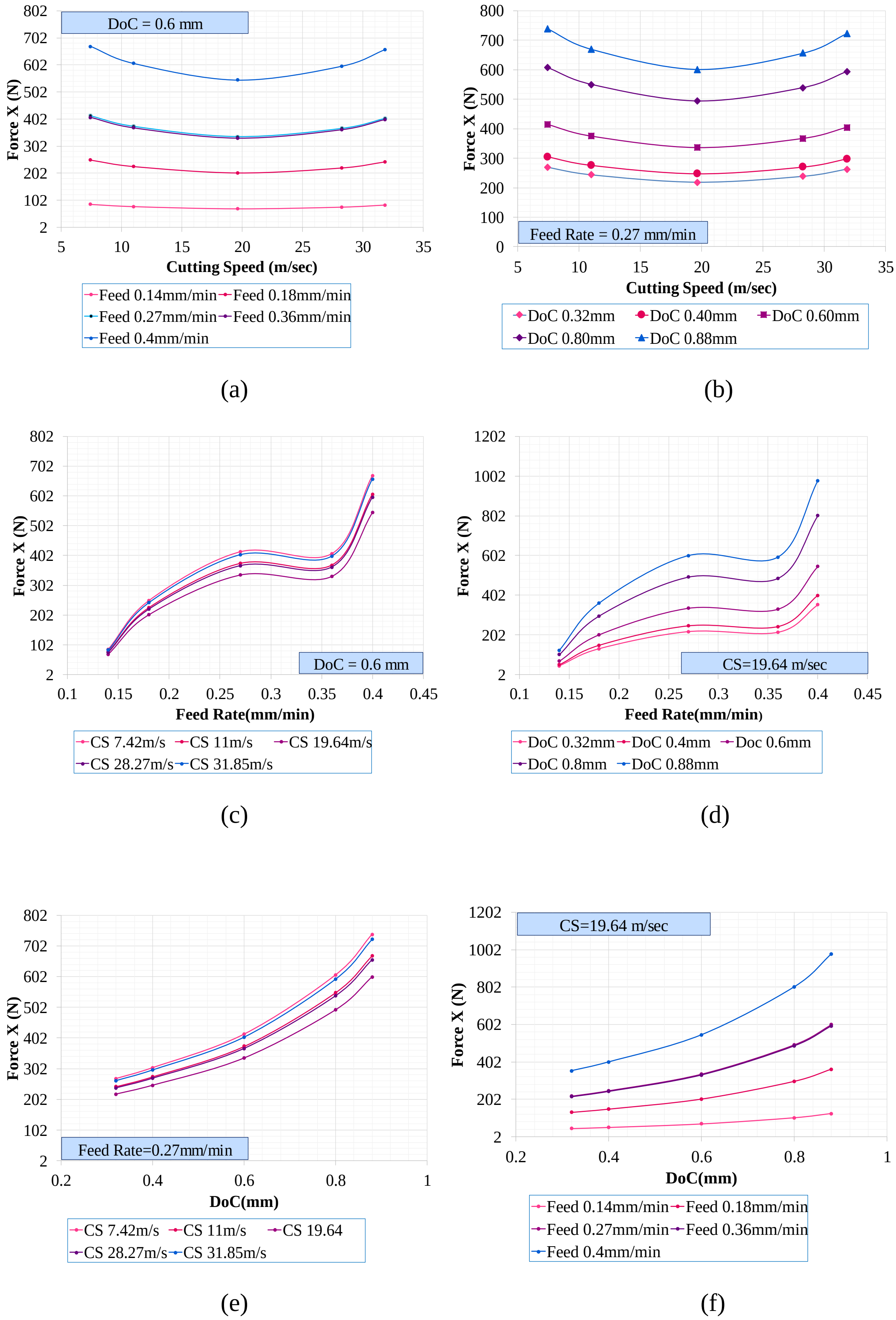


Figure: Force X versus (a) & (b) cutting speed, (c) & (d) feed rate, (e) & (f) depth of cut

