“Investigation of Surface Roughness During Hot Air Streaming Turning Process of Different Materials and Optimization of Parameters Using Particle Swarm Optimization”

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Dedicated

To

Our Beloved Parents

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List of Acronyms

D.O.C	Depth Of Cut
RPM	Revolution per minute
M.S	Mild Steel
S.S	Stainless Steel
CBN	Cubic Boron Nitride
PSO	Particle Swarm Optimization
FE	Fitness Evaluation
lbest	Local Best
gbest	Global Best
N.P.P	Normal Probability Plot
PCD	Poly Crystalline Diamond

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Abstract

Different types of coolants are widely used in different metal cutting processes to improve the machining responses. But the suitability of using the correct cutting fluid is very important considering the concept of green environment. In this study, hot air is used as an alternative approach for hot machining process which is considered to initially heat the work-piece for easy machining operation. Firstly, two different velocities of hot air have been applied during the machining of mild steel in turning process. Next, the hot air has been kept at a fixed temperature and applied to three different materials (Brass, Aluminum and Stainless Steel) during turning operation keeping the other process parameters same. With the variation of different process parameters, it has been observed that surface roughness at different cutting conditions using hot air is improved significantly. A clear comparison has been made to investigate the responses of surface roughness at different cutting conditions in between the hot air and normal machining processes. Finally Particle Swarm Optimization (PSO), a relatively new, modern, and powerful method of optimization has been applied to perform well on these optimization problems and to find the global optimum solution in a complex search space. This thesis aims at providing a review and discussion of an established procedure which may be used as an alternative approach in the dry cutting research in the days to come as well as PSO algorithm which exposes the most active research topics that can give initiative for future work and help the practitioner improving better result with little effort.

Keywords: Hot air, Surface roughness, Turning operation, Optimization, Swarm intelligence, Particle Swarm Optimization, Social-network, Convergence.

Chapter One: Introduction

1.1 Background

Surface roughness resembles the component of surface texture. It is quantified by the deviations in the direction of the normal vector of a real surface from its ideal form. It these deviations are large, the surface is rough. If they are small, the surface is smooth. However in practice it is often necessary to know both the amplitudes & frequency to ensure that a surface is fit for a purpose. Roughness plays an important role in defining characteristics of a surface roughness is often a good predictor of the mechanical component since irregularities in surface may form nucleation sites for cracks & corrosion. Surface irregularities of a component or material may be created by machining but they also can be created by a wide range of factors such as tool wobbling caused by motor vibration during machining ,the quality of tool edge, the nature of the machine material. The form & size of irregularities vary and are superimposed in multiple layers, so difference in the irregularities impact quality and functions of surface. Result of these irregularities can control the performance of the end product in aspects such as friction, durability, operating noise, energy consumption & airtightness. The surface irregularities of a component or material may be intentionally created by machining, but they can also be created by a wide range of factors such as tool wobbling caused by motor vibration during machining, the quality of the tool edge, and the nature of the machined material. The results of these irregularities can control the performance of the end product in aspects such as friction, durability, operating noise, energy consumption, and airtightness. The surface quality is an important parameter to evaluate the productivity of machine tools and also machine components. Achieving the desired quality of surface is of great importance for the functional behavior of the mechanical parts . Now a day's in manufacturing industry , special attention is given to dimensional accuracy and surface finish. So measuring and characterizing the surface finish can be reified as the predictor of the machining performance. Turning is the primary operation is most of the production process in the industry. The turning operation meets the critical features that require specific surface finish. The operators working on lathe use their own experience and machining guidelines to achieve the best desire surface finish. Due to inadequate knowledge and surrounding factor may cause high production costs and low quality. So, the proper selection of cutting tools and process parameters is very important in turning operation.

1.2 Objective of This Work

We focused on the application of hot air which is an alternate approach for machining process. Here hot air preheats the job piece and eases the machining operation. Moreover, no health hazards like using coolants will occur here. While performing the machining operation two distinct velocities of air has been applied and in terms of surface roughness its effect is evaluated.

Firstly we try to evaluate the quality of surface roughness using Hot air. So for our first work we kept feed rate, rpm constant three different depth of cut have been applied which are 0.25, 0.50 and 0.75 respectively. The whole process is the combination of four steps. First we have used coolant and measured surface roughness, next we have measured it at dry condition and finally we have applied two different velocities of hot air pf different temperatures. A distinct comparison has been made to observe surface roughness at various cutting conditions using hot air and normal machining process. It has been found that the surface roughness at various cutting conditions using hot air is a noteworthy improvement.

Then we analyze the surface parameters of different materials (Brass, Aluminum and Stainless Steel) in the application of hot air which is an alternate manufacturing process. Here hot air preheats the job piece and eases the machining operation. Moreover, no health hazards like using coolants will occur here. A distinct comparison has been made to observe surface roughness of different material at a fixed feed rate (f), cutting speed (v), and depth of cut (d) under two different conditions dry and hot air. It has been found that surface roughness for different materials has improved by applying hot air compared to normal dry machining conditions.

It is very important in turning process to select the appropriate cutting parameters. To meet the required roughness specification, selection of appropriate values of machining parameter is very important. Several parameters such as cutting speed, feed rate, depth of cut, cutting force, tool wear, Spindle speed (RPM), tool geometry, chip loads, chip formation, coolant etc. and material properties influences surface roughness. From these various factors some factors can be easily controlled. Among these factors we worked on spindle speed (RPM), feed rate and depth of cut. To determine the desirable cutting parameters value some process like trial and error, experience, machining handbook etc. is conducted traditionally. So, to get the desired results various set up of cutting conditions are repeated. The appropriate cutting condition is very important for the manufacturing products & efficiency of the turning operation. In recent years, particle swarm optimization (PSO), Anti colony Optimization (ACO) etc. become very popular, as these are used in various engineering applications. And finally we focused on PSO to optimize the desired values of parameters in machining.

Chapter Two: Literature review

The effect of different machining parameters on stainless steel and brass alloys, during both ultrasonic assisted preheated turning and conventional pre heated turning (CT), and evaluated improvements of cutting forces, surface roughness, surface integrity, and hot machining accuracy was investigated by Mahdy et al. [1]. Abu-Zahra et al. [2] presents an analytical model to monitor the gradual wear of cutting tools, on-line, during turning operations using ultrasound waves. S. Ranganathan [3] presents results of surface roughness of the effect of hot turning (by mixture of liquid petroleum gas & oxygen gas) in stainless steel (type 316) under different cutting condition with a temperature range of 200oc to 600oc. The effect of machining parameters for both conventional turning & hot turning was investigated to provide an optimum range for each material and is relation to surface roughness. An induction assisted hot machining was chosen and a system capable to maintain a constant temperature into the workpiece (Ti-5553) during machining (turning) was designed by Maher ali [4]. It improves the machinability. An oxy-acetylene hot machining setup was designed, fabricated and installed on a lathe machine by S.K Thandra [5]. Results found that the machining parameters were bringing down by about 34% in hot machining than conventional machining. F. Egrov [6] used forging heat in hot machining on work piece for the improvement of machining response and found significant response during the turning operation of mild steel. An experimental setup for hot machining process was installed to increase tool life with torch flame by R.D. Rajopadhye [7]. The surface quality is an important parameter to evaluate the productivity of machine tools and also machine components. Achieving the desired quality of surface is of great importance for the functional

behavior of the mechanical parts [8]. Now a day's in manufacturing industry, special attention is given to dimensional accuracy and surface finish. So measuring and characterizing the surface finish can be reified as the predictor of the machining performance [9]. Turning is the primary operation is most of the production process in the industry. The turning operation meets the critical features that requires specific surface finish. The operators working on lathe use their own experience and machining guidelines to achieve the best desire surface finish. Due to inadequate knowledge and surrounding factor may cause high production costs and low quality. So, the proper selection of cutting tools and process parameters is very important in turning operation [10]. An experimental investigation was conducted to determine the effects of cutting conditions and tool geometry on the surface roughness in the finish hard turning of the bearing steel by Sing et. al. [11]. The effect of cutting conditions on surface roughness in turning of free machining steel by ANN models was investigated by J. Paulo et. al. [12]. Analysis of surface roughness by turning process using taguchi method conducted by S. Thamizhmanii et.al. [13]. Patwari et al. introduced Investigation of surface parameters during hot air streaming turning process of mild steel [14]. An Experimental Investigation of Hot Machining with Induction to Improve Ti5553 Machinability was done by M. Baili et.al. [15]. Abou-El-Hossein, Kadisgama, Hamdi, and Benyounis (2007) discussed the development of the first and second order models for predicting the cutting force produced in end-milling using the response surface methodology to study the effect of cutting parameters on cutting force [16]. The predictive models produced values of the cutting force close to those readings recorded experimentally with a 95% confident interval. Jeang (2011) determined the optimal cutting parameters required to minimize the cutting time while maintaining an acceptable quality level [17]. The equation for predicting cutting time was determined by CATIA software along with response surface methodology. The proposed approach could produce automatic product and process design that may lead to cost reduction and quality improvement. Iqbal, He, Li, and Dar (2007) focused on the enhancement of tool life and surface finish using ANOVA, optimization module and prediction module[18]. The proposed expert system could able to recommend helix angle of the tool, milling orientation and also could predict tool life, surface roughness and cutting force for a high speed milling operation. Zain, Haron, and Sharif (2009a) applied Genetic Algorithm (GA) to find optimal cutting conditions for obtaining minimum surface roughness[19]. The analysis of the study has proved that GA technique could able to perform better than experimental sample data, regression modeling and response surface methodology. Zain, Haron, and Sharif (2009b) discussed the utilization of Artificial Neural Network (ANN) for predicting the surface roughness in the milling process[20]. Based on the experiments conducted, the author concluded that the use of high speed and low feed and rake angle is high recommended for better surface finish. Ozcelik and Bayramoglu (2006) developed a statistical model for surface roughness estimation in a high-speed flat end milling process[21]. The author found that the estimation capability of the first and second order models developed using experimental results were observed to be in good fit with the actual measured values. Benardos and Vosniakos (2002) presented Neural Network (NN) modeling approach for the prediction of surface roughness in CNC face milling[22]. ANN based procedure could able to predict the surface roughness with a mean error of 1.86% and found consistent throughout the entire range of values. Ahn, Kim, and Lee (2009) proposed a methodology to predict the surface roughness of layered manufacturing processed parts such as sphere model and teapot model[23]. The author could arrive a accuracy level of surface roughness less than 1 m based on the prediction accuracy results. Kalla, Sheikh-Ahmad, and Twomey (2010) studied the machining of carbon fiber reinforced polymers in a helical end mill and developed a methodology for predicting the cutting forces by transforming specific cutting energies from orthogonal to oblique cutting[24]. Predictions were in good agreement with the experimental data in unidirectional laminate but lesser agreement in multidirectional. Machining condition of turning operation by considering unit cost of production using dynamic programming technique and also investigated the influence of cutting parameters on surface roughness[25]. James Kennedy et al. [26] developed PSO, which is a population based search procedure that could yield global .optimum solution. Tansel et al. [27] represented the relationship between the cutting condition and machine related variables. Optimal operating conditions were also calculated to obtain the best possible compromise between roughness of machined surface and the duration. Al-Ahmari [28] 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. Srinivas et al. [29] proposed particle swarm optimization for selecting optimized machining parameters in multi-pass turning operation for a component of continuous form. Chorng- Jgh Tzeng et al. [25] found that depth of cut and cutting speed are the most significant factor for roughness average, roughness maximum, and roundness and also analyzed orthogonal array of Taguchi method using nine experimental runs.

