Surface Roughness Optimization of Stainless Steel using ABC (Artificial Bee Colony) Algorithm

Mechanical and Chemical Engineering

By

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An Undergraduate thesis submitted to the department of Mechanical & Chemical engineering of Islamic University of Technology, Board Bazar, Gazipur in partial fulfillment of the requirements for the degree

OF

BACHELOR OF SCIENCE IN MECHANICAL ENGINEERING

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Thesis approved as to style and content for the degree of B.Sc Engineering (Mechanical and Chemical Engineering)

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CANDIDATES 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

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Dedicated

To

Our Beloved Parents

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Of course, any errors are ours alone. We seek excuses if there is any mistake found in this report.

ABSTRACT

In any machining operation surface roughness results inaccuracy and inefficiency. So it is always desirable to ensure minimum level of surface roughness. Both of them depend on some parameters like feed, spindle speed and depth of cut. Optimization of these parameters ensures existence surface roughness under the tolerance limit. In this project, our aim is to devise a way of predicting surface roughness for a given set of parameters. To do that, we collected experimental results of surface roughness for twenty sets of parameters which were selected by Central Composite Design (CCD). Surface roughness was measured by taking microscopic images of tool edge and job piece surface after each machining operation and then by using Image Processing Tool of MATLAB. The obtained results were then used for developing ABC (Artificial Bee Colony) Algorithm which was then used for the prediction of tool wear and surface roughness for a given set of parameters. The prediction and actual result were then compared and it was seen that both results coincide with each other.

Table of Contents

Chapter 1: Introduction

Turning is a conventional machining process .It is the removal of metal from the outer diameter of a rotating cylindrical work piece. It is used to reduce the diameter of the work piece to a specific dimension and to produce a smooth finish on the metal. Turning is usually done on a conventional lathe machine but now a day, state of the art CNC lathe machines are also used. In a turning operation, the power to turn the work piece at a given rotational speed and to feed the cutting tool at a specified rate and depth of cut is provided by a lathe. The time of operation is very crucial because increase of operation time increases the tool wear and it eventually causes rough surface finish. So there are four parameters in a turning operation. These are

- Spindle Speed,
- Feed
- Depth of cut and

Cutting performance depends on surface roughness, tool flank and nose wear. The cutting parameters mentioned above are the functions of tool wear and surface roughness. So tool wear and surface roughness in a turning operation depends on the selection of spindle speed, feed and depth of cut. An appropriate selection of these parameters can minimize the tool wear and surface roughness drastically upto a certain extent. So before starting a turning operation, if it can be examined that how much tool wear and surface roughness will be resulted by the set of parameters to be used in that turning operation, we can optimize the parameters to minimize the tool wear and surface roughness. So a system is to be developed to predict the tool wear and surface roughness for a given set of parameters. It can be done in two steps:

1. To conduct a set of experiments using different sets of parameters for each machining operation and then measure the resulted tool wear and surface roughness on each operation.
2. To develop an intelligent system by using these experimental results that is capable of future prediction of tool wear and surface roughness for a given set of parameters.

In the current work, we present a generic single-objective approach for the optimization based on another such, relatively new swarm intelligence technique—Artificial Bee Colony (ABC). In social insects, every individual is autonomous. They can only obtain local information, and interact with their geographical neighbours. All these features characterize swarm intelligence. Examples of systems like this can be found in nature, including bee colonies, ant colonies, bird flocking, animal herding, fish schooling etc. Inspired by the bee behaviour, Artificial Bee Colony is one of the generally applicable techniques used for optimizing numerical functions and real-world problems. Compared with GA and other similar evolutionary techniques, ABC has some attractive characteristics and in many cases proved to be more effective. Both GA and ABC have been used extensively for a variety of optimization problems and in most of these cases. ABC has proven to have superior computational efficiency . Further, ABC does not use any gradient-based information. It incorporates a flexible and well-balanced mechanism to adapt to the global and local exploration and exploitation abilities within a short computation time. Hence, this method is efficient in handling large and complex search spaces. ABC with its ability to handle combinatorial explosive problems appears to be very promising for the single-objective optimization problem (Roughness) addressed in this paper.

(i) Cutting Tool and work piece material:

In all experiments, same cutting tool and work piece material were used. All the experiments were performed in CNC lathe machine. The experiments were conducted as a dry cut i.e. in the absence of any coolant. The following parameters were kept constant in the entire experiment:

Parameters	Description
Work material	Stainless steel (Grade201)
Cutting tool	CNMG tungsten carbide turning insert
Tool overhang	30 mm
Cutting Condition	Dry

(ii) Objectives:

1. To optimize the values of roughness for various cutting conditions by using ABC algorithm
2. To make a central composite design of the experiment
3. To measure the roughness in various cutting conditions(CS, DOC, Feed)
4. To work with the ABC code in MATLAB

(iii) Organization of the thesis:

This thesis comprises of seven chapters. ***Chapter 1*** gives a brief overview of the background and concept of this study. Finally, significance of the research and the objectives of this study are summarized. This chapter also outlines the organization of this dissertation.

A comprehensive literature review is given in the ***Chapter 2***, which categorized into three sections. First section describes the existing researches on turning operation: In the second section, Works done on turning operation using ABC algorithm are discussed . Finally, extensive literature review on CCD process is discussed such as process parameter and their effect, process modeling and process control.

Chapter 3 describes the methodology of the experiment. The steps including the experiment is described in a flow chart.

Chapter 4 describes the modeling the CCD structure, which is developed with the help of a computer based software named **Stat-Ease Design Expert v7.0.0** . Moreover, we analysis the error by comparing our experimental data with the equational data. The equation was formed by the software.

Chapter 5 presents the a brief discussion abot Artificial Bee Colony (ABC) Algorithm. It also presents how the it works.

In ***Chapter 6*** our experimental result and equational result is compared.

The conclusions and summary of the contributions are presented in ***Chapter 7***.

Chapter 2: Historical review

(a) Existing researches on turning operation:

Turning is one the most important machining operation in industries. A significant pool of turning studies has been surveyed in an attempt to achieve better understanding of tool wear, chip formation, surface finish, white layer formation, micro-hardness variation and residual. Stress on the basis of varying tool edge geometry, cooling methods and cutting parameters Most of the works were aimed to find the reasons of tool wear and surface roughness, the parameters related to tool wear and surface roughness and the optimization of these parameters to get minimum tool wear and surface roughness.

Surface roughness generation in a turning operation is examined by using a FFT analyzer. It is found that the roughness profile of a work piece is composed of several periodical components: the cutting tool feed component, the spindle rotational error component, and the chatter vibration error component. To examine the origin of these error components, a series of cutting tests were carried out with different spindle bearing arrangements and with different types of work piece material. ***(1)***

Finite element method (FEM) was used in a work to predict cutting process variables, which are difficult to obtain with experimental methods. In this paper, modeling techniques on continuous chip formation by using the commercial FEM code ABAQUS are discussed. A combination of three chip formation analysis steps including initial chip formation, chip growth and steady-state chip formation is used to simulate the continuous chip formation process. Steady chip shape, cutting force, and heat flux at tool/chip and tool/work interface are obtained. Further, after introducing a heat transfer analysis, temperature distribution in the cutting insert at steady state is obtained. In this way, cutting process variables e.g. contact pressure (normal stress) at tool/chip and tool/work interface, relative sliding velocity and cutting temperature distribution at steady state are predicted. Many researches show that tool wear rate is dependent on these cutting process variables. ***(2)***

