MEASUREMENT OF CHIP-TOOL INTERFACE TEMPERATURE FOR ORTHOGONAL CUTTING

DISSERTATION

Submitted in partial fulfillment of the requirement

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PRODUCTION ENGINEERING

Submitted By

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DECLARATION

I, **Surabhi Lata**, hereby declare that the project work, which is being presented in this dissertation entitled "**Measurement of Chip-Tool Interface Temperature for Orthogonal Cutting"** in the partial fulfillment for the award of degree of Master of Engineering in Production Engineering, is an authentic work carried out by me at Delhi Technological University under the guidance of **Dr (Prof.) Reeta Wattal** of Mechanical, Production & Industrial and Automobile Engineering Department.

I have not submitted the work in this dissertation for the award of any other degree or diploma.

Surabhi Lata

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CERTIFICATE

This is to certify that the report entitled "**Measurement of Chip-Tool Interface Temperature for Orthogonal Cutting"** submitted by **Surabhi Lata (Roll No. - 2K11/PIE/26)** in partial fulfillment for the award of Masters of Technology in Production engineering from Delhi Technological University, is a record of bonafide project work carried out by her under my supervision and guidance.

To the best of my knowledge the result contained in this thesis have not been submitted in part or full to any other university for the award of any other degree or diploma.

Dr (Prof.) Reeta Wattal

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ABSTRACT

Cutting is one of the most important and common manufacturing processes in industry. Machining process is not an easy process to investigate and to model due to the inherent difficulty to know exactly what happens in the region around the tool tip. In metal cutting operations, the importance of knowledge on the temperature distribution in cutting tool is well recognized due to its controlled influence on tool life as well as on the quality of the machined part. The effect of process parameters such as cutting speed, feed rate, depth of cut etc in the metal cutting process is determined by correlating the process parameters with the tool temperature, tool life, wear rate, production cost etc.

The main objective of this experiment was to determine the chip-tool interface temperature in orthogonal turning process depending on cutting parameters i.e. cutting speed and depth of cut for different tool and work material combinations using the tool-work thermocouple method. The design matrix was prepared on the basis of two factors, two levels, full factorial design to identify the limits of process parameters. Response surface methodology and regression analysis was used to develop the mathematical model correlating the process parameters with the response variable (chip-tool interface temperature). The calculations were carried out using the software package Minitab 16. The models once developed were checked for adequacy using the ANOVA technique. The significant terms were selected using the p test from the adequate models. Following this the final model was proposed and the main and interaction effects of the process variables on the response variable were plotted and interpreted from the developed graphs. The developed model was used for prediction of response variable by selecting the appropriate process parameter values.

The function of the optimization model was to minimize the chip tool interface temperature in orthogonal cutting process using an optimization technique. Genetic algorithm technique was used for modeling the cutting process. Predictive equations previously formulated by RSM method were used in the development of GA architecture for the determination of the temperature for a given set of inputs in the metal cutting problem. A comparative analysis of the performance of RSM model and GA model was done.

It was concluded that when the cutting speed and the depth of cut were increased the chip-tool interface temperature increased and also observed that the cutting speed has a significant effect on the chip-tool interface temperature in comparison to the effect of depth of cut. These conclusions were verified by the correlation coefficients. The results obtained from the simulation model presented a fast and suitable solution for automatic selection of the machining parameters. The results are further analyzed with the literature available.

This experimental work includes discussion on the important input parameters, their effects, conclusions and the several considerations for future work.

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Nomenclature

V	Cutting Speed (m/min)
D	Depth of Cut (mm)
T	Chip-tool Interface Temperature (°C)
PCD	Poly Crystalline Diamond
HSS	High Speed Steel
EMF	Electromotive Force (mV)
RA	Regression Analysis
RSM	Response Surface Methodology
ANOVA	ANalysis Of Variance
GA	Genetic Algorithm
SQP	Sequential Quadratic Programming
ANN	Artificial Neural Network

Chapter 1

INTRODUCTION

1.1 MANUFACTURING: AN INTRODUCTION

Manufacturing is the production of work pieces having defined geometric shapes. It is the economic term for making goods and services available to satisfy the human needs. It converts the raw materials (from nature or industry) to finished products to be used for some purpose. The development of the finished product from raw material undergoes a number of processes such as selecting a material, reviewing the basic design model, selecting the parameters, type of operations to be performed, economics involved, quality testing and inspection, assembling, final testing etc.

The manufacturing processes are the methods which are required to produce parts and then to assemble them to develop a finished product. These processes are mainly categorized as:

a. Primary Shaping Processes
b. Forming or Metal Working Processes
c. Machining (Metal removal) Processes
d. Joining and Assembly processes
e. Surface Finishing Processes

1.2 METAL CUTTING

The process of metal removal is a process in which a wedge-shaped tool engages a workpiece to remove a layer of material in the form of a chip. It is the process of working with metals to develop individual parts, assemblies or large scale structures. It involves a wide range of work from large ships and bridges to precise and intricate engine parts and jewellery.

After the selection and refinement of the basic metals, they are given suitable shapes by primary processes for metal machining. Final product is obtained by machining the metals to the pre-designed dimensions.

The simplest model to understand the mechanics of metal cutting is the orthogonal cutting process while the simplest form of cutting tool is the single point cutting tool. The geometry of the cutting tool decides the efficiency of operation and surface appearance. Therefore, the selection of cutting tool depends on various parameters related to work material and machine tool.

1.2.1 ORTHOGONAL CUTTING PROCESS

This process is the idealized process which is based upon assumptions. In this process, the cutting tool is perpendicular to the direction of the cut and it is assumed that there is no lateral flow of material and no chip curvature exists. All the parts of the chip have the same velocity. Here the tool is assumed to be stationary while the work piece is moving. For analysis consider the following Figure 1.1 [1].