4.1.6 Effects of cutting parameters on Force Y

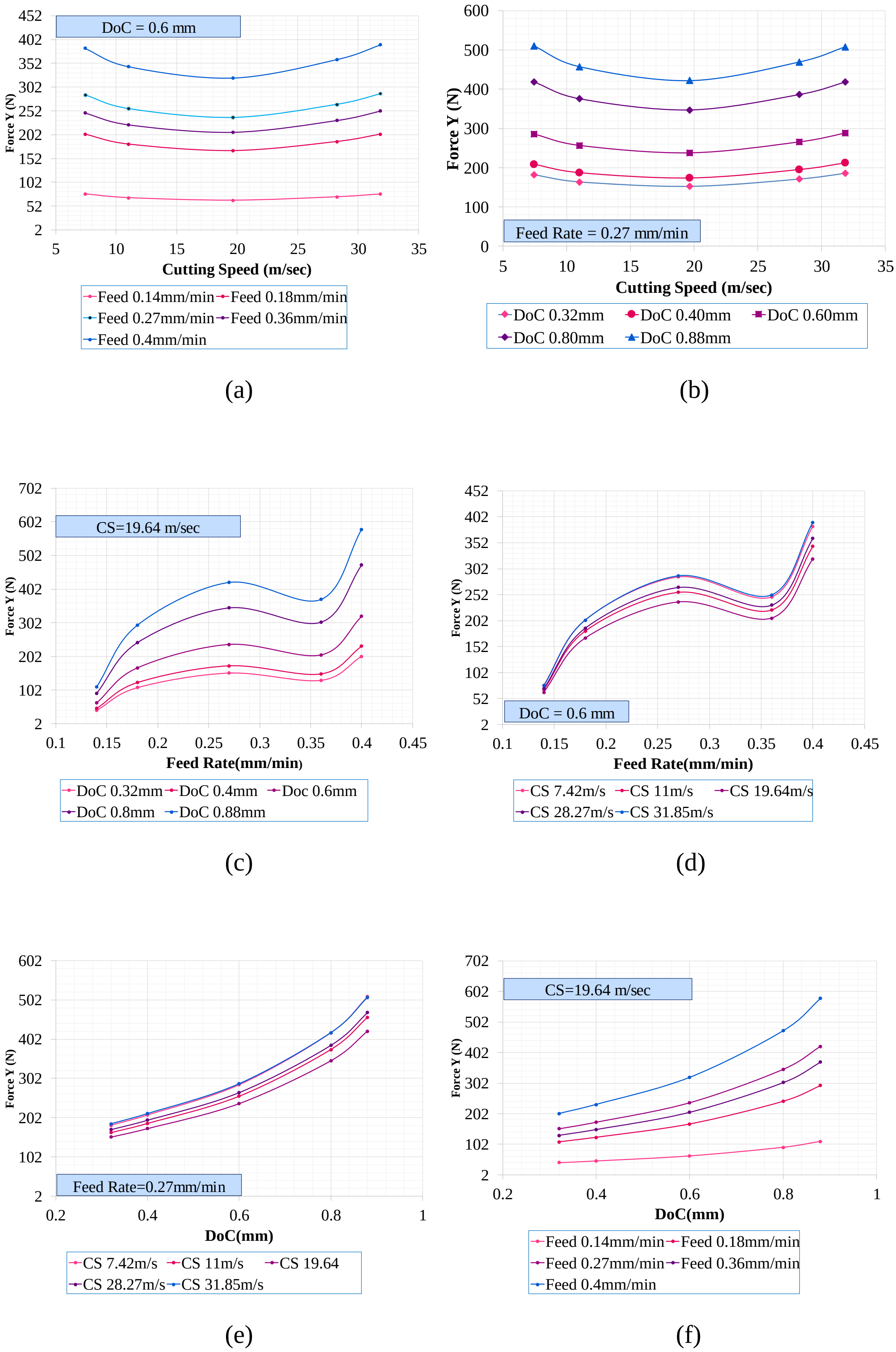


Figure: Force Y versus (a) & (b) cutting speed, (c) & (d) feed rate, (e) & (f) depth of c