A plan of experiments, based on the techniques of Taguchi, was designed and executed on controlled machining with cutting conditions prefixed in work pieces. Afterwards, the roughness was evaluated on work pieces using two different profilometers. The objective was to establish a correlation between cutting velocity, feed and depth of cut with the roughness evaluating parameters R_a and R_t, following the international norms. These correlations were obtained by multiple linear regressions. Finally, confirmation tests were performed to make a comparison between the results predicted from the mentioned correlations and the theoretical results. ***(3)***

Experiments have been carried out in an attempt to monitor the change of workpiece surface roughness caused by the increase of tool wear, through the variation of the vibration in finish turning, under different cutting conditions. The vibration was measured by two accelerometers attached to the tool and the parameter used to make the correlation with surface roughness was the r.m.s. of the signal. The tool of one experiment was photographed at different stages of the cut in order to explain the wear formation and the behavior of surface roughness as the cutting time elapsed. The material machined was AISI 4340 steel and the tool was coated carbide inserts. The results show that vibration of the tool can be a good way to monitor on-line the growth of surface roughness in finish turning and, therefore, it can be useful for establishing the end of tool life in these operations. Another conclusion is that, when coated tools are used, the behavior of surface roughness as cutting time elapses is very different from that when uncoated tools are used. ***(5)***

The effects of cutting parameters are studied in many times. The process of turning is influenced by many parameters such as the cutting velocity, feed rate, depth of cut, geometry of cutting tool cutting conditions etc. The finished product with desired attributes of size, shape, and surface roughness and cutting forces developed are functions of these input parameters. Properties wear resistance, fatigue strength, coefficient of friction, lubrication, wear rate and corrosion resistance of the machined parts are greatly influenced by surface roughness. Forces developed during cutting affect the tool life hence the cost of production. In many manufacturing processes engineering judgment is still relied upon to optimize the multi-response problem. Therefore multi response optimization is used in this study to optimization problem to finds the appropriate level of input characteristics**. *(6)***

From these works mentioned above, it is clear that the tool wear and surface roughness in turning operation depends on some parameters like feed, depth of cut, Spindle speed, vibration, forces developed during cutting.

(b) Works done on turning operation using ABC algorithm:

Artificial Bee Colony Algorithm (ABC) is nature-inspired metaheuristic, which imitates the foraging behavior of bees. ABC as a stochastic technique is easy to implement, has fewer control parameters, and could easily be modify and hybridized with other metaheuristic algorithms. Due to its successful implementation, several researchers in the optimization and artificial intelligence domains have adopted it to be the main focus of their research work.. Many applications of ABC algorithm to real world and benchmark optimization problems have been reported, whereas substantial portion of the publications also compared the performance of ABC with other optimization algorithms. In the following subsections, some areas to which ABC was applied are discussed in detail. These areas include benchmark optimization, scheduling, bioinformatics, image processing, clustering, economic dispatch problem, engineering design and applications.

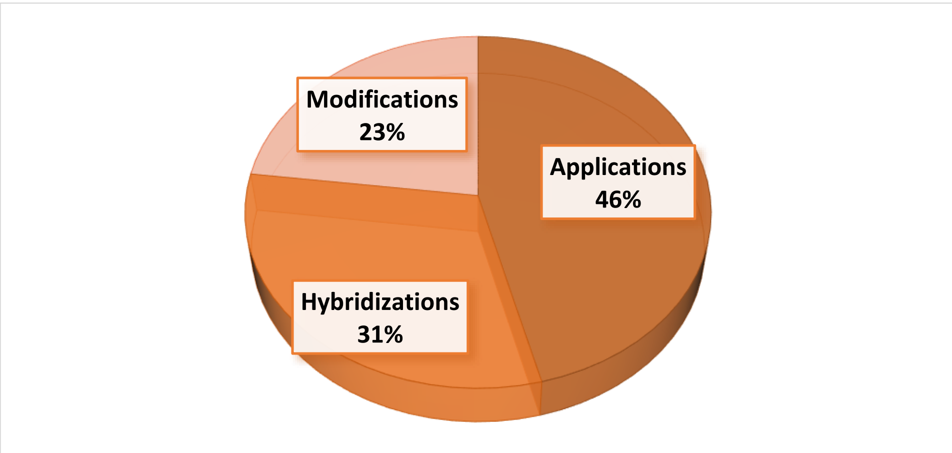


Figure 1: The Distribution Of Published Research Articles On ABC

Factors such as cutting force, cutting temperature and vibration signals can be effectively used to predict tool wear. Even though, each of these factors can be used individually to predict tool wear. A regression model and an artificial neural network model were used to predict the tool flank wear. Here cutting force, cutting temperature and displacement of tool vibration signals are effectively used in predicting the tool flank wear .It is found that neural network is superior to the regression model in its ability to predict tool wear. **(13)** For automatic turning operation, prediction of surface finish and dimensional deviation is an essential prerequisite. In a work on surface finish, it is found that using neural network, surface finish can be predicted within a reasonable degree of accuracy by taking the acceleration of radial vibration of tool holder. It was observed that improves with increasing feed up to some feed where from it starts deteriorating with further increase of feed while turning the steel rod with Tin coated carbide tool, This type of behavior is not observed in turning with HSS tool. Hence, neural network prediction models were developed separately for both cases. Factors like Radial component of cutting force and acceleration of radial vibration were taken to predict dimensional deviation. In the Neural Network, both dry and wet cutting conditions were taken as two different factors. **(15)**

A number of works were done on the effect of tool wear on surface roughness. Surface roughness increases with the increase of tool wear. So, neural networks were used to predict the surface roughness by using a set of previously collected data of tool wear and surface roughness. Further investigation found that tool wear and surface roughness has the same factors like cutting speed, depth of cut, feed etc.

An investigation on inaccuracy in turning operation found that the main source of inaccuracy in production is machine tool errors. Positional, geometrical, and thermally induced errors of machine tools are responsible for inaccurate turning operation. So, neural network was used to predict the machine tool errors during a turning operation. By predicting, machine tool errors were minimized and accuracy of the turning operation was improved. **(16)**

So from the above ,it is seen that a number of successful works were performed on turning operation by identifying the parameters responsible for tool wear, surface roughness, inaccurate machining and by using the ABC algorithm as a prediction tool.

(c) Concluding Remarks:

It was mentioned earlier that that our aim is to predict the tool wear and surface roughness in turning operation using the Artificial Neural Network. A number of works were done on turning machine incorporating Neural Network with it. Most of the works focused on finding the tool wears, surface roughness, inaccurate machining which are caused by parameters like feed, depth of cut, cutting speed, vibration and the geometrical and positional error of machine tool. But in our project of finding out tool wear and surface roughness, we are using four parameters, two of them are widely used which are feed and depth of cut. Other parameters are spindle speed (N) and Time of operation.

We know cutting speed,

$V = \pi DN/60$

D=Diameter, N=Spindle speed

So it is clear that when the diameter is constant, cutting speed (V) is directly proportional to spindle speed (N). In our experiment, the job piece diameters were almost same so we can consider the diameter as constant and in spite of using cutting speed as a parameter, we can use Spindle speed. Our intention to do that is there are various machining operations where diameter of the job pieces remains constant. So for those cases, our project work can be a good resource.

In high speed turning operations, the more the time of operation, the more the tool and job piece will be heated. There are various metallurgical properties like hardness and toughness which are influenced by the heat generated during machining. It has a direct effect on the tool wear and surface roughness. So the time of operation can also be considered as a parameter of tool wear and surface roughness.

Besides, the surface roughness is traditionally measured by Profilometer. But in our project, we first took the microscopic images of the job piece surfaces and then used the Image Processing Tool of MATLAB to find out the surface roughness.