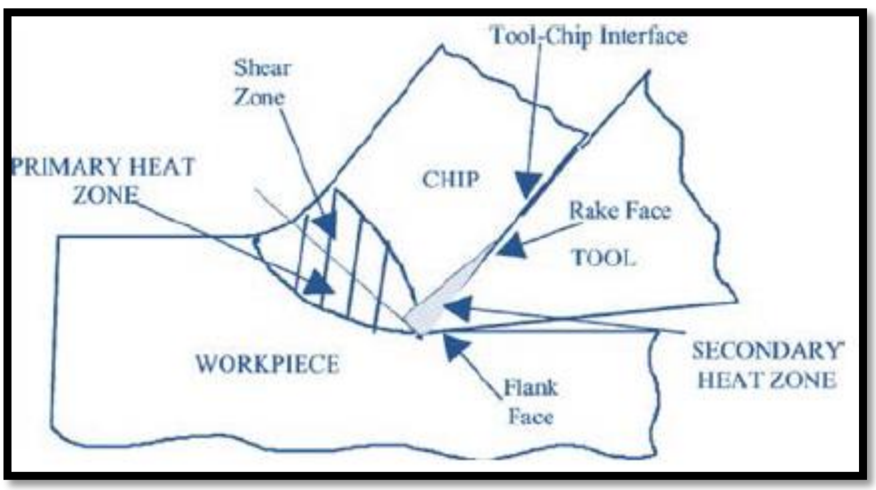


Figure 1.1 Orthogonal Cutting Tool Model with Heat Generation Zones [1]

It is assumed that the chip is severed from the work piece by the action of shear force across the plane. Since the chip so developed is in compression against the face of the tool, a frictional force is also developed. Therefore the work of chip making process must overcome both the shearing force and the frictional force.

This cutting process involves large plastic deformation of the work piece material which increases the cutting zone temperature. High temperature at the cutting zone contributes to the thermal deformation of the cutting tool. Figure 1.1 shows the three heat generation zones related to the plastic deformation around the tool-chip contact area. These zones are Primary deformation zone, Secondary deformation zone and Tertiary deformation zone (tool-work interface) [2]. The primary deformation zone represents 80-85% of total heat generation, secondary deformation zone represents 10-15% of total heat generation and the tertiary deformation zone represents 1-3% of total heat generation.

1.2.2 TURNING PROCESS

The turning process is the process for producing a cylindrical surface with a single point cutting tool on the lathe machine tool. The workpiece is held in the chuck and is rotated on the spindle while the cutting tool is fed into it radially, axially or both. The variables used for this process are cutting speed, feed rate and the depth of cut. As the depth of cut is usually five times the feed rate, the chip is produced in plane strain and hence the width of the chip is equal to the undeformed chip width.

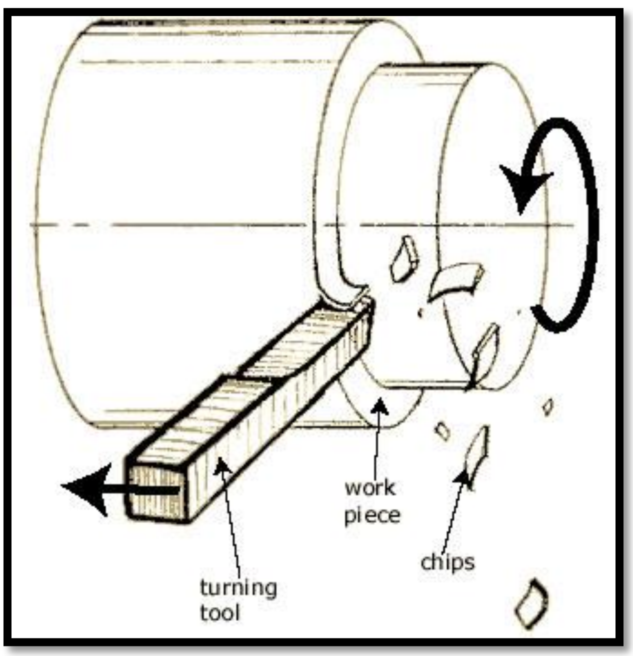


Figure 1.2 Turning process on a lathe machine tool [2]

Materials appropriate for the turning process are usually soft metals. The cutting tool material should always be harder than the material being turned.

Chapter 2

LITERATURE REVIEW AND PROBLEM FORMULATION

2.1 REVIEW OF LITERATURE

Research in metal cutting was started with Cocquilhat in 1851 which measured the work required to remove a given volume of material in drilling. The attempt made by Time led to the explanation of formation of chips in 1870 and further research was made by Tresca in 1873. Later in 1881, Mallock suggested that the cutting process was the shearing of workpiece to form the chip and emphasized the importance of the effect of friction occurring on the cutting tool face as the chip was removed. Further, Taylor investigated the effect of tool material and cutting conditions on tool life during rough operations. Latest fundamental work has been carried out by Ernst and Merchant in 1941 dealing with the mechanics of metal cutting process.

Large number of literature is available on the determination of chip-tool interface temperature, factors affecting the interface temperature and techniques of optimization of machining parameters including cutting speed, feed rate, cutting zone temperature, etc.

D.O' Sullivan et al [1] determined the temperature in a single point turning process. The total work done by a cutting tool in removing metal can be determined from the force components on the cutting tool. Approximately, all of this work or energy is converted into heat which is dissipated into the chip, tool and workpiece material. The wear of the tool is related to the cutting forces. Initial experiments conducted involved the simultaneous measurement of forces and temperatures. These experiments focused on the use of embedded thermocouple (in the work piece) and using the infrared thermal camera to monitor the process.

N.A. Abukhshim et al [3] reviewed the previous research work. Research on heat generation and heat dissipation in the orthogonal machining process is critically studied. In addition, temperature measurement techniques applied in metal cutting are also reviewed. The emphasis is on the comparability of test results obtained by a thermal imaging camera in high speed cutting of high strength alloys. Finally, latest work on these topics in metal machining is also reviewed. The paper then proposes some modeling requirement for computer simulation of high speed machining process.

Ismail Lazoglu et al [4] predicted the tool chip temperature in continuous and interrupted machining. In this a numerical model based on the finite difference method is presented to predict tool and chip temperature fields in continuous and interrupted machining and time varying milling processes. Continuous or steady state machining operations like orthogonal cutting are studied by modeling the heat transfer between the tool and chip at the tool-rake face contact zone. The shear energy created in the primary zone, the friction energy produced at the face-chip contact zone and the heat balance between the moving chip and stationary tool is considered. The temperature distribution is solved using the finite difference method.