Chapter Three: Experimental Details

3.1 Working Materials

3.1.1 Materials:

ASTM A36 is the most commonly used mild and hot-rolled steel. It has excellent welding properties and is suitable for grinding, punching, tapping, drilling and machining processes. Yield strength of ASTM A36 is less than that of cold roll C1018, thus enabling ASTM A36 to bend more readily than C1018. Normally, larger diameters in ASTM A36 are not produced since C1018 hot roll rounds are used.

3.1.2 Chemical Composition

Table 3.1:Chemical Composition of mild steel

Sl. No.	Element	Content
1	Carbon, C	0.25 - 0.290 %
2	Copper, Cu	0.20 %
3	Iron, Fe	98.0 %
4	Manganese, Mn	1.03 %
5	Phosphorous, P	0.040 %
6	Silicon, Si	0.280 %
7	Sulfur, S	0.050 %

3.1.3 Mechanical Properties

Table 3.2:Mechanical Properties Of Mild Steel

Mechanical Properties	Metric	Imperial
Tensile Strength, Ultimate	400 - 550 MPa	58000 - 79800 psi
Tensile Strength, Yield	250 MPa	36300 psi
Elongation at Break (in 200 mm)	20.0 %	20.0 %
Elongation at Break (in 50 mm)	23.0 %	23.0 %
Modulus of Elasticity	200 GPa	29000 ksi
Bulk Modulus (typical for steel)	140 GPa	20300 ksi
Poisson's Ratio	0.260	0.260
Shear Modulus	79.3 GPa	11500 ksi

3.2 Lathe Machine

The Centre lathe used for the machining process was manufactured by Gate Inc. (model L-1/180). Lathe is a machine which removes the metal from a piece of work to the required shape and size.

Specification of the Lathe:

- Centre height in mm: 180
- Centre distance in mm: 1000-750
- Bed width in mm: 250
- Swing over front part of bed in mm: 380
- Swing over bed ways in mm: 360
- Swing over gap in mm: 510
- Gap length in front of face plate in mm: 120
- Swing over carriage in mm: 340
- Swing over cross slide in mm: 200
- Main spindle bore in mm: 42
- Main spindle nose: DIN 55022-5
- Main spindle tapper: 4
- Number of speeds: 9
- Speed range in rpm: 60-2000
- Number of longitudinal feeds: 20
- Range of longitudinal feeds in mm: 0.047-0.86
- Number of cross feeds: 20

- Range of cross feeds in mm: 0.021-0.39
- Number of metric threads: 20
- Range of metric threads in mm: 0.5-9
- Number of whit worth threads: 16
- Range of whit worth threads in t.p.i: 56-4
- Number of modular threads: 20
- Range of modular threads: 0.25-4.5
- Thread of lead screw: 6
- Cross slide travel in mm: 260
- Tool post slide travel in mm: 115
- Turn off tool post slide: 1800
- Maximum tool dimension in mm: 20×20
- Tailstock shank diameter in mm: 48
- Tailstock shank travel in mm: 145
- Tailstock taper: 3
- Main motor power in HP: 4
- Power motor power HP: 1/8HP

Figure 3.1: Lathe Machine

3.3 **Cutting Tool Insert Used:**

For machining the above work material the following Uncoated Carbide Inserts was used:

CNMG 12 04 08: Three different tool inserts are used to take into account the effect of nose radius. Cutting tools are often designed with inserts or replaceable tips (tipped tools). In these, the cutting edge consists of a separate piece of material, brazed, welded or clamped on to the tool body. Common materials for tips include Tungsten Carbide, Polycrystalline Diamond (PCD), and Cubic Boron Nitride (CBN)

3.3.1 **Insert Designation**:

The details of cutting insert CNMG 12 04 08 is explained below.

C: Insert Shape= Diamond 8^0
N: Clearance Angle= 0^0 No rake
M: Medium Tolerance= d+/-0.05 m+/-0.08 s+/-0.13
G: Insert Type (Pin / Top clamping double sided)
12: means length of each cutting edge is 12 mm
04: stands for nominal thickness of the insert is 4 mm
08: stands for nose radius is 0.8mm

(a) (b)

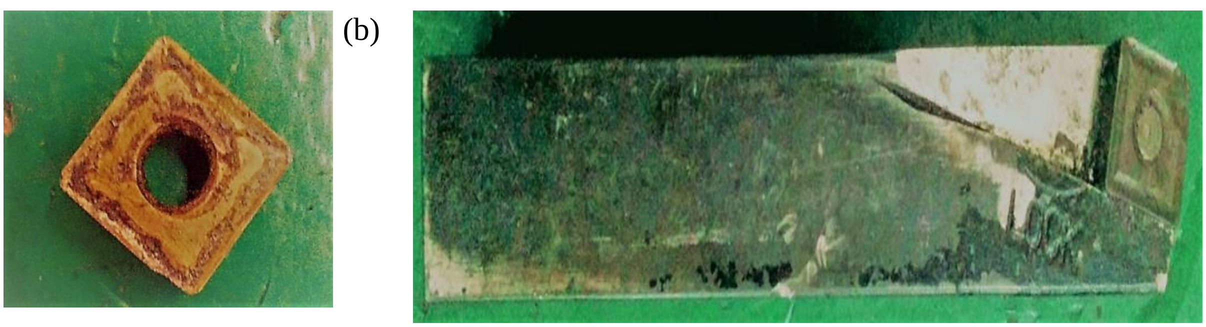


Figure 3.2: (a) Carbide coated insert (b) Tool Holder

3.3.2 **Properties of Carbide Inserts:**

They are stable and moderately expensive. It is offered in several "grades" containing different proportions of Tungsten Carbide and binder (usually Cobalt). High resistance to abrasion. High solubility in iron requires the additions of Tantalum Carbide and Niobium Carbide for Steel usage. Its main use is in turning tool bits although it is very common in milling cutters and saw blades. Hardness up to HRC 90. Sharp edges generally not recommended.

3.4 Specification of Hot air gun

Table 3.3:Specification of Hot air gun

Hot Air	Air Velocity (m/sec)	Air Flow Rate (liter/sec)	Voltage (Volt)	Frequency (Hz)	Nozzle Diameter (mm)
Level 1	3.60	300	220-230	50	Outer = 23.3
Level 2	1.60	500			Inner = 20.1

Figure shows the calibration curve of hot air temperature at different time. The hot air gun was calibrated to ensure the correct temperature of hot air blown in the shaft.

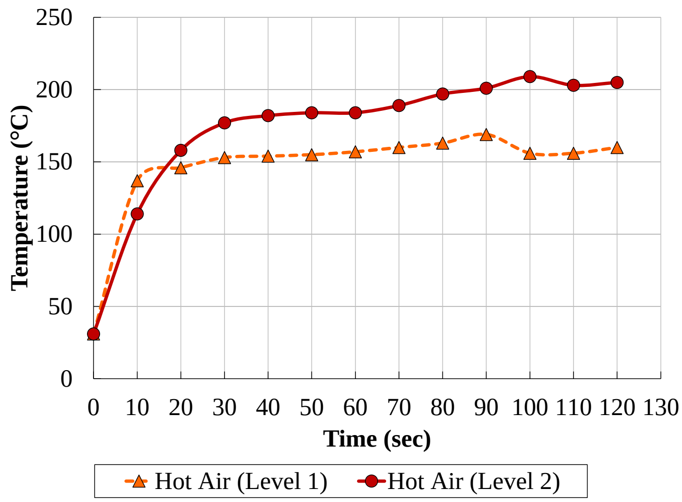


Figure 3.3: Calibration of time vs temperature graph

3.5 Hot air streaming turning process of mild steel

In this research, several experiments were carried out under two different temperature of hot air with variations of depth of cut (D.O.C). Experiments were carried out under coolant, dry and hot conditions. Feed was fixed at a low value of .095 mm/rev to investigate effect of D.O.C and different temperature of hot air with a constant cutting speed (220 rpm) for all the experiment.