4.2 Results

Gray analysis has 4 steps. After performing the steps of the Gray analysis on the 20 sets of parameters, most optimized set has been found. The optimized parameter is having cutting speed 19.64 m/s, feed rate of 0.4 mm/min, and depth of cut of 0.6 mm.

Gray analysis is only applicable for this 20 sets of data and that is why we used Whale Optimized Algorithm. WOA is used to get the most optimized set within the specified range of values from the table.

After 150 iterations, the algorithm has converged to find the most optimized set of parameters which is using the lowest cutting speed, depth of cut and feed rate. This is realistic because using lower cutting speeds and depth of cut, produces lesser stress on the cutting tool, thus generating small temperature rise and requires less power. Usually a higher cutting speed gives a lower surface roughness but here multiple parameters are being optimized simultaneously, we end up need lower cutting speed rather than high.

Chatper 5 Bibliography

Kalpakjian, S., Schmid, S.R., 2001. Manufacturing Engineering and Technology, International, Fourth ed. Prentice Hall Co., New Jersey, pp. 536–681

Yang, W.H., Tarng, Y.S., 1998. Design optimization of cuttingparameters for turning operations based on the Taguchi method. J. Mater. Process Technol. 84, 122–129

Davim, J.P., 2003. Design of optimization of cutting parameters forturning metal matrix composites based on the orthogonal arrays. J. Mater. Process. Technol. 132, 340–344

Manna, A., Bhattacharyya, B., 2004. investigation for optimal parametric combination for achieving better surface finish during turning of Al/SiC-MMC. Int. J. Adv. Manuf. Technol. 23, 658–665

Aslan, E., Camuscu, N., Birgoren, B., 2007. Design optimization of cutting parameters when turning hardened AISI 4140 steel (63 HRC) with Al2O3 +TiCN mixed ceramic tool. Mater. Des. 28, 1618–1622.

Nalbant, M., Gokkaya, H., Sur, G., 2007. Application of Taguchi method in the optimization of cutting parameters for surface roughness in turning. Mater. Des. 28, 1379–1385

EI Baradie, M.A., 1996. Cutting fluids: part I characterization. J. Mater. Process. Technol. 56, 786–797 Deng, J.L., 1989. Introduction to Grey system theory. J. Grey Syst. 1, 1–24

Huang, J.T., Lin, J.L., 2002. Optimization of machining parameters setting of die-sinking EDM process based on the Grey relational analysis with L18 orthogonal array. J. Technol. 17, 659–664

Fung, C.P., Huang, C.H., Doong, J.L., 2003. The study on theoptimization of injection molding process parameters with Gray relational analysis. J. Reinf. Plast. Comp. 22, 51–66.

Gau, H.S., Hsieh, C.Y., Liu, C.W., 2006. Application of Grey correlation method to evaluate potential groundwater recharge sites. Stoch. Environ. Res. Risk Assess. 20, 407–421

Shen, Y.K., Chien, H.W., Lin, Y., 2004. Optimization of the micro-injection molding process using Grey relational analysis and MoldFlow analysis. J. Reinf. Plast. Comp. 23, 1799–1814

Aggarwal, A., Singh, H., Kumar, P., Singh, M., 2008. Optimizing power consumption for CNC turned parts using response surface methodology and Taguchi’s technique e a comparative analysis. J. Mater. Process. Technol. 200, 373-384

Bhushan, R., 2013. Optimization of cutting parameters of minimizing power consumption and maximizing tool life during Al alloy SiC particle composites. J. Clean. Prod. 39, 242-254.