G. Sutter et al [5] presented an experimented setup for the measurement of temperature field in high speed machining. This paper presents an experimental setup during an orthogonal machining operation with 42 CrMo 4 steel. The technique of temperature measurement was developed on the principle of pyrometer in the visible spectral range by using an intensified CCD camera with very short exposure time and interference filter at 0.8 micrometer. Temperature gradients were obtained in an area close to the cutting edge of the tool, along the secondary shear zone. It was established that this experimental arrangement is quite efficient and can provide fundamental data on the temperature field in material during orthogonal high speed machining.

Yahya Dogu et al [6] designed a numerical model to determine temperature distribution in orthogonal metal cutting. In this study, a thermal analysis model is developed to determine temperature distribution in orthogonal in metal cutting using finite element methods. The model calculates the temperature distribution as a function of heat function of heat generation. The heat generation was introduced in the primary deformation zone, the secondary deformation zone and along the sliding frictional zone at the tool-chip interface as well. The temperature dependency of material properties was included in the model. A series of thermal simulation have been performed and the value and location of maximum temperature have been determined for various cutting condition. The comparison of the simulation with simulation with earlier work gave promising trend for the presented model.

Haci Saglam et al [7] studied the effect of tool geometry and cutting speed on main cutting force and tool tip temperature. In this paper, the effects of rake angle and entering angle in tool geometry and cutting speed on cutting force components and the temperature generated on the tool tip in turning was investigated. The data used for the investigation derived from experiments conducted on a CNC lathe according to the full factorial design to observe the effects of each factor level on the process performance. During the tests, the depth of cut and feed rate were kept constant and each test was conducted with a sharp uncoated tool insert. Finally, it was found that rake angle was effective on all the cutting force components, while cutting speed was effective on the tool tip temperature. The cutting force signal and temperature values provided extensive data to analyze the orthogonal cutting process.

Takashi Ueda et al [8] determined the temperature of a signal crystal diamond tool in turning. The temperature on the rake face of a single crystal diamond tool in precision turning is investigated experimentally and theoretically. The infrared rays radiated from the contact area between chip and the rake face, and transmitted through the diamond tool, are accepted by a chalcogenide fiber and led to a two color detector which consists of InSb and Hg Cd Te detector. The temperature distribution in the tool and in the work piece is calculated numerically using FEM. The temperature increase with the increase of cutting speed for the range of cutting speeds investigated.

Tanikic et al [9] studied the metal cutting process' parameters modeling (cutting temperature, cutting force and quality of machined surface) using artificial neural network and hybrid, adaptive neuro fuzzy systems. The main aim of this experiment is to conduct the qualitative analysis of metal cutting process, identify and resolve the frequently occurring problems and improve the productivity by reducing the manufacturing costs. The temperature at the chip tool interface was measured and monitored by the infrared camera while an appropriate tool was utilized for measuring the height of roughness of machined surface. Later, artificial neural network and neuro fuzzy system were used to model the measured data. After all the data measurement and its analysis, they concluded that there exists a possibility of implementation of artificial intelligence based systems in metal cutting process. Finally, global system for predicting the state of cutting tool was proposed (with sub-systems for cutting temperature, cutting force and arithmetic mean deviation prediction).

Fata [10] proposed the method of embedded thermocouple for temperature measurement along with infrared pyrometer. The experiments are conducted for dry and orthogonal machining condition with simultaneous measurement of temperature by embedded thermocouple and infrared pyrometer. With the help of these experiments a relation was established between tool temperature and cutting parameters such as cutting speed, feed rate and depth of cut. The results so obtained showed that if cutting speed, feed rate and depth of cut are increased then the tool temperature also increases which reduces the life of the cutting tool. These investigations revealed that the most effective cutting parameter in tool temperature rise is the cutting speed, especially at high range of cutting conditions. It also showed an increase in feed rate and depth of cut will lead to an almost straight line with low slope on the graph of tool temperature when plotted against them.

A. Jameel [11] et al focused their study on the temperature generated at two heat zones namely primary heat zone (shear zone) and secondary heat zone (tool chip interface zone). They proposed two new objective functions for optimizing the cutting temperature problems and this system used particle swarm optimization (PSO) methodology to determine the optimal temperature. The experiments showed that major amount of energy is converted into heat in the shear zone while the heat generated at the tool chip interface zone is due to the rubbing action at that interface. It was concluded that heat distribution pattern is dependent on the size and thermal conductivity of the tool-work material and the cutting conditions. Specifically the results were obtained for mild steel work and carbide insert cutting tool in dry turning operation. The study showed that main cutting force, feed rate and depth of cut greatly influence the shear zone temperature while chip thickness and friction force have low effect. Also the chip tool interface temperature increased with increase in feed rate and main cutting force while it decreased with increase in the depth of cut. Therefore, the study concluded that feed rate has a huge effect on shear zone and chip tool interface zone temperature as compared to other parameters.

A. Jabri et al [12] presented a multi-optimization technique based on genetic algorithm methodology to search optimal cutting parameters such as cutting speed, feed rate and depth of cut of multi-pass turning processes. This paper presents the optimization of two objective functions i.e. cutting cost and used tool life time simultaneously. Multi-pass turning processes are divided into multi-pass rough machining and finish machining. In order to minimize two parameters i.e. cutting cost and used tool life time six machining parameters are considered which includes three parameters for rough machining and three for finish machining. Further a genetic algorithm model is prepared which is utilized for optimization and the results are presented in Pareto frontier graphic. Therefore it was concluded that the genetic algorithm technique of optimization allowed the multi objective optimization of objective functions by selecting optimal cutting parameters.

P. P. Shirpurkar et al [13] attempted to review the literature on optimization of machining parameters in turning processes by using different tool inserts. During this review different conventional techniques employed for optimization of parameters are also studied. These techniques include geometric programming, geometric plus linear programming, non-linear programming, goal programming, sequential unconstrained minimization technique and dynamic programming. Later the latest optimization techniques are also discussed, specifically genetic algorithm, fuzzy logic, ant colony technique, Taguchi technique and response surface methodology. These techniques are successfully applied in the industrial applications for optimal selection of process control variables. The paper concluded that Taguchi approach has the potential for savings in experimental time and cost on product or process, development and quality improvement and therefore is widely used in industries.