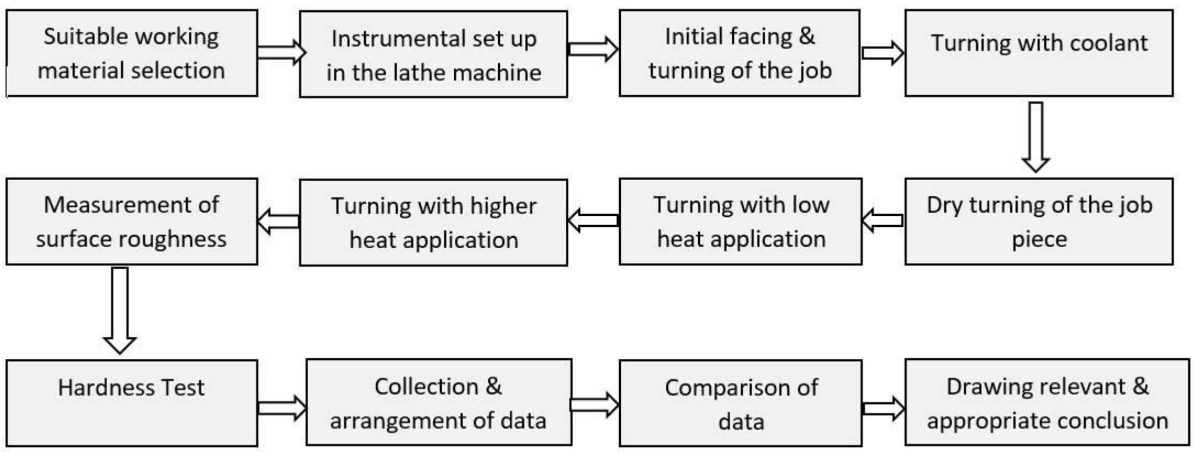


Figure 3.4: Flow Chart of the Working Procedure

Actually, two different temperature of hot air were used with two different air velocities at two different switches. The process variables with their units (and notations) are listed below. Mild steel shafts were used as the work piece material of the experiments. The diameter of the shaft was always kept same at 32mm. The total work piece length was 200 mm. Experimental length was 150mm and 50mm was used for holding the work piece in the chuck. Each experiment was carried out over 30mm length with 10mm gap after every experiment. Thus four experiments were done on each single piece. First experiment was done by coolant, then coolant, then dry and lastly by hot air. Tungsten carbide coated insert was used in different experiments. Figure shows the work piece used in these experiment.

To provide hot air, a hot air gun was used which is able to generate hot air at temperature 31°C to 205°C in 120s. The hot air gun is able to apply hot air on the mild steel. A switch was used to produce different temperature. Figure shows the schematic diagram of the experimental setup.

Figure 3.5: Experimental set up

During preheating the hot air gun was kept at an angle of 450 at a distance 2 inch from the work piece for the time of 1 minute and 40 seconds. And when the turning was going on it was moved to 5 inches distance keeping the previous time as default. The mitutoyo SURFTEST SJ-210, a contact profilometer, was used in this study to measure the surface roughness of the machined surface.

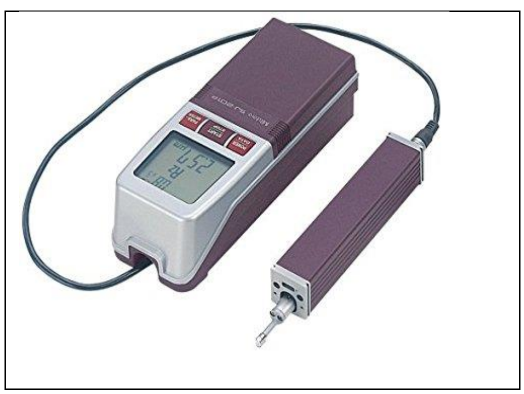


Figure 3.6: Profilometer

Table 3.4: Process Parameters

Feed Rate (mm/rev)	Depth of cut (mm)	Spindle Speed (rpm)	Cutting Speed (mm/min)
0.95	0.25 0.50 0.72	220	21.77

3.6 Hot air turning process of different material

The process flow diagram is illustrated below consisting of different steps which include the set up in the lathe machine, dry turning, hot air turning and surface roughness evaluation.

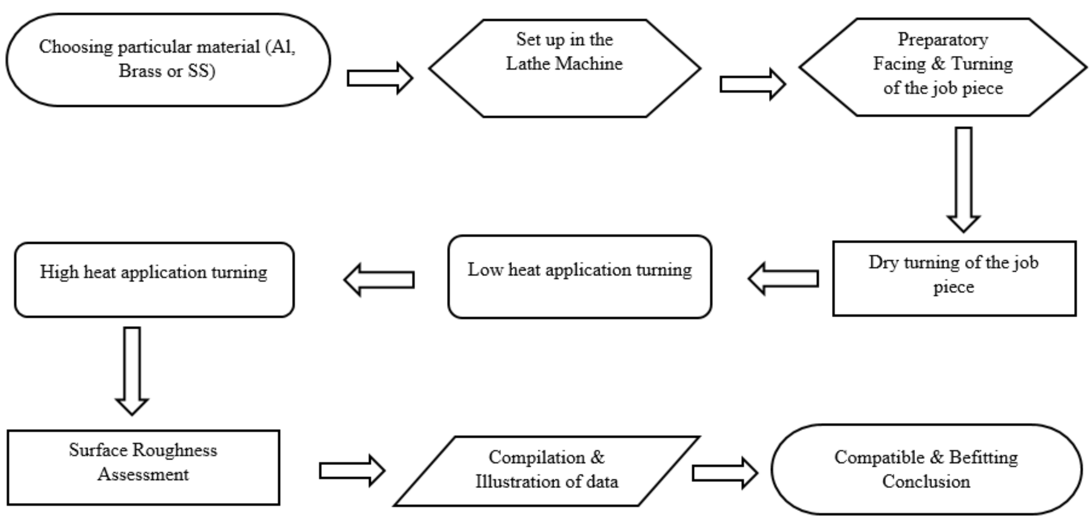


Figure 3.7: Flow Chart of the Working Procedure

In this research, a handful of experiments were done under dry and hot conditions at constant different process parameters, which is shown in Table 1.

Table 3.5: Process Parameters

Feed Rate (mm/rev)	**Depth of cut (mm)**	**Spindle Speed (rpm)**	**Cutting Speed (mm/min)**
0.95	0.75	220	21.77

3.6.1 Analysis of Chip Formation

The chips produced during the machining operation were collected and presented below. Firstly for the Aluminum is shown in Figure 4 (a)-(c). From left hand side serially the chips are for dry turning operation, turning operation using level 1 hot air and level 2 hot air. Initially the chips strands were continuous and closed winding. Gradually the strand windings were less compact. Secondly, the chips for Brass during machining operation using dry turning, level1 hot air and level 2 hot air is shown in Figure 4 (d)-(f). The chips were discontinuous type of regular shape & size. Gradually the shape and size of the chips decreased on application of several levels of hot air. Finally, here are the chips of stainless steel formatted during machining operation of dry turning, level1hot air and level 2 hot air is shown in Figure 4 (g)-(i).

At the beginning, chips were continuous but afterwards on the application of heat the chips became segmented type with a long strand winding.

Table 3.6: Cutting chips for different materials at different conditions

	Dry	Hot Air (Level 1)	Hot Air (Level 2)
Aluminum	 (a)	 (b)	 (c)
Brass	 (d)	 (e)	 (f)
Stainless steel	 (g)	 (h)	 (i)

3.7 Optimization of cutting parameters during hot air streaming turning process of mild steel using PSO

To meet the required roughness specification, selection of appropriate values of machining parameter is very important. Several parameters such as cutting speed, feed rate, depth of cut, cutting force, tool wear, spindle speed (RPM), tool geometry, chip loads, chip formation, coolant etc. and material properties influences surface roughness. From these various factors some factors can be easily controlled. Among these factors we worked on spindle speed (RPM), feed rate and depth of cu.

Table 3.7: Different Levels of Parameters

Variables		Values of different levels		
Designation	**Description**	**Low**	**Medium**	**High**
RPM	Spindle Speed	220	530	860
D.O.C	Depth of cut(mm)	0.5	1	1.5
FEED	Feed rate(mm/rev)	0.095	0.19	0.38

To find the optimum machining parameters in order to get the minimum surface roughness. Particle Swarm Optimization (PSO) is used and the results are illustrated. A number of 27 samples were taken during turning operation considering the speed, feed and depth of cut and their respective surface roughness.

Table 3.8: Experimental Values

Experiment Number	**Speed(RPM)**	**Depth of cut, D.O.C (mm)**	**FEED (mm/rev)**	**Surface Roughness, Ra (µm)**
01	860	1.5	0.38	6.42
02	860	1.5	0.19	1.78
03	860	1.5	0.095	1.13
04	860	1	0.38	6.16
05	860	1	0.19	1.46
06	860	1	0.095	1.07
07	860	0.5	0.38	6.10
08	860	0.5	0.19	1.82
09	860	0.5	0.095	1.03
10	530	1.5	0.38	6.06
11	530	1.5	0.19	4.35
12	530	1.5	0.095	4.47
13	530	1	0.38	5.23
14	530	1	0.19	5.93
15	530	1	0.095	2.91
16	530	0.5	0.38	8.53
17	530	0.5	0.19	3.69
18	530	0.5	0.095	2.31
19	220	1.5	0.38	8.64
20	220	1.5	0.19	5.55
21	220	1.5	0.095	4.06
22	220	1	0.38	10.53
23	220	1	0.19	5.78
24	220	1	0.095	2.79
25	220	0.5	0.38	6.64
26	220	0.5	0.19	3.94
27	220	0.5	0.095	2.77

Chapter Four: Particle Swarm Optimization (PSO)

4.1 **Particle swarm optimization**:

Particle swarm optimization (PSO) algorithms are nature-inspired population-based metaheuristic algorithms originally accredited to Eberhart and Kennedy. These algorithms mimic the social behavior of birds flocking and fishes schooling. Starting around the search space by means of a set of simple mathematical expressions which model some inter particle communications. These mathematical expressions in their simplest and most basic form, suggest the movement of each particle toward its own best experienced position and the swarm's best position so far, along with some random perturbations. There is an abundance of different variants using different updating rules, however. Though being generally known and utilized as an optimization technique, PSO has its roots in image rendering and computer animation technology where a particle system as a set of autonomous individuals working together to form the appearance of a fuzzy object like a cloud or an explosion. The idea was to initially generate a set of points and to assign an initial velocity vector to each of them. Using these velocity vectors, each particle changes its position iteratively while the velocity vectors are being adjusted by some random factors. The notion of inter-object communication system to introduce a flocking algorithm in which the individuals are able to follow some basic flocking rules such as trying to match each other's velocities. Such a system allowed for modeling more complex group behaviors in an easier and more natural way.