Chapter 3: Methodology

In process planning optimal cutting conditions are to be determined using reliable mathematical models representing the machining conditions of a particular work-tool combination. The development of such mathematical models requires detailed planning and proper analysis of experiments. In this case the mathematical models for Tungsten-coated carbide tools and stainless steel 201 grade were developed based on the design and analysis of machining experiments. The different steps including in this experiment is shown in a flow chart below:

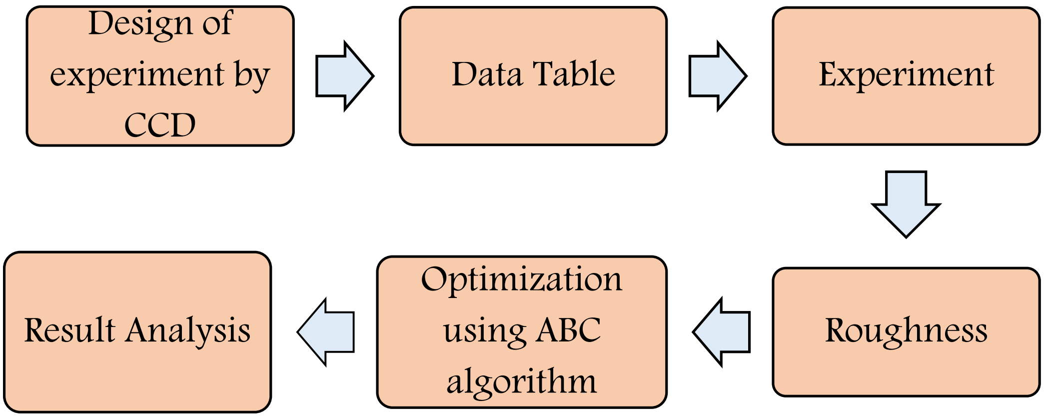


Figure 2: Different Steps including the experiment

Chapter 4: Experimental Design

In this project, our aim is to predict surface roughness. It is obvious that the more data we will use, the better prediction we will get. But we have limitation of time and resource. Besides, a huge number of operations will cause inefficiency of the whole project. To get rid of these problems, experimental designing was done. It is widely used in many processes for controlling the effect of parameters. Its usage decreases the number of experiments, using time and material resource.

4.1 Design of experiment

Factors	$-\sqrt{2}$	-1	0	1	$+\sqrt{2}$
CS(m/min)	71.72	80	100	120	128.284
Feed (mm/rev)	0.1189	0.15	0.25	0. 3	0.331
DOC (mm)	0.437	0.5	0.65	0.8	0.862

A flow chart to get the design of experiment by CCD is given below:

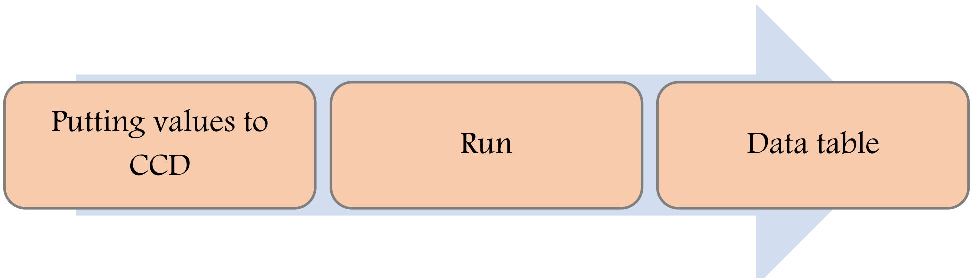


Figure 3: A Flow Chart for getting design by CCD

4.2 Central Composite Design (CCRD):

The experimental design techniques commonly used for process analysis and modeling are the full factorial, partial factorial and central composite rotatable designs. A full factorial design requires at least three levels per variable to estimate the coefficients of the quadratic terms in the response model. A partial factorial design requires fewer experiments than the full factorial. However, the former is particularly useful if certain variables are already known to show no interaction. The central composite design (CCD) is a design widely used for estimating second order response surfaces. It is perhaps the most popular class of second order designs. In machinability studies investigations, statistical design of experiments is used quite extensively. Statistical design of experiments refers to the process of planning the experiment so that the appropriate data can be analysed by statistical methods, resulting in valid and objective conclusions .Design and methods such as factorial design, response surface methodology (RSM) now widely use in place of one-factor-at-a-time experimental approach which is time consuming and exorbitant in cost. Here Stat-Ease Design Expert v7.0.0 software have been used to serve this purpose

4.3 Conduction of experiments and measurement surface roughness:

By using CCD, we found out that for three variables, we need to conduct twenty experiments. The CCD itself also can combine the parameters ta produce twenty sets of parameters. These twenty sets of parameters were used as inputs in the CNC lathe machine. job piece surface were taken by microscope. The same procedure was repeated for each set of parameters. In this way, twenty set of inputs were used to conduct twenty operations and after each operation, images of job piece surface was taken.

After taking all the images, Image processing tool of MATLAB was used to measure surface roughness. Image processing tool develops a graph for the deviation of the job piece surface. Then it takes the average deviation as the tool wear and surface roughness.

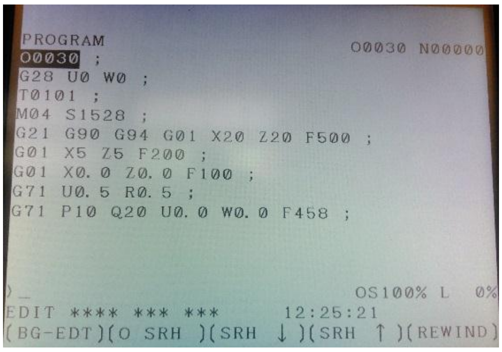
These surface roughness results are our output. By using this results, the final table was built which was then used for developing the machine learning algorithm.

(i) Data table by CCD:

	Std	Run	Block	Factor 1 A:CS m/min	Factor 2 B:Feed mm/rev	Factor 3 C:DOC mm	Response 1 Roughness micro meter
	1	18	Block 1	80.00	0.15	0.50	
	2	8	Block 1	120.00	0.15	0.50	
	3	5	Block 1	80.00	0.30	0.50	
	4	10	Block 1	120.00	0.30	0.50	
	5	13	Block 1	80.00	0.15	0.80	
	6	4	Block 1	120.00	0.15	0.80	
	7	6	Block 1	80.00	0.30	0.80	
	8	7	Block 1	120.00	0.30	0.80	
	9	1	Block 1	71.72	0.22	0.65	
	10	9	Block 1	128.28	0.22	0.65	
	11	19	Block 1	100.00	0.12	0.65	
	12	15	Block 1	100.00	0.33	0.65	
	13	2	Block 1	100.00	0.22	0.44	
	14	12	Block 1	100.00	0.22	0.86	
	15	14	Block 1	100.00	0.22	0.65	
	16	3	Block 1	100.00	0.22	0.65	
	17	20	Block 1	100.00	0.22	0.65	
	18	11	Block 1	100.00	0.22	0.65	
	19	17	Block 1	100.00	0.22	0.65	
	20	16	Block 1	100.00	0.22	0.65	

(ii) Experiment for roughness:

Then the data table is used to continue our machining process on our job piece by CNC Lathe machine. The CNC machine takes command as G-code. Customary G-codes were used for machining in different condition according to the data table.



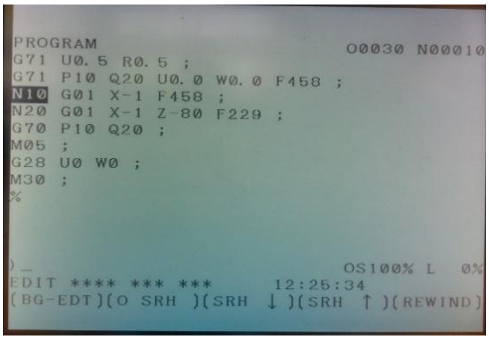


Figure 4: Sample G-Code used for machining

Then we take 5 readings for roughness for each of the 20 cases. Finally we take the mean value of five results in each case.