A. H. Suhail et al [14] optimized the cutting parameters using two performance measures, work piece surface temperature and surface roughness. Optimal cutting parameters were obtained by using Taguchi techniques. In order to study the performance characteristics in turning operation the orthogonal array, signal to noise ratio and analysis of variance was used. The experimental results showed that workpiece surface was efficiently sensed and can be effectively utilized as an indicator to control cutting performance and improve the optimization process. Therefore it can be concluded that in the automated manufacturing environment there exist a possibility of increase in machine utilization and decrease in production cost.

G. Mohankumar et al [15] conducted experiments in order to determine the machining parameters for continuous profile machining taking in account the factor of minimum production time. The final profile of the cylindrical bar was done in two stages, rough machining and finish machining and number of passes for rough machining was also decided. The factors to which the optimal machining parameters were subjected were practical constraints, cutting force, power, surface finish and dimensional accuracy. The problem was formulated for using genetic algorithm and particle swarm optimization techniques in order to optimize the objective function. The results so obtained were compared and the conclusion drawn was particle swarm optimization method gave better results. Therefore using this technique can further minimize the machining time for the given set of machining parameters.

F Cus et al [16] proposed an optimization technique based on genetic algorithm for determining the parameters in machining operations. The methodology presented is for continual improvement in the cutting conditions with GA. It modifies the recommended cutting conditions received from machining data, analyzing them with neural networks and substituting the better cutting conditions with the previously existing ones. The proposed model shows that GA based procedure for solving optimization problem is effective and efficient and can be easily integrated with any intelligent manufacturing system to reduce the production cost, production time and improve the product quality. The results so obtained are comparable with the results of simulated annealing, fuzzy approach and linear programming approach.

P. E. Amiolemhen et al [17] proposed genetic algorithm based optimization technique for determining the cutting parameters in multi-pass machining operations which included multi-pass roughing and single-pass finishing operation. The cylindrical bar stock is converted into a continuous finished profile involving seven machining operations, each subjected to practical constraints. In order to assess the result for each machining operation a non-linear, constraint cutting model is developed which is based on genetic algorithm. Therefore it was concluded that the proposed model proved efficient and effective in optimizing the machining parameters and can be extended to other operations such as external and internal threading.

R. Q. Sardinas et al [18] presented a multi-objective optimization technique based on genetic algorithm in order to optimize the cutting parameters in turning process. The objectives of tool life and operation time are formulated to optimize them using the proposed model of microGA. The results are built on the Pareto front graph and are analyzed for several different production conditions. The aspects like diversity maintenance and constraint handling have been successfully sorted for the formulated cutting problem. Therefore it can be concluded that Pareto front information help in decision making process. This paper also lists the advantages of multi-objective optimization approach over the single-objective optimization.

D. M. D. Addona et al [19] developed an optimization paradigm based on genetic algorithm for determining the cutting parameters in machining operations. Considering the technological and material constraints proposed model has to yield minimum production time. The proposed model has the advantage to perform multi-objective optimization while considering the constraints. The formulated objective is optimized using the two point crossover and then mutation operations. A two point crossover with high crossover probability helps in diversity preservation and hence a better optimal result is obtained. The experimental results obtained from simulation model are comparable with other techniques and this model can be integrated with other intelligence techniques in order to solve many complex problems.

D Petkovic et al [20] discussed the optimization problem of machining using genetic algorithm methodology. The experiments were performed to determine the optimal cutting parameters specifically cutting speed and feed rate. The GA model was formulated in order to minimize cost of the turning process. The constraints which were utilized in the proposed model were non-linear constraints. The results obtained by GA model were checked by the sequential quadratic programming algorithm. The comparison of the results showed the same values of machining cost, cutting speed and feed rate but concluded that GA method is better than SQP in terms of execution time and number of iterations. Therefore they conclude that GA method successfully optimize the results based on different cutting parameters.

L. B. Abhang et al [21] experimentally measured the tool-chip interface temperature using the tool-work thermocouple technique. Using the response surface methodology mathematical models of first and second order were developed in terms of machining parameters. The results so obtained were analyzed statistically and graphically. The first order model explains the main effect of the cutting parameters while the quadratic model shows the variation of chip-tool interface temperature with major interaction effect between cutting parameters. The empirical relation formulated agrees well in velocity with Shaw's non-dimensional model. Also this model produce smaller errors and has satisfactory results as the multiple regression coefficient is approximately 0.99. Therefore, it was concluded that increase in cutting speed, feed rate and depth of cut increases the cutting temperature while an increase in tool nose radius reduces the tool-chip interface temperature. The tool-work thermocouple technique proved to be the best method for measuring the average chip-tool interface temperature during metal cutting.

K. Kadirgama et al [22] determined the temperature distribution on cutting tool during machining operation. First order temperature model was developed using response surface methodology in order to minimize the number of experiments. This methodology helped in formulation of relationship between the variables (cutting speed, feed rate and depth of cut) and the response (temperature). Later the result was verified by the finite element analysis which showed clear relation between the cutting variables and the response. The predicted values of temperature were quite close to the experimental results. It was observed that the tool temperature was significantly affected by the feed rate factor. Therefore conclusion drawn from the measured results was that an increase in the cutting parameters increases the cutting temperature.

S. R. Das et al [23] presented an optimization method of cutting parameters (cutting speed, feed rate and depth of cut) to achieve minimum tool wear and low workpiece surface temperature. The experimental model was designed based on Taguchi's orthogonal array technique and analysis of variance (ANOVA) was used to identify the effect of cutting parameters on the response variables. The result obtained showed that depth of cut and cutting speed are the most influencing parameter on the response variables. Later on, optimal ranges of tool wear and workpiece surface temperature was predicted. Multiple regression analysis was utilized to develop the relationship between factors and performance measures. The results concluded that Taguchi parameter design is an effective way of determining the optimal cutting parameter for achieving low tool wear and low workpiece surface temperature.

H. M. Mohammad [24] proposed an empirical model to increase the cutting tool life and improve the workpiece surface quality by predicting workpiece surface roughness and cutting tool temperature. Empirical equations were formulated using the experimental results of the turning process. The results indicated that cutting speed and feed rate has a major effect on workpiece surface roughness and cutting tool temperature. Letar the results were compared which showed an agreeable correlation. It was concluded that increasing cutting speed and feed rate improves the surface roughness while depth of cut did not show any considerable effect on the response factors. Hence these facors can be utilized as an indicator for the cutting performance.