Goparsamy, B.M., Mondal, B., Ghosh, S., 2009. Taguchi method and ANOVA: an approach for process parameter optimization of hard machining while machining hardened steel. Journal of Scientific & Industrial Research 68, 686-695

Mukherjee, I., Ray, P.K., 2006. A review of optimization techniques in metal cutting processes. Computers & Industrial Engineering 50, 15-34

A.M. Abuelnaga, M.A. El-Dardiry, Optimization methods for metal cutting, Int. J. Mach. Tool Des. Res. 24 (1) (1984) 1–18.

P.L.B. Oxley, Modelling machining processes with a view to their optimization and the adaptive control of metal cutting machine tools, Robot. Comput.-Integrated Manuf. 4 (1988) 103–119.

G. Chryssolouris, M. Guillot, A comparison of statistical and AI approaches to the selection of process parameters in intelligent machining, ASME J. Eng. Ind. 112 (1990) 122–131.

Y. Yao, X.D. Fang, Modelling of multivariate time series for tool wear estimation in finish turning, Int. J. Mach. Tools Manuf. 32 (4) (1992) 495–508.

C. Zhou, R.A. Wysk, An integrated system for selecting optimum cutting speeds and tool replacement times, Int. J. Mach. Tools Manuf. 32 (5) (1992) 695–707.

M.S. Chua, M. Rahman, Y.S. Wong, H.T. Loh, Determination of optimal cutting conditions using design of experiments and optimization techniques, Int. J. Mach. Tools Manuf. 33 (2) (1993) 297–305.

G. Taguchi, Introduction to Quality Engineering, Asian Productivity Organization, Tokyo, 1990.

P.J. Ross, Taguchi Techniques for Quality Engineering, Mc-Graw-Hill, New York, 1988.

G.S. Peace, Taguchi Methods: A Hand-on Approach, Addison-Wesley, Reading, MA, 1993

Hauschild, M., Jeswiet, J., Alting, L., 2005. From life cycle assessment to sustainable production: status and perspectives. Annals of the CIRP 54 (2), 1-21

Vijayaraghavan, A., Dornfeld, D., 2010. Automated energy monitoring of machine tools. CIRP Annals e Manufacturing Technology 59, 21-24.

Hanafi, Issam, Khamlichi, Abdellatif, 2012. Optimization of cutting conditions for sustainable machining of PEEK-CF30 using TiN tools. Journal of Cleaner Production 33, 1-9 Huseyin Cetin, M., Ozcelik, Babur, Kuram, Emel, Demirbas, Erhan, 2011.

Evaluation of vegetable based cutting fluids with extreme pressure and cutting parameters in turning of AISI 304L by Taguchi method. Journal of Cleaner Production 19 (17-18), 2049-2056
Cakir MC, Gurarda A (1998)

Optimization and graphical representation of machining conditions in multi-pass turning operations. Comput Integr Manuf Syst 11:157–170 2.
Meng Q, Arsecularratne JA, Mathew P (2000) Calculation of optimum cutting conditions for turning operations using a machining theory. Int J Mach Tools Manuf 40:1709–1733 3.
Lee BY, Tarng YS (2000) Cutting parameter selection for maximizing production rate or minimizing production cost in multistage turning operations. J Mater Process Technol 105:61–66
Zuperl U, Cus F (2003) Optimization of cutting conditions during cutting by using neural networks. Robot and Comput Integrated Manuf 19:189–199 10.
Cus F, Balic J (2003) Optimization of cutting process by GA approach. Robot and Comput Integrated Manuf 19:113–121
Ezugwu EO, Fadare DA, Bonney J, Silva RB, Sales WF (2005) Modeling the correlation between cutting and process parameters in high speed machining of Inconel 718 alloy suing an artificial neural network. Int J Mach Tools Manuf 45:1375–1385
Sardinas RQ, Santana MR, Brindis EA (2006) Genetic algorithm based multi-objective optimization of cutting parameters in turning processes. Eng Appl Artif Intell 19:127–133
Al-Ahmari AMA (2007) Predictive machinability models for a selected hard material in turning operations. J Mater Process Technol 190:305–311
Dereli, D., Filiz, I.H., Bayakosoglu, A., 2001. Optimizing cutting parameters in process planning of prismatic parts by using genetic algorithms. International Journal of Production Research 39 (15), 3303–3328.
Kumar, R., Kumar, V., 2000. Optimum selection of machining conditions in abrasive flow machining using neural networks. Journal of Material Processing Technology 108, 62–67
Sonmez, A.I., Baykasoglu, A., Dereli, T., Filiz, I.H., 1999. Dynamic optimization of multipass milling operation via geometric programming. International Journal of Machine Tools & Manufacturing 39, 297–320.
Taylor, F.W., 1907. On the art of cutting metals. Transactions of the ASME 28, 310–350
Liang, M., Mgwatu, M., Zuo, M., 2001. Integration of cutting parameter selection and tool adjustment decisions for multipass turning. International Journal of Advanced Manufacturing