Figure 5: Work piece and Cutting tools

Figure 6: Roughness Measuring Apparatus

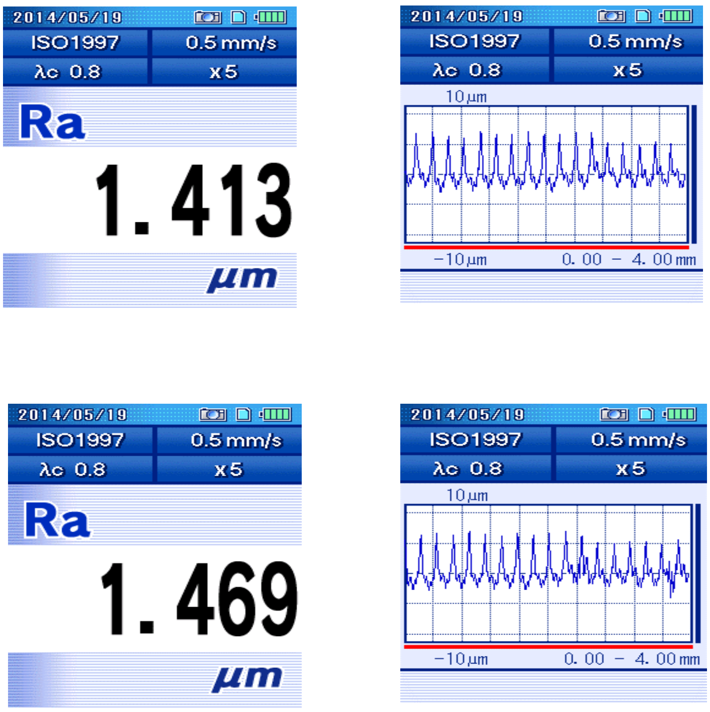


Figure 7: Average Roughness values
from apparatus

(iii) Final Data Table:

Std	Run	Factor 1	Factor 2	Factor 3	Response					
		A: CS	B: Feed	C: DOC	Roughness (µm)					
		m/min	mm/rev	mm	R1	R2	R3	R4	R5	Average
1	4	80.00	0.150	0.50	0.989	1.086	1.001	0.932	1.098	1.021
2	18	120.00	0.150	0.50	2.879	2.516	2.917	2.835	2.852	2.800
3	8	80.00	0.300	0.50	2.271	2.431	2.410	2.301	2.536	2.390
4	3	120.00	0.300	0.50	4.740	4.722	4.706	4.857	4.883	3.409
5	17	80.00	0.150	0.80	4.484	2.963	4.053	4.370	3.841	1.023
6	11	120.00	0.150	0.80	1.139	1.460	0.992	1.140	1.126	1.171
7	10	80.00	0.300	0.80	3.137	3.089	3.167	3.017	2.916	3.065
8	13	120.00	0.300	0.80	2.704	2.284	2.467	2.894	2.984	2.667
9	1	71.72	0.225	0.65	1.936	1.961	1.901	1.550	1.307	1.731
10	7	128.28	0.225	0.65	1.318	1.144	1.435	1.668	1.667	1.446
11	15	100.00	0.119	0.65	2.171	1.880	1.930	1.648	1.679	1.862
12	14	100.00	0.331	0.65	3.525	3.418	3.616	3.624	3.617	3.560
13	16	100.00	0.225	0.44	2.878	2.862	2.829	2.868	2.887	2.865
14	9	100.00	0.225	0.86	1.729	1.576	1.421	1.542	1.637	1.581
15	12	100.00	0.225	0.65	3.282	3.275	3.336	3.327	3.182	3.280

16	6	100.00	0.225	0.65	3.550	3.759	3.756	3.751	3.550	3.673
17	5	100.00	0.225	0.65	2.789	2.789	2.898	2.875	2.870	2.844
18	2	100.00	0.225	0.65	3.087	3.065	3.192	3.162	3.125	3.126
19	20	100.00	0.225	0.65	3.282	3.275	3.336	3.327	3.182	3.280
20	19	100.00	0.225	0.65	2.552	2.306	2.387	2.506	2.531	2.456

(iv) EQUATION FOR ROUGHNESS:

- We select natural log when response is a variance :

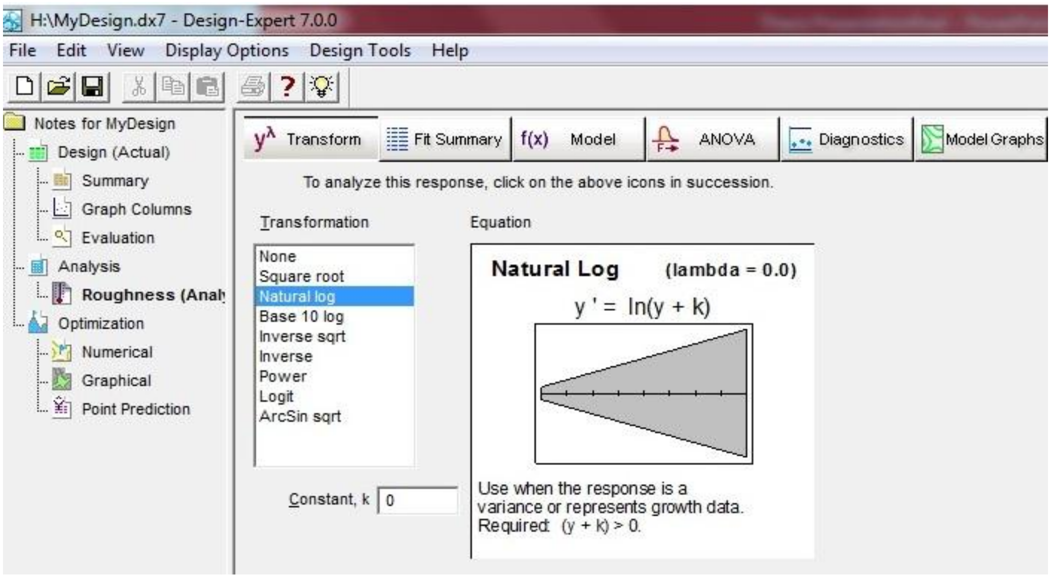
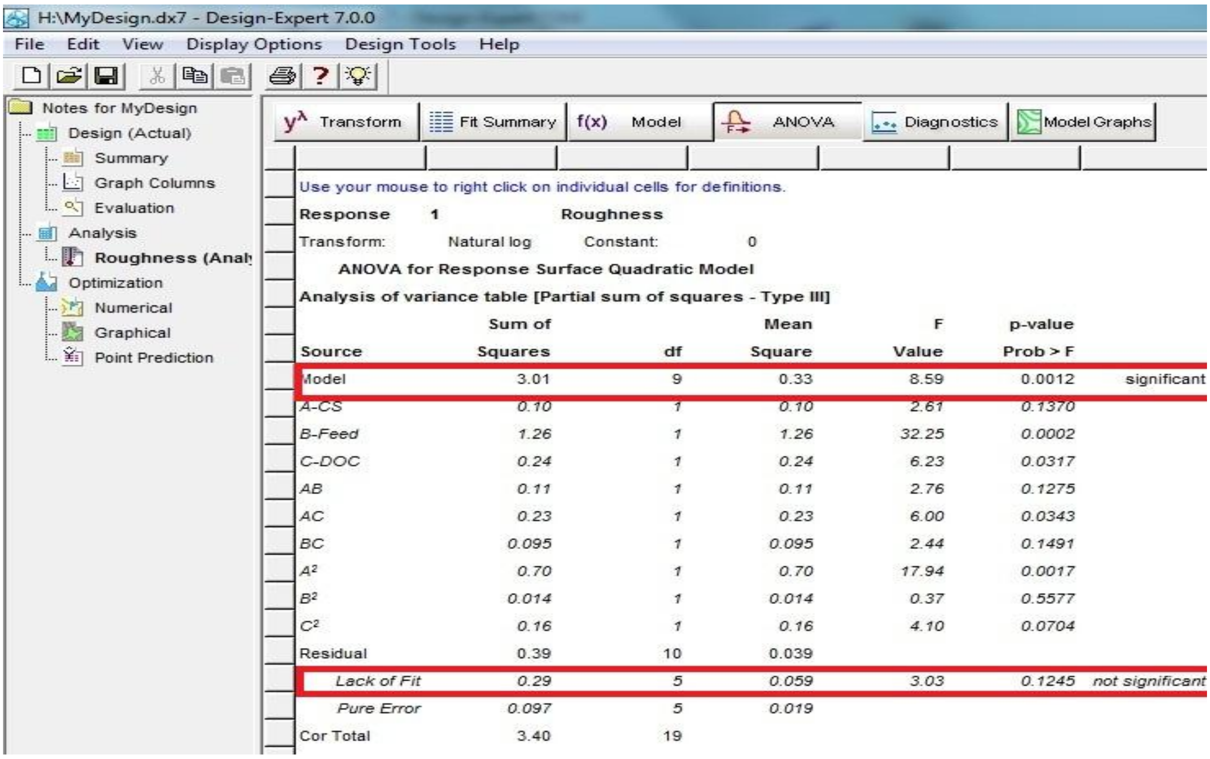