Kovac et al [25] reviewed the experimental techniques for the measurement of temperature generated in the material removal processes. Various factors are studied which are affected by the temperature generated in the material removal processes such as tool wear, tool life duration, quality of surface finish, chip segmentation and lubrication choice. The techniques which are developed to quantify the temperature are discussed taking into account the thermal aspect which becomes significant at high cutting speeds. The study concluded that techniques to be used for measurement of temperature depends on the material used, cutting parameters used etc. The optical and infrared radiation pyrometers require elaborate instrumentation and require special environment while some techniques give average values such as tool-work thermocouple technique. Methods which provide fast response such as tribo-induced thermo-luminescence were also reviewed.

N. Lungu et al [26] studied the effect of cutting speed and feed rate on tool geometry, temperature and cutting forces using finite element method simulation. FEM was used as it provides information on deformations, stresses and temperatures that occur during the machining process. It also explains the chip shape and tool wear rate. For the research purpose six trial runs of simulation were conducted. The machining parameters (cutting speed and feed rate) were variable while tool geometrical parameters were kept constant. Further FEM simulation was performed which resulted in the conclusion that increasing the cutting speed increases the temperature but decreases the cutting force. The Deform 2D software provided a good prediction of tool displacement, temperature, cutting forces, strains and stresses. The conclusion was drawn by comparing results obtained by FEM and experimental tests and further optimization was done using statistical methods.

A.Belloufi et al [27] used a new hybrid genetic algorithm-sequential quadratic programming for the resolution of the cutting conditions of the multi-pass turning process. Using this method the production cost was minimized under a set of machining constraints. They considered six decision variables i.e. cutting speed for rough and finish machining, feed rates for rough and finish machining and depth of cut for rough and finish machining. Depending on these variables the unit production cost was minimized and the optimized results were obtained and compared with the results of genetic algorithms, simulated annealing, particle swarm intelligence, scatter search, ant colony approaches. The hybrid GA-SQP obtained near optimal solution; therefore it can be used for machining parameter selection of complex machined parts that require many machining constraints. Further, it can be extended to solve the other metal cutting optimization problems such as milling, drilling etc.

A.Aryahnfar et al [28] studied the cutting operations which consist of two stages namely roughing and finishing. In the finishing stage, machining parameters including cutting speed, feed rate and depth of cut were determined. In roughing stage, in addition to these parameters, the number of rough cut passes was also decided. They proposed a non-linear constrained mathematical programming model for determination of the aforementioned parameters. An optimization technique based on genetic algorithms (GA) was proposed to simultaneously optimize the multi-pass roughing and single-pass finishing parameters. The objective function was formulated to minimize unit production cost and further result was compared with other traditional and non-traditional techniques. Further, the proposed technique can be modified to multi-objective constrained optimization problems in turning and also other machining problems, such as milling and grinding operations.

A K Sahoo et al [29] presented an experimental investigation on cutting temperature during hard turning of EN 24 steel (50 HRC) using TiN coated carbide insert under dry environment. The prediction model was developed using response surface methodology and optimization of process parameter was performed by desirability approach. A stiff rise in cutting temperature was noticed when feed and cutting speed were elevated. The experimental and predicted values were found very close to each other. The optimal combination for process parameter was depth of cut at 0.2mm, feed of 0.1597 mm/rev and cutting speed of 70m/min. Based on these combination, the value of cutting temperature was found to be 302.950 °C whose desirability is one. It was concluded that the cutting temperature value increases with increase of cutting speed, feed and depth of cut. ANOVA of second order model was found to be significant as its p-value is less than 0.05.

D Tanikic et al [30] studied the heat generation in the cutting zone which occurs as a result of the work done in metal cutting process, which is consumed in plastic deformation of the cutting layer and overcoming of friction, that occurs on the contact area of the cutting tool (i.e. cutting insert) and work material (i.e. workpiece). In order to model the temperature they carried out large number of experiments at different cutting conditions, synchronously measuring the chip's top temperature using the infrared camera. The infrared method gives a relatively good indication of the measured temperature, comparing with other methods for temperature measurement, such as: thermocouples, radiation methods, metallographic methods etc. Results obtained in the first phase were used for modelling of the cutting temperature using the response surface methodology model (RSM model), feed forward artificial neural networks (ANN model), radial basis function network (RBFN model), generalized regression neural network (GRNN model) and adaptive neuro-fuzzy system (NF model). The accuracy of the proposed models was presented, as well as their suitability for use in concrete problems. The primary goal of this work as the examination of the possibility of using various models (most of them based on artificial intelligence) in metal cutting temperature modeling which was successfully achieved. The maximum chip's top temperature was adopted as relevant factor.

N. Z. Basha et al [31] investigated the effect of process parameter in turning operation to predict the surface roughness. Aluminium 6061 was used as the workpiece as it is found in many manufacturing industries such as aircraft and aerospace components, marine fittings, transport, bicycle frames, camera lenses, drive, shafts, electrical fittings and connectors, brake components, valves, couplings. This paper presented the effect of process parameter by considering the Spindle speed, Feed rate and Depth of cut as the decision variables while the main objective was to predict the surface roughness. A second order mathematical model was developed using regression technique of Box-

Behnken of Response Surface Methodology (RSM) in design expert software 8.0 and optimization was carried out by using genetic algorithm in matlab8.0. This investigation found that optimal solution of the cutting conditions achieved was on spindle speed (rpm)= 1999.999, feed rate (mm/min)= 0.041 and depth of cut (mm)=0.6 for giving the minimum value of surface roughness(μm)=0.611 using genetic algorithm. The confirmatory test was conducted and found that the percentage of error within 0.32%.

G. Ceau et al [32] investigated on the temperature at the edge of the tool, during turning of unalloyed steel, depending on the parameters of the cutting process with conventional values. For the determination of the temperature values of the cutting edge an experimental setup with natural and artificial thermo-couples, infrared camera and optical pyrometer was used. To analyze the influence of the variation of the cutting parameters on the temperature of the cutting edge an analytical relation, determined through the method of symmetrical measurement plans and through mathematical regression was used. The temperature was measured using an experimental setup with natural thermocouple while the data acquisition was accomplished by using the LabVIEW instrumentation. The temperatures, as well as the temperature profiles were obtained through analytical calculus using the MATLAB program and the mathematic regression method. The successful check of the determined model for other cutting conditions showed the validity of the applied theory. The results have emphasized the major influence of the cutting speed. It was concluded that the temperature of the cutting edge can reach high values even for conventional cutting conditions or for the lower limit of the HSC.