Technology 17, 861–869
Wang, J., Kuriyagawa, T., Wei, X.P., Gou, G.M., 2002. Optimization of cutting conditions using a deterministic approach. International Journal of Machine Tools & Manufacture 42, 1023–1033
Saravanan, R., Asokan, P., Vijayakumar, K., 2003. Machining parameters optimisation for turning cylindrical stock into a continuous finished profile using genetic algorithm (GA) and simulated annealing (SA). International Journal of Advanced Manufacturing Technology 21, 1–9
Cus, F., Balic, J., 2003. Optimization of cutting process by GA approach. Robotics and Computer Integrated Manufacturing 19, 113–121
Amiolemhen, E., Ibhadode, A.O.A., 2004. Application of genetic algorithms—determination of the optimal machining parameters in the conversion of a cylindrical bar stock into a continuous finished profile. International Journal of Machine Tools and Manufacture 44 (12–13), 1403–1412
Chua, M.S., Loh, H.T., Wong, Y.S., Rahman, M., 1991. Optimization of cutting conditions for multi-pass turning operations using sequential quadratic programming. Journal of Materials Processing Technology 28 (1–2), 253–262
Ko, T.J., Kim, H.S., 1998. Autonomous cutting parameter regulation using adaptive modeling and genetic algorithms. Precision Engineering 22 (4), 243–251
Chien, W.T., Tsai, C.S., 2003. The investigation on the prediction of tool wear and the determination of optimum cutting conditions in machining 17-4PH stainless steel. Journal of Material Processing Technology 140 (1–3), 340–345
Molinari, A., Nouari, M., 2002. Modeling of tool wear by diffusion in metal cutting. Wear 525, 135–149
Lee, B.Y., Tarng, Y.S., 2000. Cutting-parameter selection for maximizing production rate or minimizing production cost in multistage turning operations. Journal of Materials Processing Technology 105 (1–2), 61–66.
Zuperl, U., Cus, F., 2003. Optimization of cutting conditions during cutting by using neural networks. Robotics and Computer Integrated Manufacturing 19, 189–199
Cus, F., Balic, J., 2003. Optimization of cutting process by GA approach. Robotics and Computer Integrated Manufacturing 19, 113–121.
Van Veldhuizen, D.A., Lamont, G.B., 2000. Multiobjective evolutionary algorithms: analizing the state-of-the-art. Evolutionary Computation 8, 125–147
Abbass, H.A., Sarker, R., Newton, Ch., 2001. PDE: A Pareto–frontier differential evolution approach for multi objective optimization problems. Proceedings of the Congress on Evolutionary

Computation, Vol. 2, Piscataway NJ, pp. 971–978

Soodamani, R., Liu, Z.Q., 2000. GA-based learning for a model-based object recognition system. International Journal of Approximate Reasoning 23, 85–109