Figure 8: Selecting natural log

- Analysis of variance ANOVA : It shows that model is valid because Lack of fit is not significant.



Use your mouse to right click on individual cells for definitions.

Response 1 Roughness

Transform: Natural log Constant: 0

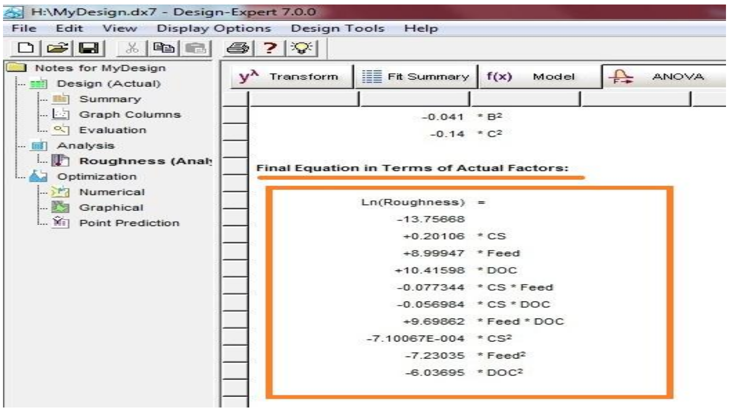
ANOVA for Response Surface Quadratic Model

Analysis of variance table [Partial sum of squares - Type III]

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Model	3.01	9	0.33	8.59	0.0012	significant
A-CS	0.10	1	0.10	2.61	0.1370	
B-Feed	1.26	1	1.26	32.25	0.0002	
C-DOC	0.24	1	0.24	6.23	0.0317	
AB	0.11	1	0.11	2.76	0.1275	
AC	0.23	1	0.23	6.00	0.0343	
BC	0.095	1	0.095	2.44	0.1491	
A^2	0.70	1	0.70	17.94	0.0017	
B^2	0.014	1	0.014	0.37	0.5577	
C^2	0.16	1	0.16	4.10	0.0704	
Residual	0.39	10	0.039			
Lack of Fit	0.29	5	0.059	3.03	0.1245	not significant
Pure Error	0.097	5	0.019			
Cor Total	3.40	19				

Figure 9: ANOVA

- And we get equation for roughness:



-0.041 * B²
-0.14 * C²

Final Equation in Terms of Actual Factors:

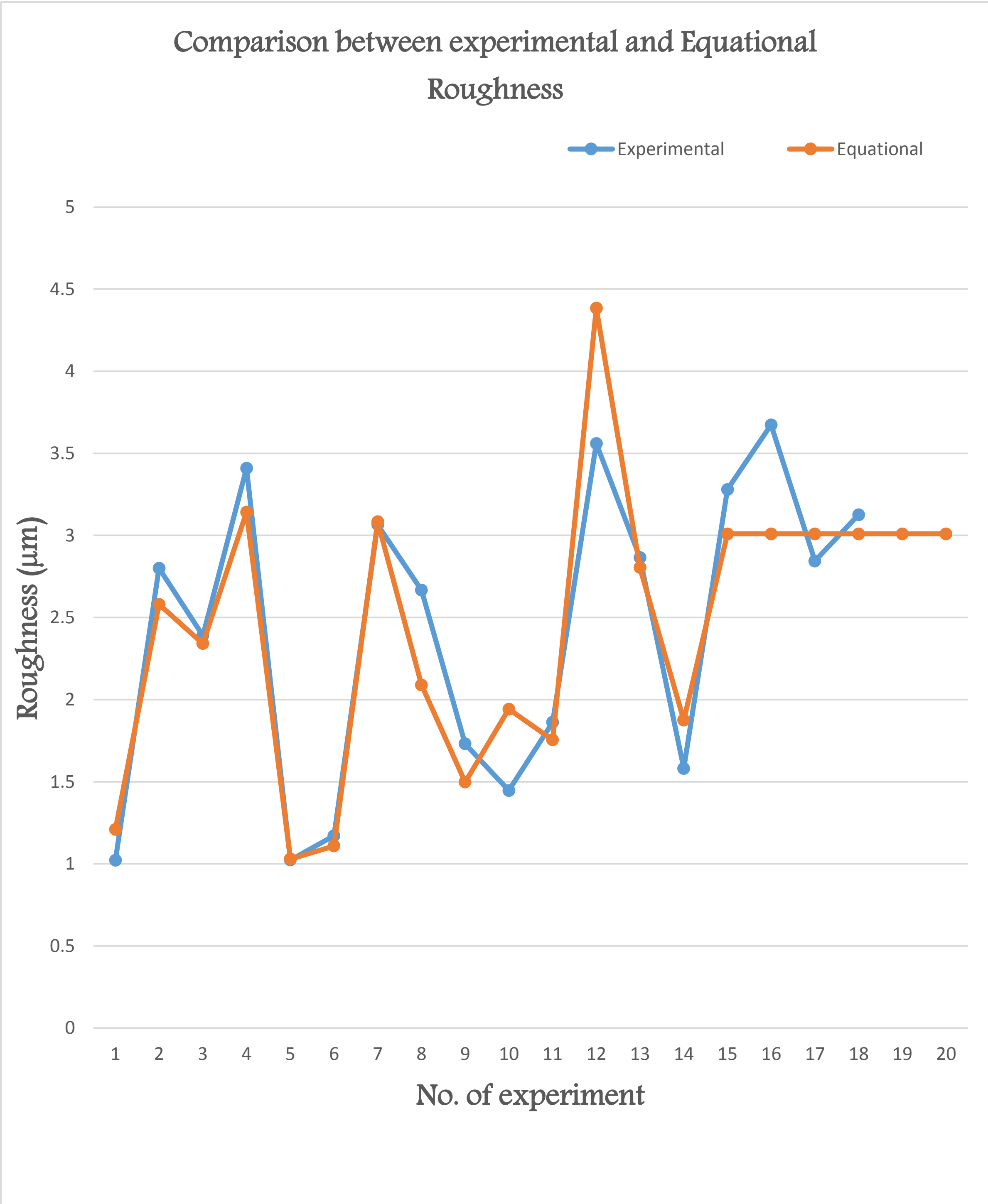
$$
\begin{aligned}
Ln(Roughness) =\ & -13.75668 \\
& +0.20106 \cdot CS \\
& +8.99947 \cdot Feed \\
& +10.41598 \cdot DOC \\
& -0.077344 \cdot CS \cdot Feed \\
& -0.056984 \cdot CS \cdot DOC \\
& +9.69862 \cdot Feed \cdot DOC \\
& -7.10067E\text{-}004 \cdot CS^2 \\
& -7.23035 \cdot Feed^2 \\
& -6.03695 \cdot DOC^2
\end{aligned}
$$