M. Bagheri et al [33] determined the tool-chip interface temperature in cutting of ST37 steel workpiece by applying HSS as the cutting tool in dry turning. Two different approaches were implemented for temperature measuring: an embedded thermocouple (RTD) in to the cutting tool and infrared (IR) camera. Comparisons were made and studied between experimental data and results of MSC.SuperForm and FLUENT software. An investigation of heat generation in cutting tool was performed by varying cutting parameters at the stable cutting tool geometry and results were recorded after which graphs were plotted between tool temperature and various cutting parameters. The experimental results reveal that the main factors of the increasing cutting temperature are cutting speed, feed rate and depth of cut, respectively. It was also determined that simultaneously change in cutting speed and feed rate has the maximum effect on increasing cutting temperature. It was concluded that by increasing the cutting speed, tool temperature intensely rises and also temperature will increase by increasing the depth of cut; nevertheless, its impact is less than two other parameters as cutting speed and feed rate.

M B Silva et al [34] reviewed the analytical and experimental methods used to measure cutting temperature. Some experimental results were also used presenting the different methods of measurement. Several attempts which have been made to predict the temperatures involved in the process as a function of many parameters, as well as many experimental methods to measure temperature directly were analyzed. The analytical models were used to show the effects of cutting parameters, such as cutting speed and feed rate. It was concluded that the majority of methods used to measure the temperature are concerned with the temperature at the chip–tool interface, and for this the tool–work thermocouple is the best method. It gives the aspect of the temperature trend with the cutting parameters, such as cutting speed, feed and depth of cut. Also the infrared method gives a good indication of the maximum temperature and the cooling rate of the work.

G. List et al [35] conducted an experiment through a finite elements model using the Abaqus TM code to predict the interface cutting temperature and its dependence with the crater wear mechanism. They focused their work on the domain of the high speed machining above 20m/s and detailed analysis was done on the mechanical and thermal parameters that influence the temperature distribution at the tool rake face. A method based on some analytical preliminary calculations was proposed to determine the adequate values of the friction shear stress and the heat partitioning factor between the tool and the chip. Numerical simulations and specific experimental approaches were mutually conducted to establish a finite element model in orthogonal cutting process. The results were related to the machining of mild steel with an uncoated carbide tool for cutting speeds from 20 to 60 m/s and a cutting depth ranging from 0.26 to 0.48 mm. the results obtained were successfully analyzed analytically and experimentally.

I Korkut et al [36] in their paper presented the regression analysis (RA) and artificial neural network (ANN) for the prediction of tool–chip interface temperature depends on cutting parameters in machining. The RA and ANN model for prediction tool–chip interface temperature were developed and mathematical equations derived for tool–chip interface temperature prediction were obtained. The tool–chip interface temperature results obtained from mathematical equations with RA and ANN model and the experimental results available in the literature obtained by using AISI 1117 steel work piece with embedded K type thermocouple into the uncoated cutting tool were compared and analyzed. It was concluded that the correlation obtained by the training ANN model were better than the one obtained by training RA model. The results showed that the tool–chip interface temperature equation derived from RA and ANN model can be used for prediction and also RA model had slightly high accuracy.

2.2 IDENTIFIED GAPS IN THE LITERATURE

After a comprehensive study of the existing literature, a number of gaps have been observed in the research work done on the chip-tool interface temperature in orthogonal cutting process.

1. All the research investigated the effect of cutting parameters on responses such as production time, machining time, production cost, surface roughness etc.
2. Much effort has not been made to optimize the cutting temperature in terms of cutting speed, feed rate and depth of cut.
3. A lot of work has been done on the effects of chip-tool interface temperature on other variables such as tool wear rate, work surface roughness, crater wear, tool life etc.
4. Literature study shows the mathematical techniques being used for modeling the metal cutting problems are very limited. Most of the research work has been carried out using neural network, quadratic programming and Taguchi approach.
5. There is very less literature available on effect of the depth of cut on chip-tool interface temperature.

2.3 MOTIVATION AND OBJECTIVE

The motivation of this project was to determine the chip–tool interface temperature depending on other machining parameters and further optimize it using one of the optimization techniques. It also holds the interest to develop the experimental set up for determination of temperature and to study the effects of this temperature with other machining parameters specifically less explored such as depth of cut, tool nose radius etc.

The main objective of this project is:

1. To determine the chip tool interface temperature for different tool and work material.
2. To make a comparison of the tool chip interface temperature for different tool and work materials.
3. To develop the mathematical model and establish predictive equations and validate the experimental results.
4. To optimize the chip tool interface temperature using genetic algorithm optimization technique and further analyze the results with the analytical and experimental outputs.

2.4 STATEMENT OF THE PROBLEM

"Measurement of Chip-Tool Interface Temperature for Orthogonal Cutting"

The research work describes the development of the mathematical models through experimental observations made on various tool and work materials using RSM and development of genetic algorithm architecture for determining the temperature for a given set of inputs. A further comparison between analytical and experimental results is to be studied and validated.