The PSO algorithm maintains multiple potential solutions at one time. It is a population based method. During each iteration of the algorithm a solution is evaluated by an objective function to determine its fitness. In PSO the population of the solutions always called swarm and the feasible solutions are called particles. Each particle is composed of three vectors and two fitness values. In the three vectors, x-vector records the current position of the particle in search space, p-vectors records the location of the best solution found so far by the particle and the v-vector contains a gradient for which particle will travel and in the two fitness values the x-fitness records the fitness of the x-vector and the p-fitness records the fitness of the p-vector.

Each particle maintains position in the search space, velocity and individual best position and the swarm maintains its global best position by communicating either directly or indirectly with one another search directions (gradient).

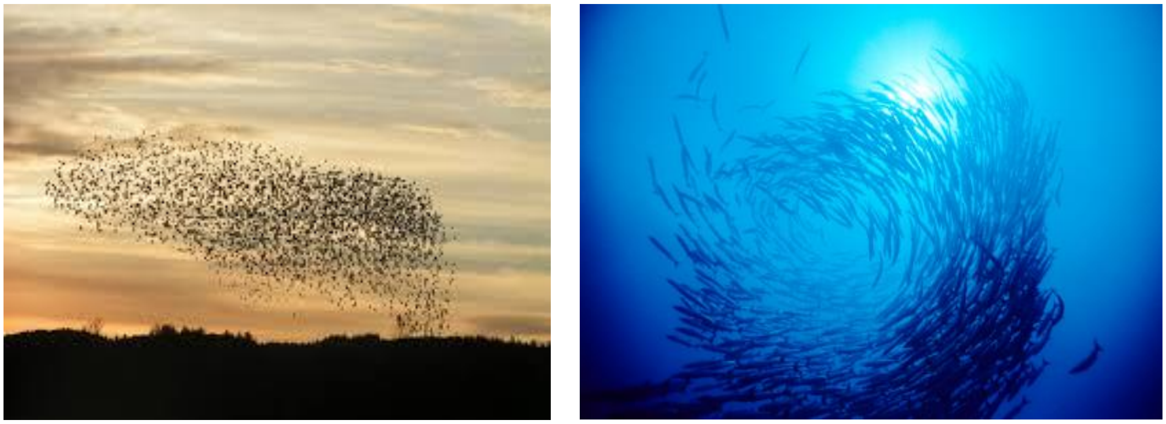


Figure 4.1: Social Behavior of Birds & Fishes

The PSO algorithm consists of three steps –

1. Evaluate fitness of each particle
2. Update individual and global best
3. Update velocity and position of each particle

These steps are repeated until the desired conditions are met.

4.2 **Geometric Illustrations:**

The following figure illustrates how all particles are attracted by their immediate neighbors in the search space using lbest PSO and there are some subsets of particles where one subset of particles is defined for each particle from which the local best particle is then selected. Figure (a) shows particles *a*, *b* and *c* move towards particle *d*, which is the best position in subset 1. In subset 2, particles *e* and *f* move towards particle *g*. Similarly, particle *h* moves towards particle i, so does j in subset 3 at time step. Figure (b) for time step, the particle *d* is the best position for subset 1 so the particles *a*, *b* and *c* move towards *d*.

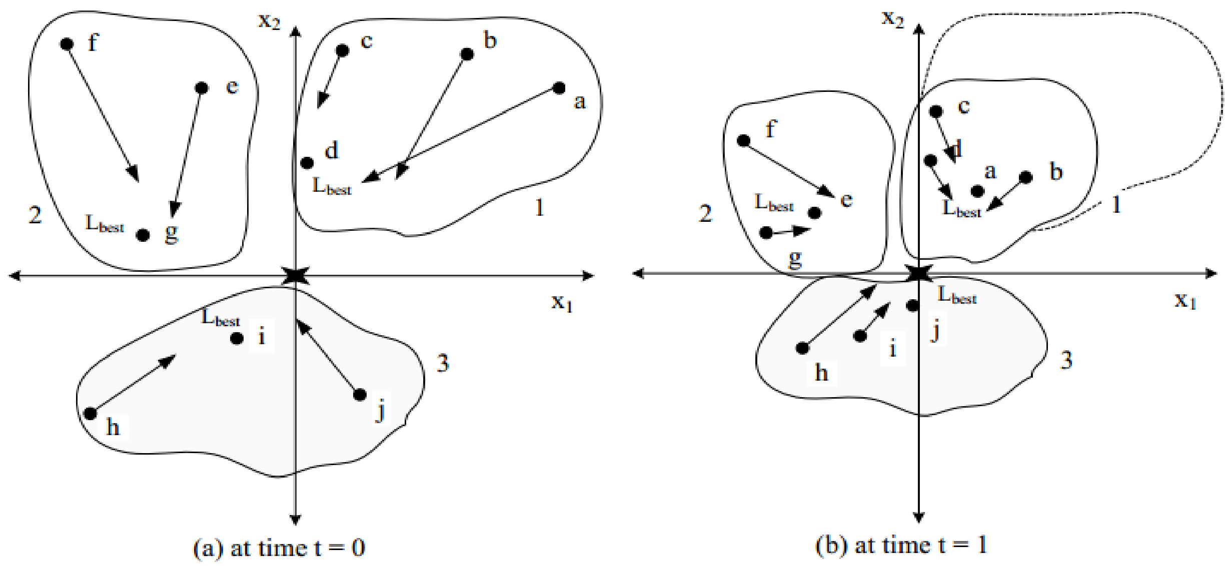


Figure 4.2: Velocity and Position update for Multi-particle in lbest PSO

Next the figure shows the position updates for more than one particle in a two dimensional search space and this figure illustrates the gbest PSO. The optimum position is denoted by the colored black symbol. Figure (a) shows the initial position of all particles with the global best

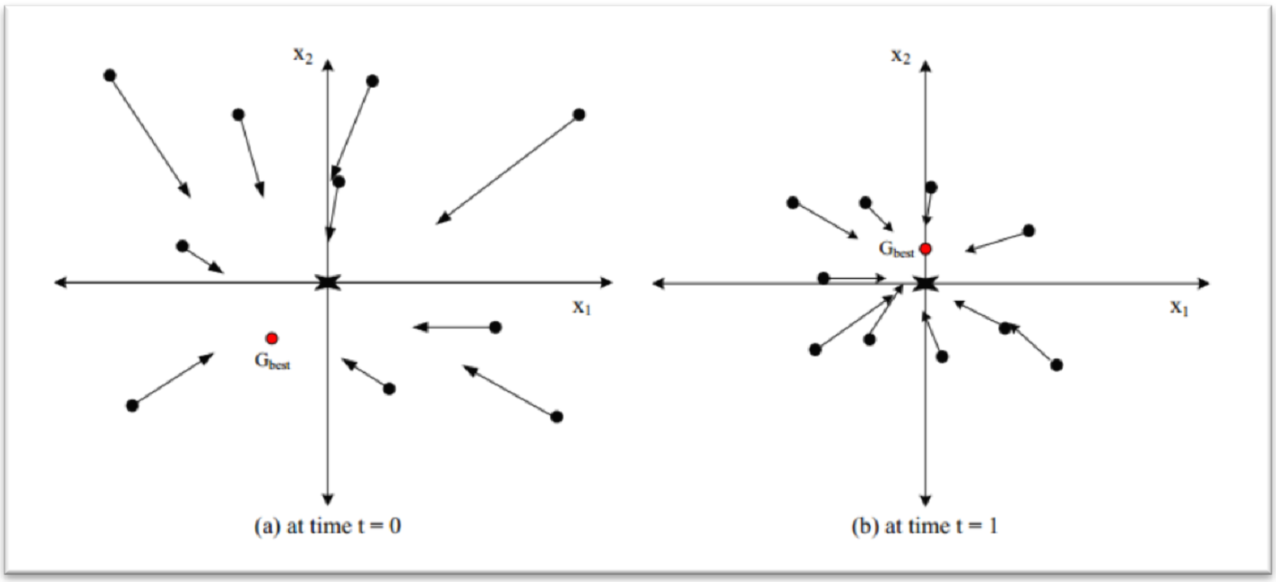


Figure 4.3: Velocity and Position update for Multi-particle in gbest PSO.

position. The cognitive component is zero at and all particles are only attracted toward the best position by the social component. Here the global best position does not change. Figure (b) shows the new positions of all particles and a new global best position after the first iteration i.e. at t=1

4.3 **Process Flowchart:**

The particle swarm optimization algorithm has been arranged in a sequential manner to find out the global optimum solution.