Figure 10: Equation for Roughness

(v) ERROR ANALYSIS:

It is a comparison between the equational roughness value with experimental roughness value. In this analysis we also calculated the percentage of error for each condition. Also a graph is plotted from which we can see the deviation of experimental roughness value from the equational one.

Experimental Roughness	Equational Roughness	Error (%)
1.021	1.209	18.366
2.800	2.580	7.858
2.390	2.341	2.027
3.409	3.142	7.839
1.023	1.029	0.607
1.171	1.109	5.360
3.065	3.084	0.628
2.667	2.089	21.666
1.731	1.497	13.541
1.446	1.942	34.259
1.862	1.755	5.731
3.560	4.384	23.136
2.865	2.804	2.128
1.581	1.875	18.604
3.280	3.009	8.284
3.673	3.009	18.092
2.844	3.009	5.782
3.126	3.009	3.760
3.280	3.009	8.284
2.456	3.009	22.482



Comparison between experimental and Equational Roughness
Experimental
Equational
Roughness (µm)
No. of experiment
0
0.5
1
1.5
2
2.5
3
3.5
4
4.5
5
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20

Chapter 5: Artificial Bee Colony (ABC) Algorithm

5.1 Introduction

Artificial Intelligence (AI) is one of the oldest and best known research fields. There are different definitions in the literature for AI of that the most widely used one belongs to John McCarthy, who defined it as “the science and engineering of making intelligent machines” (McCharty 2007). Computational intelligence (CI) is a fairly new research area and commonly referred to as AI, too. It is defined as the study of the design of intelligent agents where an intelligent agent is a system that perceives its environment and then takes actions to maximize its chances of success. While CI techniques are counted as AI techniques, there is a clear difference between them. For example, CI uses subsymbolic knowledge processing whereas classical AI uses symbolic approaches. CI includes a set of nature-inspired computational methodologies and approaches to address complex problems of the real world applications. Subjects in CI include neural networks which are trainable systems with very strong pattern recognition capabilities, fuzzy systems which are techniques for reasoning under uncertainty and evolutionary computation (EC) which is a form of stochastic optimization search. Forms of EC include swarm intelligence (SI) based algorithms and evolutionary algorithms. The evolutionary algorithms usually begin with a population of organisms (initial solutions) and then allow them to mutate and recombine, selecting only the fittest to survive each generation (refining solutions).The well-known evolutionary algorithms are genetic algorithms (GA), genetic programming, evolution strategies (ES), evolution programming and differential evolution (DE)

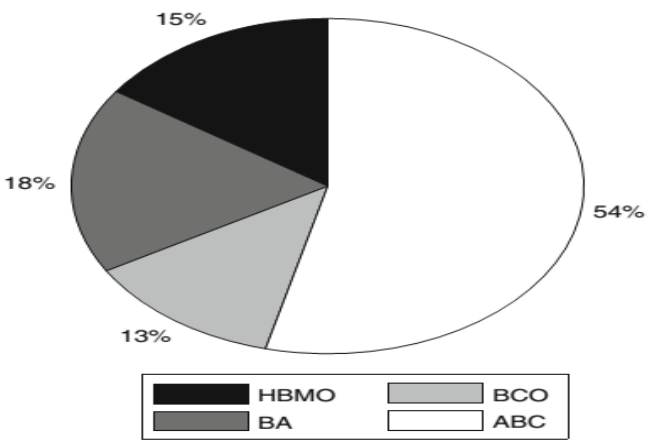


Figure 11: Percentages of publications regarding to some algorithms based on bee swarms

Some known algorithms based on bee SI are virtual bee, the bees, BeeAdHoc, the marriage in honeybees, the BeeHive, bee system, bee colony optimization and ABC. Virtual bee algorithm was developed byYang(2005) to solve the numerical function optimizations. In the model, a swarm of virtual bees are generated and they are allowed to move randomly in the phase space and these bees interact when they find some target nectar. Nectar sources correspond to the encoded values of the function. The solution for the optimization problem can be obtained from the intensity of bee interactions. The bees algorithm was described byPham et al.(2005) and mimics the foraging behaviour of honey bees. In its basic version, the algorithm performs a kind of neighbourhood search combined with random search and can be used for both combinatorial optimization and functional optimization. BeeAdHoc algorithm, defined byWedde and Farooq(2005), is a routing algorithm for energy efficient routing in mobile ad-hoc networks. The algorithm is inspired by the foraging principles of honey bees.

5.2.1. General features of intelligent swarms

There are so many kind of swarms in the world. It is not possible to call all of them intelligent or their intelligence level could be vary from swarm to swarm. Self-organization is a key feature of a swarm system which results collective behaviour by means of local interactions among simple agents (Bonabeau et al. 1999).Bonabeau et al.(1999) interpreted the self-organization in swarms through four characteristics:

(i) **Positive feedback:** promoting the creation of convenient structures. Recruitment and reinforcement such as trail laying and following in some ant species can be shown as example of positive feedback.

(ii) **Negative feedback:** counterbalancing positive feedback and helping to stabilize the collective pattern. In order to avoid the saturation which might occur in terms of available foragers a negative feedback mechanism is needed.

(iii) **Fluctuations:** random walks, errors, random task switching among swarm individuals which are vital for creativity. Randomness is often significant for emergent structures since it enables the discovery of new solutions.

(iv) **Multiple interactions:** agents in the swarm use the information coming from the other agents so that the information spreads throughout the network.

Additional to these characteristics, performing tasks simultaneously by specialized agents, called division of labour, is also an important feature of a swarm as well as self-organization for the occurrence of the intelligence (Bonabeau et al. 1997). According to Millonas, in order to call a swarm intelligent, the swarm must satisfy the following principles (Millonas 1994):

(i) The swarm should be able to do simple space and time computations (the proximity principle).

(ii) The swarm should be able to respond to quality factors in the environment (the quality principle).

(iii) The swarm should not commit its activities along excessively narrow channels (the principle of diverse response).

(iv) The swarm should not change its mode of behaviour upon every fluctuation of the environment (the stability principle).

(v) The swarm must be able to change behaviour mode when needed (the adaptability principle).

5.2.2: Foraging behaviour of honey bees

The minimal model of forage selection that leads to the emergence of collective intelligence of honey bee swarms consists of three essential components: food sources, employed foragers and unemployed foragers, and the model defines two leading modes of the behaviour: the recruitment to a rich nectar source and the abandonment of a poor source.

(i) Food Sources: The value of a food source depends on many factors such as its proximity to the nest, its richness or concentration of its energy, and the ease of extracting this energy. For the sake of simplicity, the "profitability" of a food source can be represented with a single quantity (Seeley 1995).

(ii) Employed foragers: They are associated with a particular food source which they are currently exploiting or are "employed" at. They carry with them information about this particular source to the hive and the information can be the distance and direction from the nest, the profitability of the source and share this information with a certain probability.