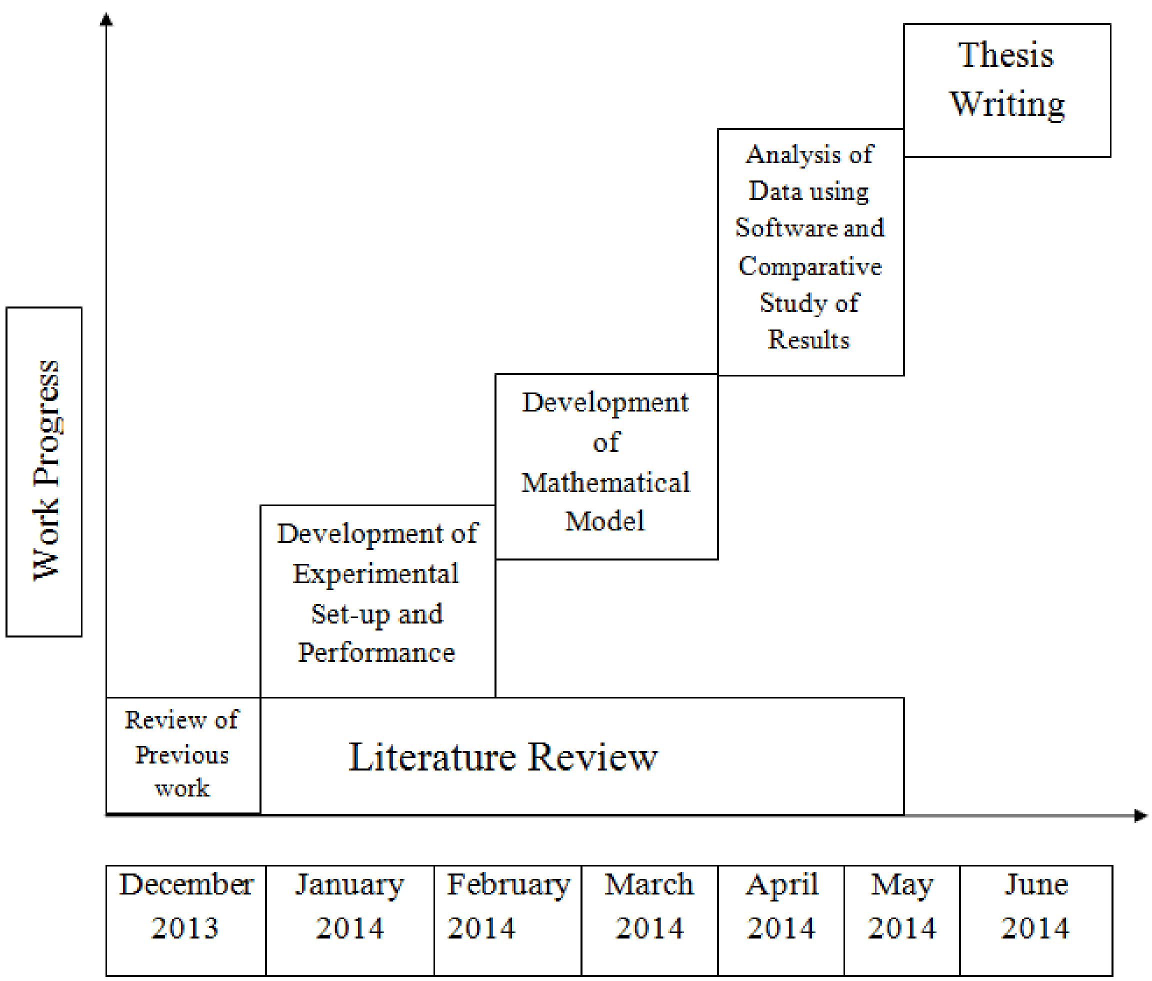
2.5 PLAN OF INVESTIGATION

The research work was planned to be carried out in the following steps:

1. Identification of important process control parameters based on the literature review.
2. Selection of working range of process control parameters viz. cutting speed and depth of cut.
3. Development of experimental set-up and conduction of experiment.

4. Collection and assessment of responses viz. chip-tool interface temperature.
5. Development of mathematical models.
6. Establishment of predictive equations and further checking of model adequacy.
7. Finding the significant co-efficient and exponents.
8. Development of the final proposed model.
9. Plotting of conclusions on graphs.
10. Development of the GA architecture to model and predict the response.
11. Comparison of performance of mathematical model, experimental model and GA model.
12. Discussion of result and its effect on process variables.

2.6 PROJECT PLAN



Chapter 3

THEORY AND EXPERIMENTATION

3.1 INTRODUCTION

In today's modern industry, with all the sophisticated equipment and techniques being used, the basic mechanics of forming a chip remains same. A chip is a shaving or swarf removed from the metal during metal cutting operation. The first attempts to explain how chips are formed were made by Time in 1870 and the French scientist Tresca in 1873.

3.1.1 MACHINE TOOLS

A machine tool is a machine for shaping or machining metal usually by cutting, boring, grinding, shearing or other forms of deformation. All machine tools have some means of constraining the workpiece and provide a guided movement of the parts of the machine. Thus, the relative movement between the workpiece and the cutting tool (called as the "toolpath") is controlled or constrained by the machine. Machine tools are the kinds of machines on which metal cutting or metal forming processes are carried out. The functions of the machine tools are:

a. Hold the workpiece
b. Hold the cutting tool
c. Move the tool or the workpiece or both relative to each other
d. Supply power or energy required to perform the metal cutting process

3.1.2 PRINCIPLE OF MACHINE TOOL

The principle used in all the machine tools is the generation of surfaces required by providing suitable relative motions between the cutting tool and the workpiece. The cutting edge or edges on the cutting tool remove a layer of work material known as a shaving or a chip. The simplest surfaces generated are flat surfaces and internal or external cylindrical surfaces. Thus, there are two kinds of relative motion which must be provided by the metal cutting machine tool. These motions are called primary motion and feed motion which are depicted in the following figure 3.1.

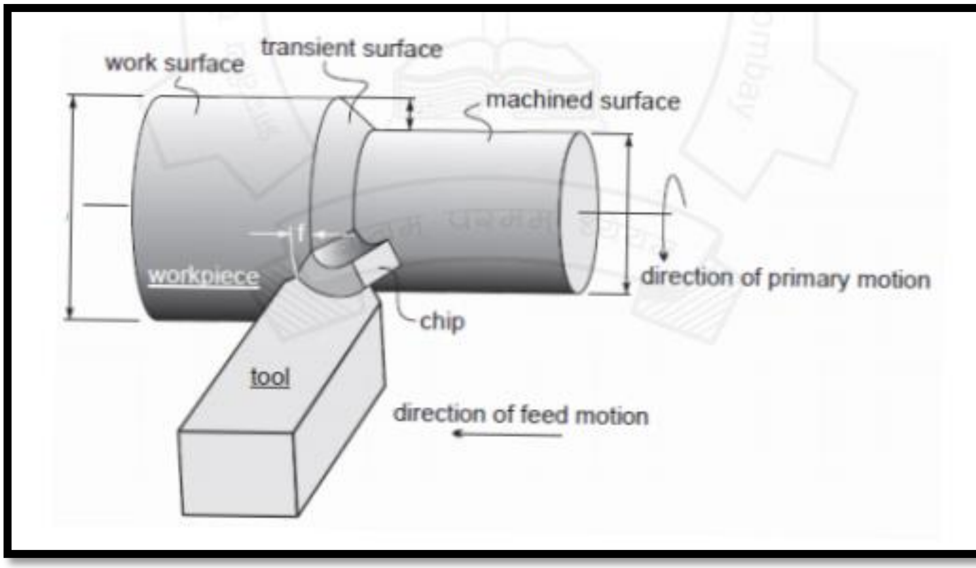


Figure 3.1 Schematic depiction of turning operation (G. Boothroyd)