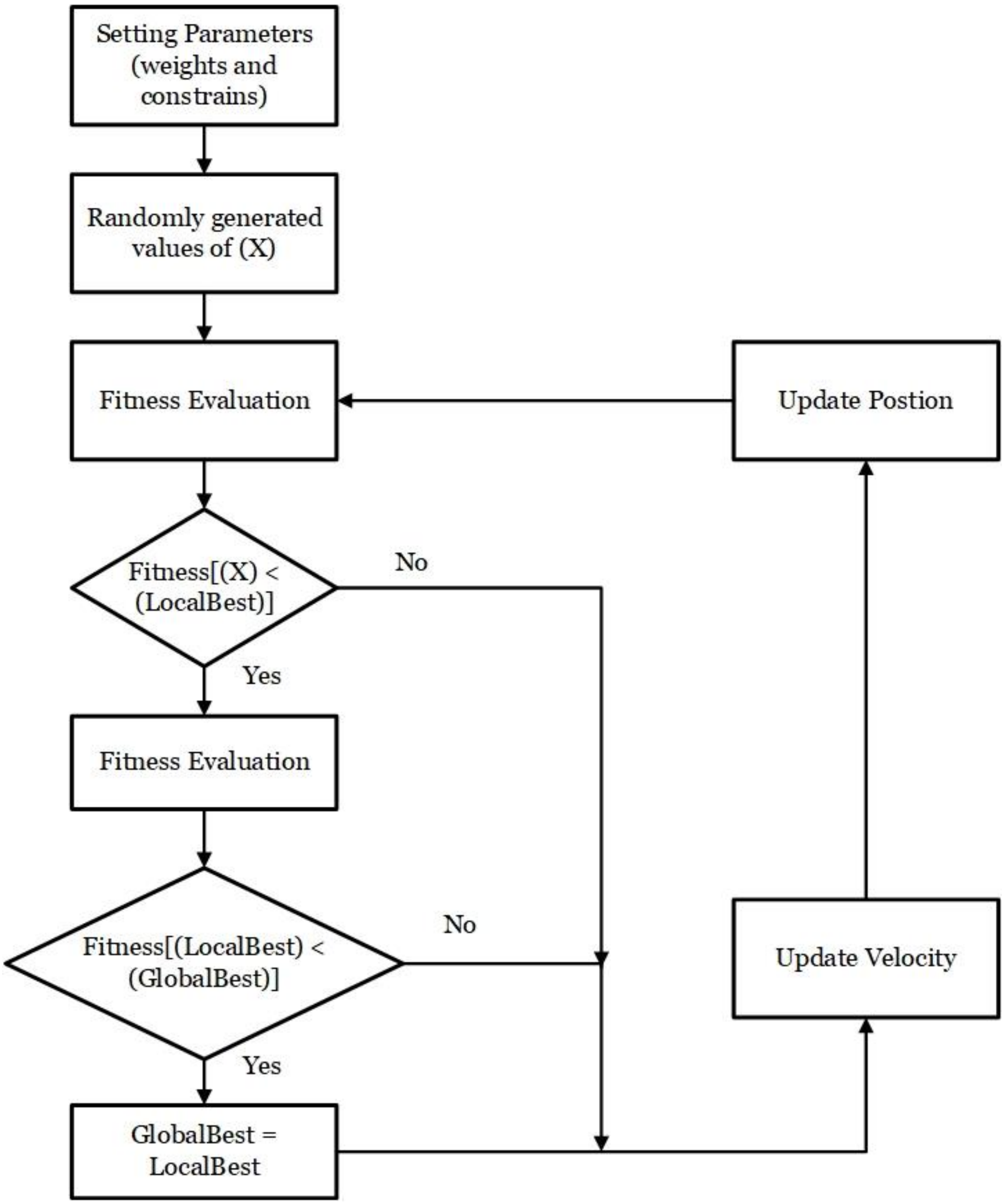


Figure 4.4: Particle Swarm Optimization Algorithm

4.4 Formulation of Objective Function:

The full development of machining process planning is based on optimization of the economic criteria subject to technical and managerial constraints. The economic criteria are the objectives of machining operations in terms of quality. The objectives considered in this paper are surface roughness to be minimized.

```
function f=ofun(x)

 f = 0.001612195541580*x(1) + 3.246190563121023*x(2) + 15.681457466329853*x(3) –
0.000003905540132*(x(1)^2)-0.431038981855913*(x(2)^2) +  6.843559005992312*(x(3)^2) –
0.001977445127058*x(1)*x(2) +0.001583570246527*x(1)*x(3)-3.451819514957795*x(2)*x(3)
```

4.5 PSO Convergence Characteristics:

In relation to PSO the word convergence typically refers to two different definitions:
Convergence of the sequence of solutions (stability analysis, converging) in which all particles have converged to a point in the search-space, which may or may not be the optimum or Convergence to a local optimum where all personal bests p or alternatively, the swarm's best known position g, approaches a local optimum of the problem, regardless of how the swarm behaves. Convergence of the sequence of solutions has been investigated for PSO. These analyses have resulted in guidelines for selecting PSO parameters that are believed to cause convergence to a point and prevent divergence of the swarm's particles (particles do not move unboundedly and will converge to somewhere).

However, the analyses were criticized by Pedersen [31] for being oversimplified as they assume the swarm has only one particle, that it does not use stochastic variables and that the points of attraction, that is, the particle's best known position p and the swarm's best known position g, remain constant throughout the optimization process. However, it was shown [32] that these simplifications do not affect the boundaries found by these studies for parameter where the swarm is convergent.

Chapter Five: Data Analysis

5.1 Residual plots in Minitab

A residual plot is a graph that is used to examine the goodness-of-fit in regression. Examining residual plots helps us to determine whether the ordinary least squares assumptions are being met. If these assumptions are satisfied, then ordinary least squares regression will produce unbiased coefficient estimates with the minimum variance.

5.2 Histogram of residuals

The histogram of residuals has been used to determine whether the data are skewed or whether outliers exist in the data. It can be used to check whether the variance is normally distributed. A symmetric bell-shaped histogram which is evenly distributed around zero indicates that the normality assumption is likely to be true. If the histogram indicates that random error is not normally distributed, it suggests that the model's underlying assumptions may have been violated. Here the histogram of the Residuals showing that the deviation is normally distributed.

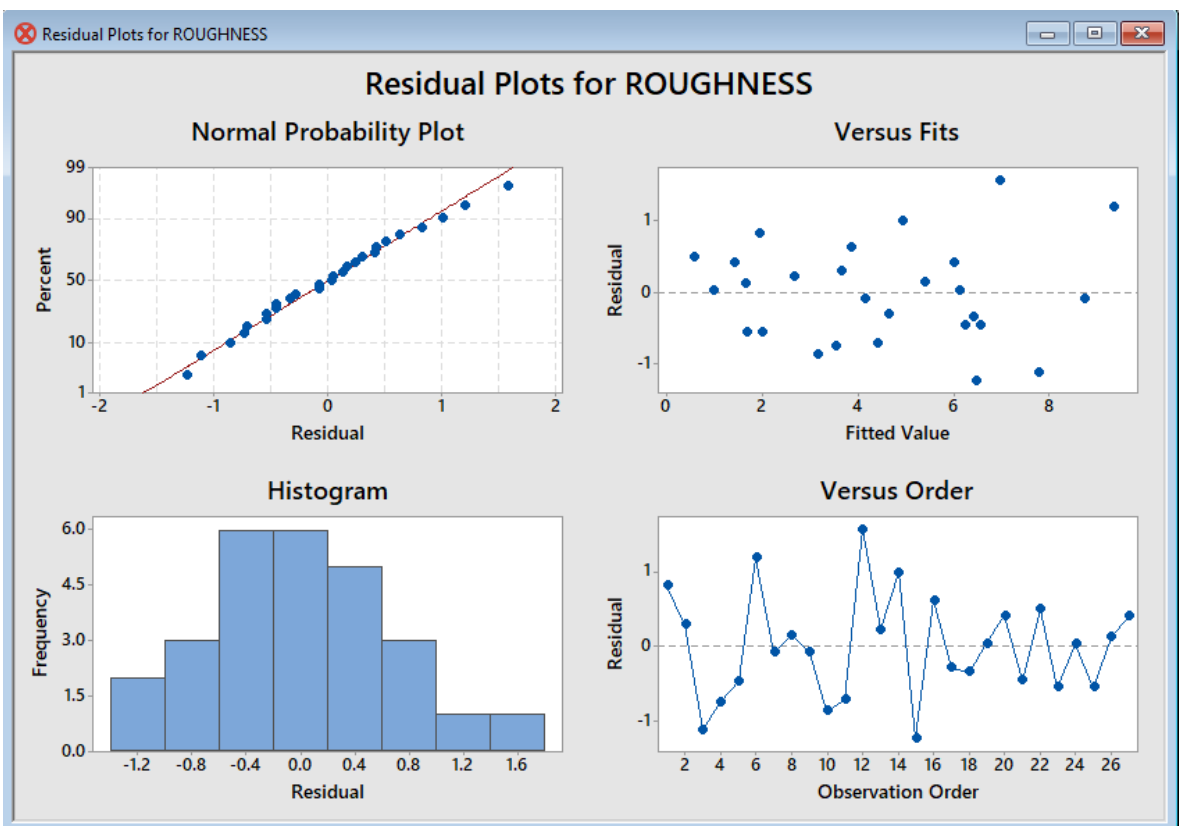


Figure 5.1: Residual plots for Surface Roughness.

5.3 Normal probability plot of residuals

The normal plot of residuals has been used to verify the assumption that the residuals are normally distributed. The normal probability plot is a graphical technique to identify substantive departures from normality. This includes identifying outliers, skewness, kurtosis, a need for transformations, and mixtures. Normal probability plots are made of raw data, residuals from model fits, and estimated parameters. In a normal probability plot (also called a "normal plot"), the sorted data are plotted vs. values selected to make the resulting image look close to a straight line if the data are approximately normally distributed. Deviations from a straight line suggest departures from normality. Normal probability plot of a sample from a normal distribution looks like a fairly straight, at least when the few large and small values are ignored.