(iii) Unemployed foragers: They are continually at look out for a food source to exploit. There are two types of unemployed foragers: scouts, searching the environment surrounding the nest for new food sources and onlookers waiting in the nest and establishing a food source through the information shared by employed foragers. The mean number of scouts averaged over conditions is about 5–10% of other bees (Seeley 1995).

The exchange of information among bees is the most important occurrence in the formation of the collective knowledge. While examining the entire hive it is possible to distinguish between some parts that commonly exist in all hives. The most important part of the hive with respect to exchanging information is the dancing area. Communication among bees related to the quality of food sources takes place in the dancing area. This dance is called a waggle dance. Since information about all the current rich sources is available to an onlooker on the dance floor, probably she watches numerous dances and decides to employ herself at the most profitable source. There is a greater probability of onlookers choosing more profitable sources since more information is circulated about the more profitable sources. Hence, the recruitment is proportional to the profitability of the food source (Tereshko and Loengarov 2005).

In the case of honey bees foraging behaviour, the four characteristics defined in the Sect.5.2.1 on which self-organization relies can be expressed as follows:

(i) Positive feedback: As the nectar amount of a food source increases, the number of onlookers visiting it increases proportionally.

(ii) Negative feedback: The exploitation process of poor food sources is stopped by bees.

(iii) Fluctuations: The scouts carry out a random search process for discovering new food sources.

(iv) Multiple interactions: Employed bees share their information about food sources with their nest mates (onlookers) waiting on the dance area. When the foraging behaviour of honey bees explained above is re-examined, it is seen that the principles defined by Millonas (1994) are fully satisfied.

5.2.3: Algorithmic structure of ABC

As in the minimal model of forage selection of real honey bees, the colony of artificial bees in ABC contains three groups of bees: employed bees associated with specific food sources, onlooker bees watching the dance of employed bees within the hive to choose a food source, and scout bees searching for food sources randomly. Both onlookers and scouts are also called unemployed bees. Initially, all food source positions are discovered by scout bees.

There after, the nectar of food sources are exploited by employed bees and onlooker bees, and this continual exploitation will ultimately cause them to become exhausted. Then, the employed bee which was exploiting the exhausted food source becomes a scout bee in search of further food sources once again. In other words, the employed bee whose food source has been exhausted becomes a scout bee. In ABC, the position of a food source represents a possible solution to the problem and the nectar amount of a food source corresponds to the quality (fitness) of the associated solution. In the basic form, the number of employed bees is equal to the number of food sources (solutions) since each employed bee is associated with one and only one food source.

The general algorithmic structure of the ABC optimization approach is given as follows:

Initialization Phase

REPEAT

Employed Bees Phase

Onlooker Bees Phase

Scout Bees Phase

Memorize the best solution achieved so far

UNTIL(Cycle=Maximum Cycle Number or a Maximum CPU time)

In the initialization phase, the population of food sources (solutions) is initialized by artificial scout bees and control parameters are set.

In the employed bees phase, artificial employed bees search for new food sources having more nectar within the neighbourhood of the food source in their memory. They find a neighbour food source and then evaluate its fitness. After producing the new food source, its fitness is calculated and a greedy selection is applied between it and its parent. After that, employed bees share their food source information with onlooker bees waiting in the hive by dancing on the dancing area.

In the onlooker bees phase, artificial onlooker bees probabilistically choose their food sources depending on the information provided by the employed bees. For this purpose, a fitness based selection technique can be used, such as the roulette wheel selection method. After a food source for an onlooker bee is probabilistically chosen, a neighbourhood source is determined, and its fitness value is computed. As in the employed bees phase, a greedy selection is applied between two sources.

In the scout bees phase, employed bees whose solutions cannot be improved through apredetermined number of trials, called “limit”, become scouts and their solutions are abandoned. Then, the scouts start to search for new solutions, randomly. Hence, those sources which are initially poor or have been made poor by exploitation are abandoned and negative feedback behaviour arises to balance the positive feedback.

These three steps are repeated until a termination criteria is satisfied, for example a maximum cycle number or a maximum CPU time.

5.2.4: The ABC Algorithm Used for Unconstrained Optimization Problems:

In ABC algorithm the colony of artificial bees consists of three groups of bees: employed bees, onlookers and scouts. First half of the colony consists of the employed artificial bees and the second half includes the onlookers. For every food source, there is only one employed bee. In other words, the number of employed bees is equal to the numberof food sources around the hive. The employed bee whose the food source has been abandoned by the bees becomes a scout.

In ABC algorithm, the position of a food source represents a possible solution to the optimization problem and the nectar amount of a food source corresponds to the quality (fitness) of the associated solution. The number of the employed bees or the onlooker bees is equal to the number of solutions in the population.

At the first step, the ABC generates a randomly distributed initial population P(G=0)of SN solutions (food source positions), where SN denotes the size of population.

Each solution x_i (i=1,2, ..., SN)is a D-dimensional vector. Here, D is the number of optimization parameters. After initialization, the population of the positions (solutions) is subjected to repeated cycles, C=1,2, ..., MCN, of the search processes of the employed bees, the onlooker bees and scout bees. An employed bee produces a modification onthe position (solution) in her memory depending on the local information (visual information) and tests the nectar amount (fitness value) of the new source (new solution). Provided that the nectar amount of the new one is higher than that of the previous one, the bee memorizes the new position and forgets the old one. Otherwise she keeps the position of the previous one in her memory. After all employed bees complete the search process, they share the nectar information of the food sources and their position information with the onlooker bees on the dance area. An onlooker bee evaluates the nectar information taken from all employed bees and chooses a food source with a probability related to its nectar amount. As in the case of the employed bee, she produces a modification on the position in her memory and checks the nectar amount of the candidate source. Providing that its nectar is higher than that of the previous one, the bee memorizes the new position and forgets the oldone.

An artificial onlooker bee chooses a food source depending on the probability value associated with that food source, P_i , calculated by the following expression

(1):

$$P_i = \frac{F(\theta_i)}{\sum_{k=1}^{S} F(\theta_k)} \ldots \qquad \ldots \qquad \ldots \qquad \ldots \qquad (1)$$

Where,

P_i: The probability of selecting the i^{th} employed bee

S : The number of employed bees

θ_i: The position of the i^{th} employed bee

$F(\theta_i)$: The fitness value

In order to produce a candidate food position from the old one in memory,

the ABC uses the following expression (2):

$$v_{ij} = x_{ij} + \varphi_{ij}(x_{ij} - x_{kj}) \qquad (2)$$

where k∈{1,2,..., SN} and j ∈{1,2,..., D} are randomly chosen indexes. Althoughkis determined randomly, it has to be different from i. $\varphi_{i,j}$ is a random number between [-1, 1]. It controls the production of neighbour food sources around $x_{i,j}$ and represents the comparison of two food positions visually by a bee. As can be seen from (2), as the difference between the parameters of the $x_{i,j}$ and $x_{k,j}$ decreases, the perturbation on the position $x_{i,j}$ gets decrease, too.

Thus, as the search approaches to the optimum solution in the search space, the step length is adaptively reduced.