5.4 Residuals versus fits

The residuals versus fits plot has been used to verify the assumption that the residuals have a constant variance. Here are the characteristics of a well-behaved residual vs. fits plot and what they suggest about the appropriateness of the simple linear regression model:

The residuals "bounce randomly" around the 0 line. This suggests that the assumption that the relationship is linear is reasonable. The residuals roughly form a "horizontal band" around the 0 line. This suggests that the variances of the error terms are equal. No one residual "stands out" from the basic random pattern of residuals. This suggests that there are no outliers.

5.5 Residuals versus order of data

The residuals versus order of data has been plotted to verify the assumption that the residuals are uncorrelated with each other. It is used as a way of detecting a particular form of non-independence of the error terms, namely serial correlation. If the data are obtained in a time (or space) sequence, a residuals vs. order plot helps to see if there is any correlation between the error terms that are near each other in the sequence.

It is a scatter plot with residuals on the y axis and the order in which the data were collected on the x axis. The residuals bounce randomly around the residual = 0 line. In general, residuals exhibiting normal random noise around the residual = 0 line suggest that there is no serial correlation.

Chapter Six: Results and discussion

6.1 Hot air streaming turning process of mild steel

The figure depicts the results obtained for different experiments. From the graphical comparison for same feed and cutting speed but different depth of cut and varying conditions a comparative illustration is made.

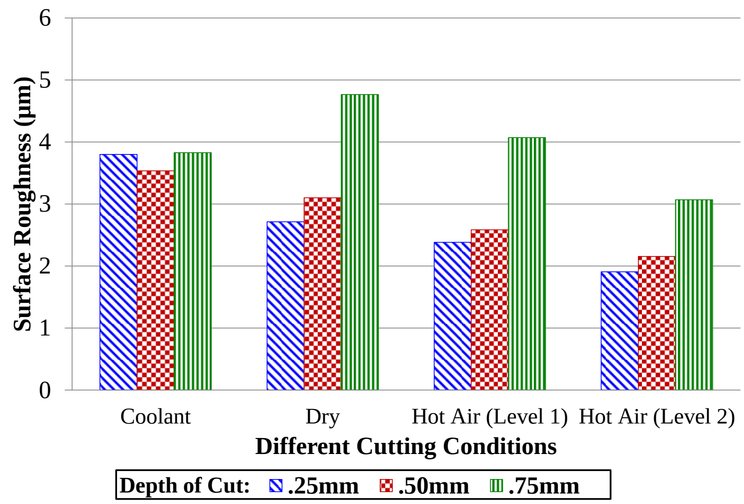
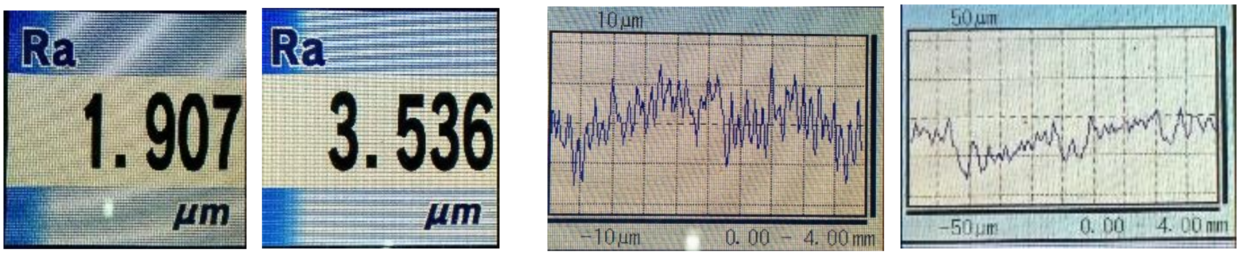


Figure 6.1: Effect of depth of cut on surface roughness

It reveals that the preheating effect on mild steel gives an excellent surface finish and cutting facility. It is clearly visible from the graph that while cutting using cutting fluids the surface finish is not so good .again in dry condition there is no significant improvement in surface. But on the application of preheating a better surface finish has been obtained. Furthermore, various depth of cut influences the surface roughness. It is very clear from the graph that for small depth of cut the surface finish is fabulous compared to the conventional machining. Some of the surface roughness measurement values has been framed here which shows us the gradual improvement in surface roughness.

The application of heat was also given at two stages. One for smaller hot air flow volume rate while the other is a bit larger rate. It is to mention that the diameter of the nozzle was kept constant.

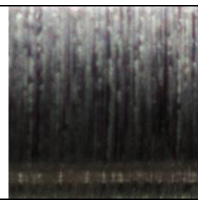
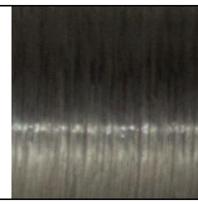
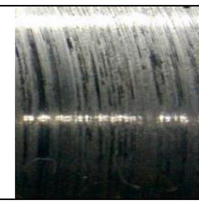
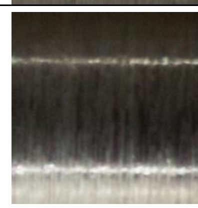
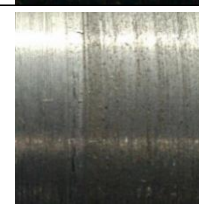
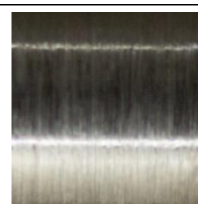
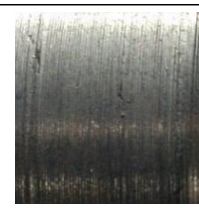
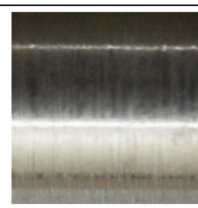
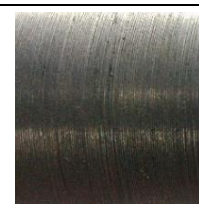


(a) (b)

Figure 6.2: (a) Surface roughness data. (b) Graph of surface roughness

From the observed values preheating was given for 1 minute & 40 seconds for closer distance. The timing was same for some distant level heat application. Finally from the above illustration it is very clear that the preheating effect on mild steel while turning operation is an effective method for the improvement of surface roughness.

Table 6.1: Images of surface for different depth of cut for cutting conditions (a, b and c) Coolant (d, e and f) Dry (g, h and i) Hot air level 1 (j, k and l) Hot air level 2

		Depth of cut		
		0.25mm	**0.50mm**	**0.75mm**
Cutting Conditions	**Coolant**	**(a)** 	**(b)** 	**(c)** 
	Dry	**(d)** 	**(e)** 	**(f)** 
	Hot Air (Level 1)	**(g)** 	**(h)** 	**(i)** 
	Hot Air (Level 2)	**(j)** 	**(k)** 	**(l)** 

.

6.2 **Hot air turning process of different material**

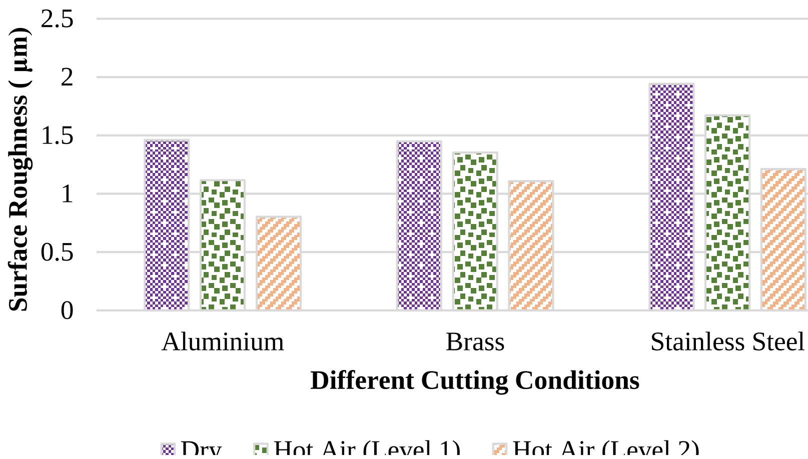
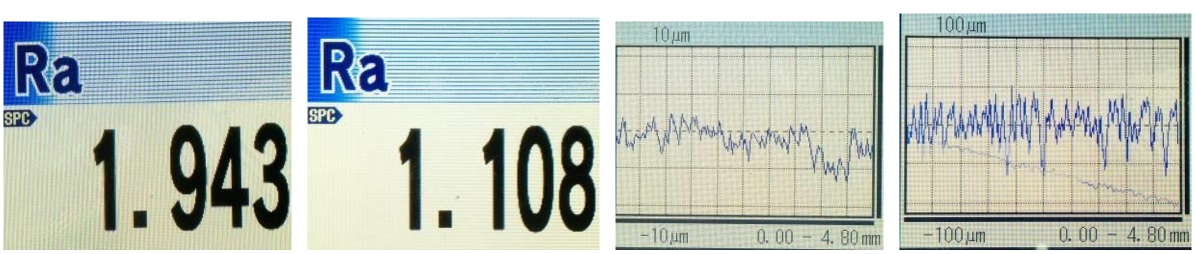


Figure 6.3: Effect of depth of cut on surface roughness

The Figure depicts the results obtained for different experiments. From the graphical comparison for same feed and cutting speed on different materials illustration is made. It can be seen from this figure that with increase of hot air temperature the surface roughness progressively increases for these three types of materials.

It exposes that the preheating effect by hot air gun on different materials gives an excellent surface finish and cutting facility. It can be found on the application of preheating, the surface finish is fabulous compared to the conventional dry machining. Some of the surface roughness measurement values has been framed here which shows us the gradual improvement in surface roughness.

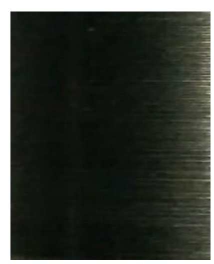


(a) (b)

Figure 6.4: (a) Surface roughness data. (b) Graph of surface roughness

The application of heat was given at two stages. One for smaller hot air flow volume rate while the other is a bit larger rate. It is to mention that the diameter of the nozzle was kept constant. Finally from the above illustration it is very clear that the preheating effect on different materials while turning operation is an effective method for the improvement of surface roughness. Figure shows the images of surface roughness at different conditions.

Table 6.2: Images of surface for different depth of cut for cutting conditions (a, d and g) Dry; (b, e and h) Hot air level 1; (c, f and i) Hot air level 2.

	Dry	Hot Air (Level 1)	Hot Air (Level 2)
Aluminum	(a) 	(b) 	(c) 
Brass	(d) 	(e) 	(f) 
Stainless steel	(g) 	(h) 	(i) 

6.3 Optimization of cutting parameters during hot air streaming turning process of mild steel using PSO

Cutting speed is defined as the speed at which the work moves with respect to the tool (usually measured in feet per minute). Feed rate is defined as the distance the tool travels during one revolution of the part. Depth of cut is the distance that the tool bit moves into the work, usually measured in thousandths of an inch or in millimeters.

Firstly, the values of surface roughness have been plotted against feed and depth of cut. With the lowering of the feed rate the surface roughness value is lower. The lowering value of depth of cut together with low feed rate shows the best surface roughness result.

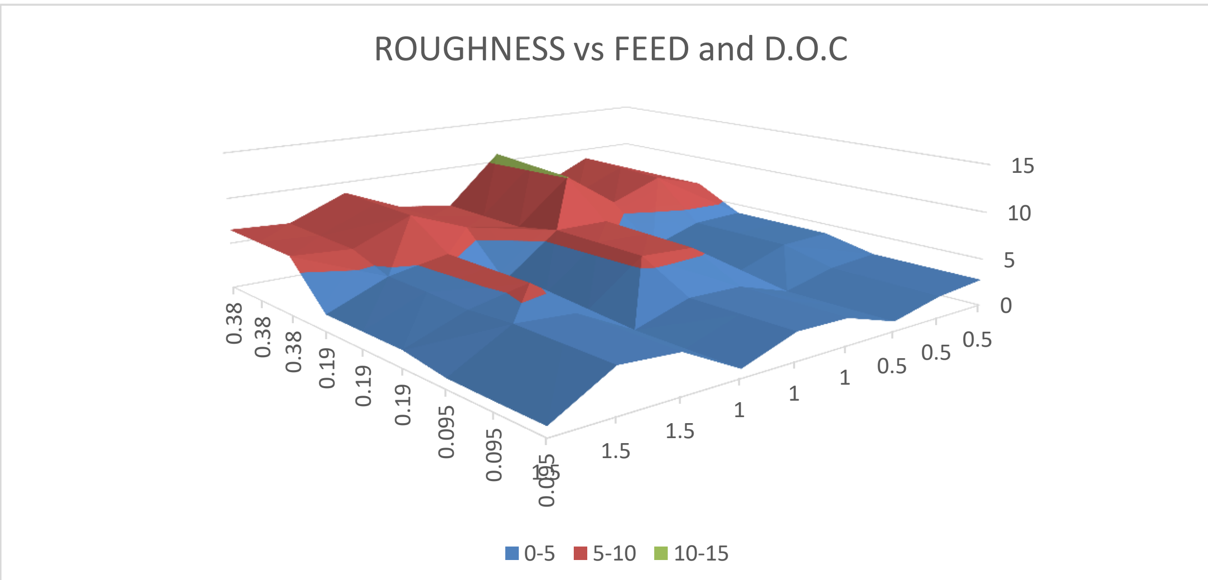


Figure 6.5: Roughness vs Feed & D.O.C

Secondly, the values of surface roughness have been plotted against rpm and depth of cut. With the lowering of the depth of cut the surface roughness value is lower. The lowering value of depth of cut accompanied by high feed rate shows the best surface roughness result.

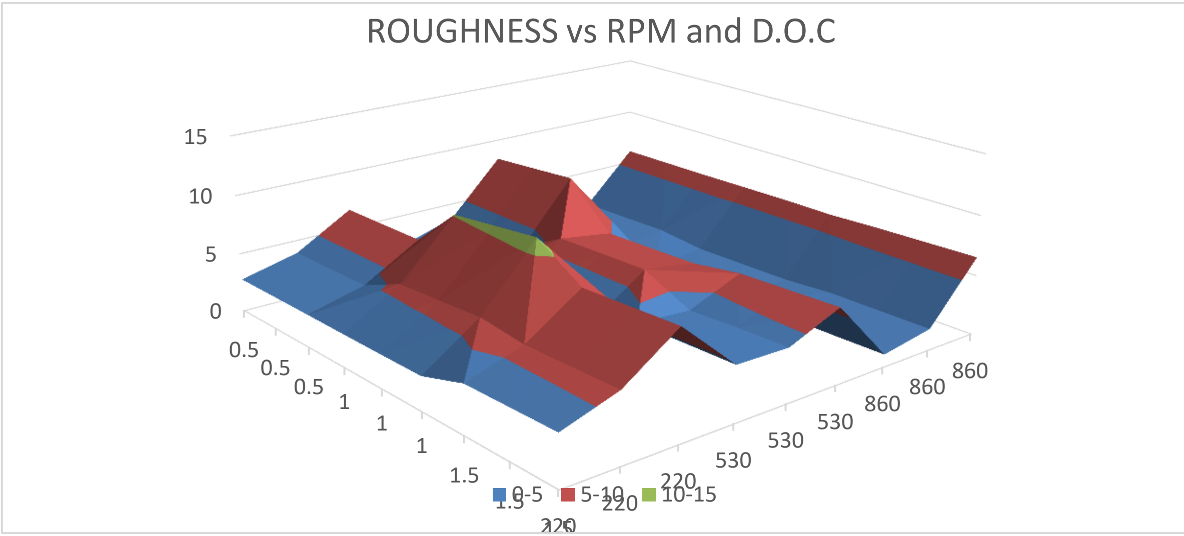


Figure 6.6: Roughness vs RPM & D.O.C

Thirdly, the values of surface roughness have been plotted against rpm and feed rate. With the lowering of the feed rate the surface roughness value is lower. The lowering value of depth of cut together accompanied by high feed rate shows the best surface roughness result.

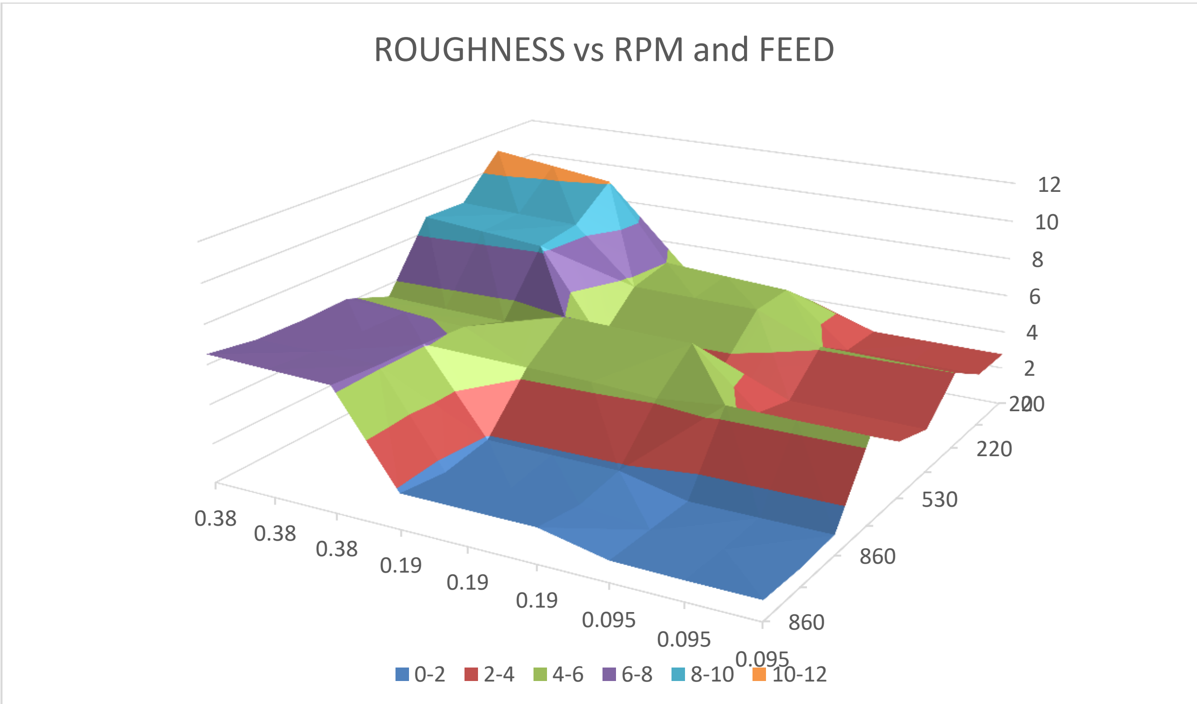


Figure 6.7: Roughness vs RPM& Feed

The aim of this work was to investigate the effects of the cutting parameters on the surface roughness during the hot air streaming turning process of ASTM A36 steel. Experimental results demonstrate that the rpm, depth of cut and feed rate are the main three controllable factors that influence the surface roughness in turning process. Relationship of surface roughness changing is established with cutting parameter changes.

Particle Swarm Optimization method provides a simple, systematic and efficient methodology for the optimization of the cutting parameters.