If a parameter value produced by this operation exceeds its predetermined limit, the parameter can be set to an acceptable value. In this work, the value of the parameter exceeding its limit is set to its limit value. The food source of which the nectar is abandoned by the bees is replaced with a new food source by the scouts. In ABC, this is simulated by producing a position randomly and replacing it with the abandoned one. In ABC, providing that a position can not be improved further through a predetermined number of cycles, then that food source is assumed to be abandoned. The value of predetermined number of cycles is an important control parameter of the ABC algorithm, which is called “limit” for abandonment. Assume that the abandoned source is x_i and $j\in\{1,2,..., D\}$, then the scout discovers a new food source to be replaced with x_i. This operation can be defined as in (3)

$$x_i^j = x_{min}^j + \text{rand}\ (0,1)\ (x_{max}^j - x_{min}^j\ ) \qquad (3)$$

After each candidate source positionvi,j is produced and then evaluated by the artificial bee, its performance is compared with that of its old one. If the new food has an equal or better nectar than the old source, it is replaced with the old one in the memory. Otherwise, the old one is retained in the memory. In other words, a greedy selection mechanismis employed as the selection operation between the old and the candidate one. It is clear from the above explanation that there are four control parameters used in the ABC: The number of food sources which is equal to the number of employed or onlooker bees (SN), the value oflimit, the maximum cycle number (MCN).

Detailed pseudo-code of the ABC algorithm is given below:

1: Initialize the population of solutions $x_{i,j}$, i=1...SN,j=1...D

2: Evaluate the population

3: cycle=1

4: repeat

5: Produce new solutions $\upsilon_{i,j}$ for the employed bees by using (2) and evaluate them

6: Apply the greedy selection process

7: Calculate the probability values $P_{i,j}$ for the solutions $x_{i,j}$ by (1)

8: Produce the new solutions $\upsilon_{i,j}$ for the onlookers from the solutions $x_{i,j}$ selected depending on $P_{i,j}$ and evaluate them

9: Apply the greedy selection process

10: Determine the abandoned solution for the scout, if exists, and replace it with a new randomly produced solution $x_{i,j}$ by (3)

11: Memorize the best solution achieved so far

12: Cycle=cycle+1

13: Until cycle=MCN

5.2.5. ABC Flowchart

The Flow chart of the Artificial Bee Colony Optimization is given below:

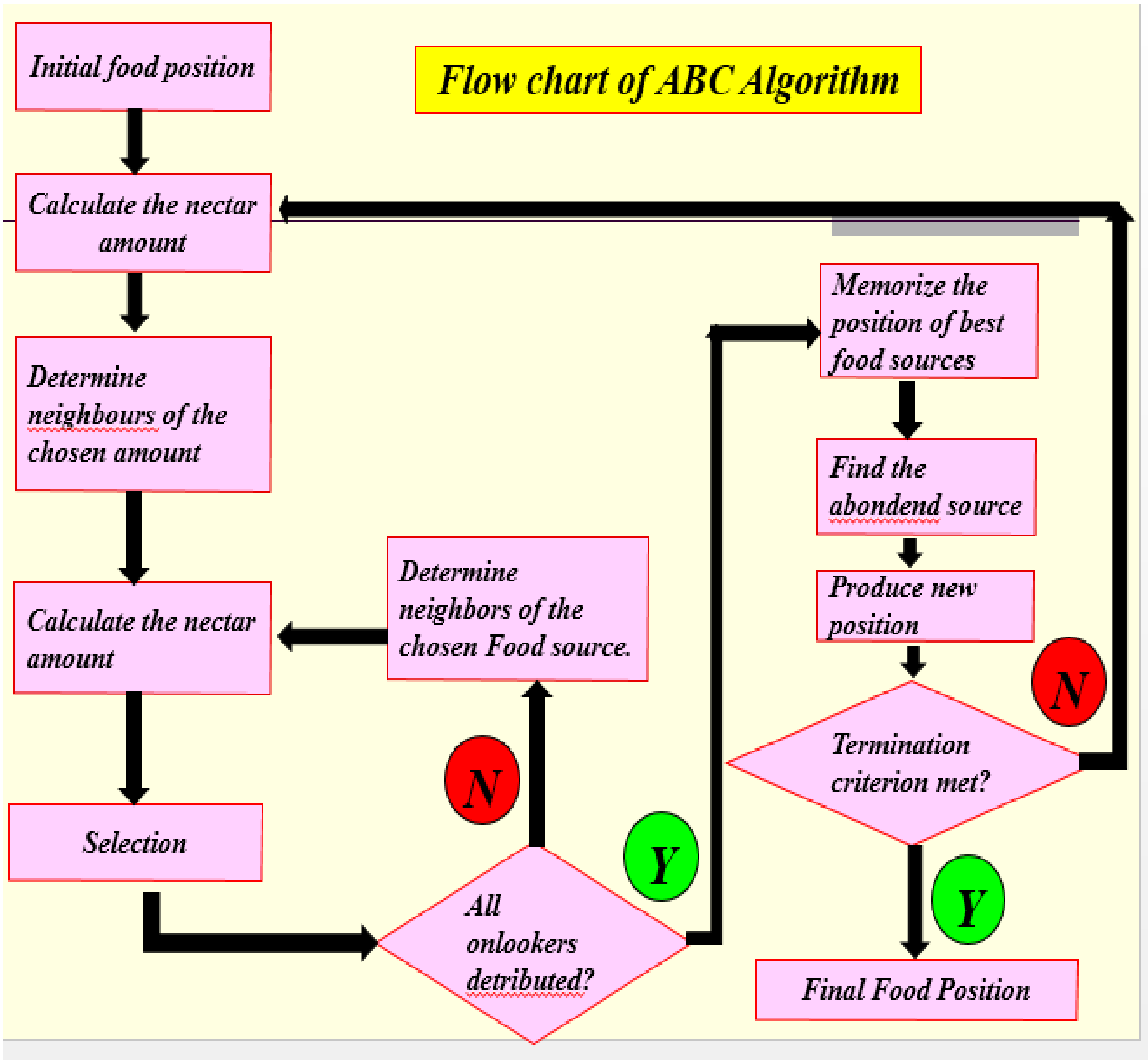


Figure 12: Flow Chart Of ABC

CHAPTER 6: RESULT ANALYSIS

Optimized Process parameters	
Parameters	Results of ABC and Desirability Analysis
Cutting Speed (CS)	71.72 m/min
Feed rate (FR)	0.12 mm/rev
Depth of Cut (DoC)	0.86 mm
Predicted Roughness	0.4916 µm

Verification of Results		
Predicted Roughness	Actual Roughness	% Error
0.4916 µm	**0.4750 µm**	**3.4%**

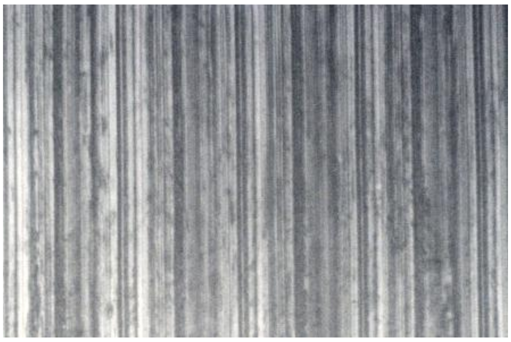


Figure 13: Image of machined surface at optimum cutting condition

Chapter 7: Conclusion

In this part of the thesis, CCD was used to determine the minimum combination of experimental data range. Using the data the experiment was done. After that a quadratic equation was formed by the CCD which was used to get the equational data.

ABC Algorithm model had been be developed by using MATLAB in a nice way. Then we optimized the datas by using ABC algorithm. The actual roughness value differs from the programmed roughness. Some other inspetions are:

- It's because program results are for Ideal condition.
- Sometimes unpredictable chattering occured
- There may be some error during data collection
- Machining conditions were not Ideal.
- Sometimes variation of speed and feeds occurs unintentionally.
- Overall percentage of error is minimal.

It has been analyzed that the experimental data and equational data are quite similar except some data. From this, we can conclude that the objectives of our project has been achieved.

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