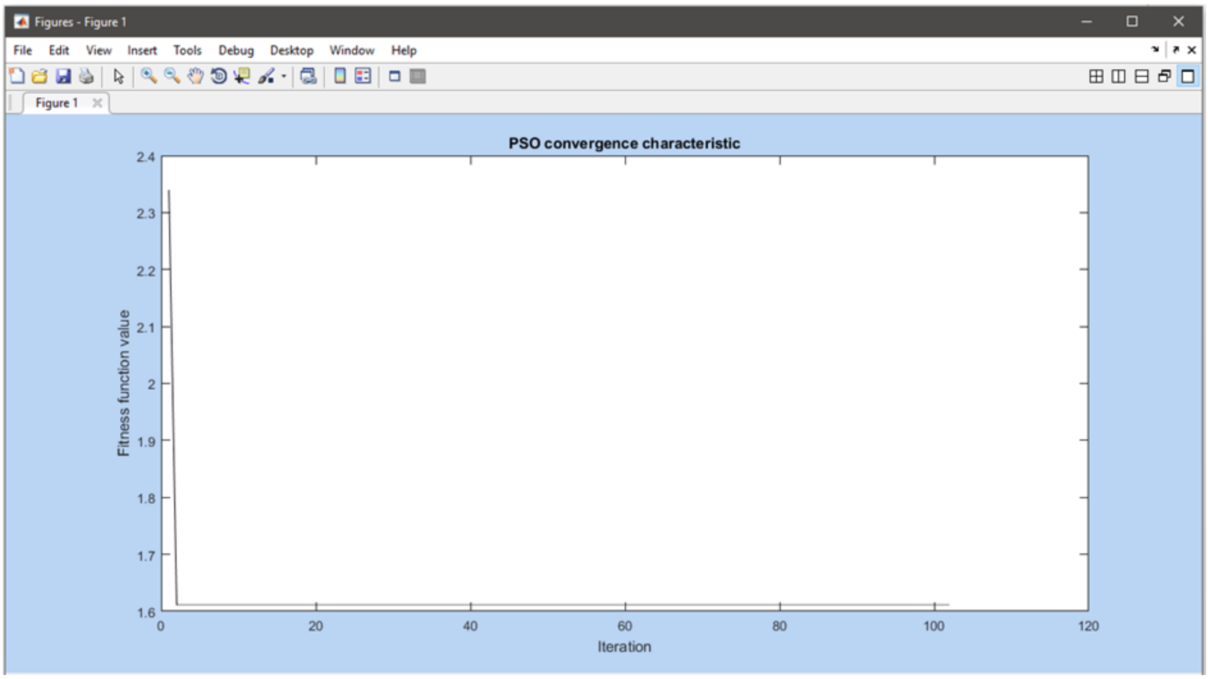


Figure 6.8: PSO convergence characteristic graph

In turning, use of greater rpm (860rev/min), low feed rate (0.095 mm/rev) and low depth of cut (0.5 mm) are recommended to obtain better surface roughness for the specific test range.

```
Command Window
*********************************************************
Final Results-----------------------------

bestfun =

   1.6276e+04


bestrun =

     1


best_variables =

  860.0000    0.5000    0.0950

*********************************************************
Elapsed time is 21.531200 seconds.
fx >>
```

Figure 6.9: Value of the best variables using PSO in MATLAB

Chapter Seven: Conclusion

1. The effect of preheating with the help of hot air stream has an enormous effect in improving the surface roughness during dry turning operation of preheated mild steel. The preheating effect facilitates the material removal rate from the surface of the material very smoothly which results in better surface finish than the conventional surface finish. It was found that a better surface finish has been obtained for a lower depth of cut during preheating keeping other parameter constant. Intensity of preheating also plays an important role in context to surface roughness. the best results has been achieved at depth of cut (0.25 mm/rev) .the surface roughness measurement unveiled fabulous results in comparison to the conventional surface finishing using cutting fluids.
2. Hot air dry turning also improves the surface roughness of Aluminum, Brass and Stainless Steel. Preheating effect expedites material removal rate from the surface of the material with ease breeding better surface finish than the traditional surface finish. The finest results have been achieved when level two hot air was applied where intensity of preheating plays an important role.
3. The optimization research demonstrates how to use Particle Swarm Optimization for optimizing machining performance. The modeling and the optimization of the experimentally obtained data were performed using the regression analysis in the MATLAB. The results of the modeling are in good agreement with the experimentally obtained data. The full development of machining process planning which is based on optimization of the economic criteria in terms of quality is established in this paper.

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APPENDIX

Appendix A

Editor - C:\Users\Minhazul Islam\Desktop\FINAL\objectivefunction.m

objectivefunction.m

```matlab
rpm=[860 860 860 860 860 860 860 860 860
    530 530 530 530 530 530 530 530 530
    220 220 220 220 220 220 220 220 220];
doc=[1.5 1.5 1.5 1 1 1 0.5 0.5 0.5
    1.5 1.5 1.5 1 1 1 0.5 0.5 0.5
    1.5 1.5 1.5 1 1 1 0.5 0.5 0.5 ];
feed=[0.38 0.19 0.095 0.38 0.19 0.095 0.38 0.19 0.095
    0.38 0.19 0.095 0.38 0.19 0.095 0.38 0.19 0.095
    0.38 0.19 0.095 0.38 0.19 0.095 0.38 0.19 0.095];
rpm=rpm';
doc=doc';
feed=feed';
b=[6.42 1.78 1.13 6.16 1.46 1.07 6.10 1.82 1.03
    6.06 4.35 4.47 5.23 5.93 2.91 8.53 3.69 2.31
    8.64 5.55 4.06 10.53 5.78 2.79 6.64 3.94 2.77];
b=b';
a=[rpm doc feed rpm.*rpm doc.*doc feed.*feed rpm.*doc rpm.*feed doc.*feed];
x=(pinv(a'*a)*a'*b);
```

Appendix B

Codes in MATLAB for Particle Swarm Optimization.

```
tic
clc
clear all
close all
rng default
LB=[220 0.5 0.095]; %lower bounds of variables
UB=[860 1.50 0.38]; %upper bounds of variables

% pso parameters values
m=3; % number of variables
n=100; % population size
wmax=0.9; % inertia weight
wmin=0.4; % inertia weight
c1=2; % acceleration factor
c2=2; % acceleration factor

% pso main program----------------------------------------start
maxite=1000; % set maximum number of iteration
maxrun=10; % set maximum number of runs need to be
for run=1:maxrun
    run
```

```
% pso initialization-------------------------------start
   for i=1:n
      for j=1:m
         x0(i,j)=LB(j)+rand()*(UB(j)-LB(j));
      end
   end
   x=x0; % initial population
   v=0.1*x0; % initial velocity
   for i=1:n
      f0(i,1)=ofun(x0(i,:));
   end
   [fmin0,index0]=min(f0);
   pbest=x0; % initial pbest
   gbest=x0(index0,:); % initial gbest
   % pso initialization---------------------------------end

   % pso algorithm-----------------------------------start
   ite=1;
   tolerance=1;
   while ite<=maxite && tolerance>10^-12
     w=wmax-(wmax-wmin)*ite/maxite; % update inertial weight

    % pso velocity updates
      for i=1:n
```

```
        for j=1:m
          v(i,j)=w*v(i,j)+c1*rand()*(pbest(i,j)-x(i,j))...
              +c2*rand()*(gbest(1,j)-x(i,j));

        end
    end

  % pso position update
    for i=1:n
        for j=1:m
            x(i,j)=x(i,j)+v(i,j);
        end
    end

% handling boundary violations
    for i=1:n
        for j=1:m
            if x(i,j)<LB(j)
                x(i,j)=LB(j);
            elseif x(i,j)>UB(j)
                x(i,j)=UB(j);
            end
        end
    end
```

```
% evaluating fitness
for i=1:n
    f(i,1)=ofun(x(i,:));
end

% updating pbest and fitness
for i=1:n
    if f(i,1)<f0(i,1)
        pbest(i,:)=x(i,:);
        f0(i,1)=f(i,1);
    end
end
[fmin,index]=min(f0); % finding out the best particle
ffmin(ite,run)=fmin; % storing best fitness
ffite(run)=ite; % storing iteration count

% updating gbest and best fitness
if fmin<fmin0
    gbest=pbest(index,:);
    fmin0=fmin;
end

% calculating tolerance
if ite>100;
    tolerance=abs(ffmin(ite-100,run)-fmin0);
```

```
        end

    % displaying iterative results
        if ite==1
            disp(sprintf('Iteration Best particle Objective fun'));
        end
        disp(sprintf('%8g %8g %8.4f',ite,index,fmin0));
        ite=ite+1;
    end

     % pso algorithm-----------------------------------end

gbest;
fvalue=0.001612195541580*x(1) +  3.246190563121023*x(2) + 15.681457466329853*x(3) -
0.000003905540132*(x(1)^2)-0.431038981855913*(x(2)^2) +  6.843559005992312*(x(3)^2) -
0.001977445127058*x(1)*x(2) + 0.001583570246527*x(1)*x(3) -
3.451819514957795*x(2)*x(3);
   fff(run)=fvalue;
    rgbest(run,:)=gbest;
    disp(sprintf('--------------------------------------'));
end

% pso main program------------------------------------end
disp(sprintf('\n'));
```

```
disp(sprintf('************************************************************'));

disp(sprintf('Final Results----------------------------'));

[bestfun,bestrun]=min(fff)

best_variables=rgbest(bestrun,:)

 disp(sprintf('%.8lf %.8lf %.8lf\n',best_variables(1),best_variables(2),best_variables(3)))

disp(sprintf('***************************************'));
toc

 % PSO convergence characteristic
plot(ffmin(1:ffite(bestrun),bestrun),'-k');
xlabel('Iteration');
ylabel('Fitness function value');
title('PSO convergence characteristic')
```