a. **Primary Motion:** It is the main motion provided by the machine tool to cause relative motion between the tool and the workpiece so that the face of the tool approaches the workpiece material. This motion absorbs most of the total power required to perform a machining operation.
b. **Feed Motion:** This is the motion that may be provided to the tool or workpiece by the machine tool which, when added to the primary motion, leads to a repeated or continuous chip removal and the creation of a machined surface with the desired geometric characteristics. It usually absorbs a small proportion of the total power required to perform a machining operation.

3.1.3 WORKING PRINCIPLE OF TURNING OPERATION

In the metal cutting process, as the cutting tool engages the workpiece, the material directly ahead of the tool is sheared and deformed under tremendous pressure. The deformed material then seeks to relieve its stressed condition by fracturing and flowing into the space above the tool in the form of a chip. Hence, the metal cutting is done by a relative motion between the workpiece and the hard edge of a cutting tool as shown in the figure 3.1 while different types of chip formation are shown in figure 3.2.

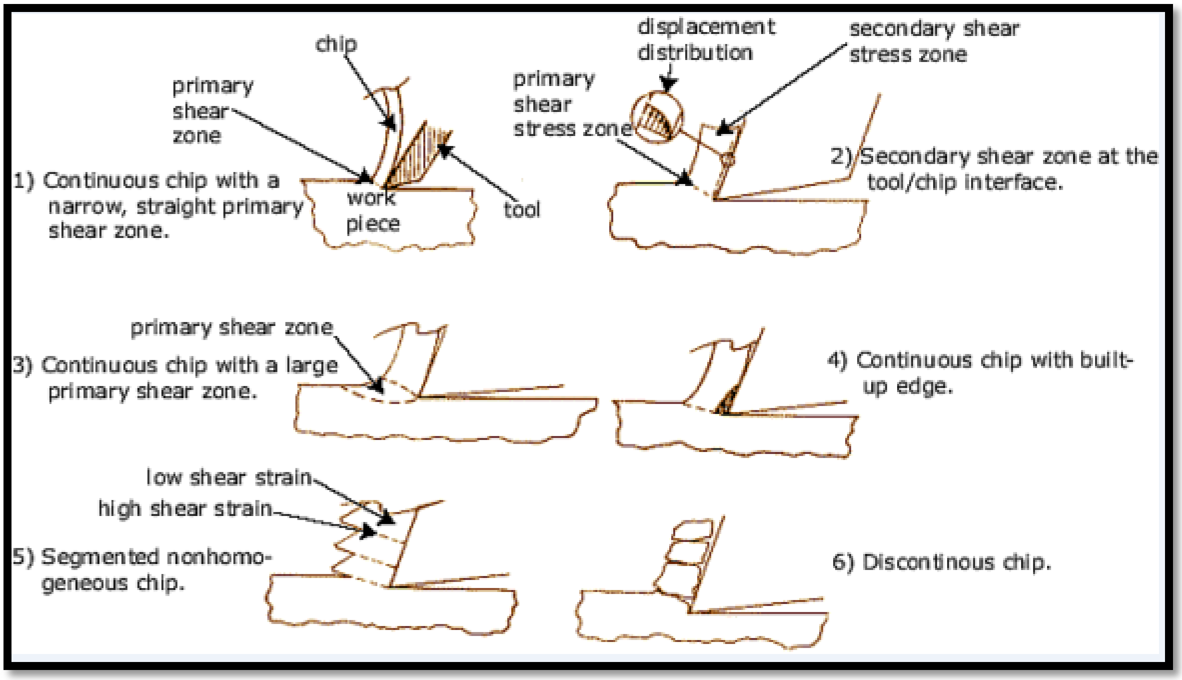


Figure 3.2 Schematic representations of different types of chip formation (M. C. Shaw)

3.1.4 PARAMETERS IN METAL CUTTING

There are number of parameters which affect the cutting operation on a machine tool. These parameters are categorized as follows:

1. Tool related
    a. Material
    b. Geometry
    c. Mounting
2. Work material related
    a. Material (Composition, Homogeneity)
    b. Geometry (Bar, Block)
3. Machine tool related
    a. Type of cutting fluid and application method
    b. Depth and width of cut
    c. Spindle speed
    d. Feed rate

3.1.5 CUTTING PARAMETERS

1. **Cutting Speed:** It is the distance travelled by the work surface in unit time with reference to the cutting edge of the tool. It is expressed in m/min.

2. **Feed:** It is the distance advanced by the tool into or along the workpiece each time the tool point passes a certain position in its travel over the surface. It is expressed in mm/rev and mm/min.

3. **Depth of Cut:** It is the distance through which the cutting tool is plunged into the workpiece surface. Thus, it is the distance measured perpendicularity between the machined surface and the un-machined (uncut) surface or the previously machined surface of the workpiece. It is expressed in mm.

Table3.1 Approximate Cutting Speed Range for Turning Operation (S. K. H. Choudhary)

S. NO.	WORKPIECE MATERIALS	CUTTING SPEED (m/min)
1	Aluminum Alloys	200 – 1000
2	Cast iron, Gray	60 – 900
3	Copper Alloys	50 – 700
4	High Temperature Alloys	20 – 400
5	Steels	50 – 300
6	Stainless Steels	50 – 300
7	Thermoplastics	90 – 240
8	Titanium Alloys	10 – 100
9	Tungsten Alloys	60 – 150

3.1.6 CUTTING TOOLS AND THEIR CHARACTERISTICS

Cutting tool is a device used to remove the unwanted material from a given workpiece. For carrying out the machining or metal removing process, cutting tool is the fundamental and essential requirement. A cutting tool must have the following characteristics:

1. **Hardness:** The tool material must be harder than the workpiece material. Higher the hardness, easier it is for the tool to penetrate the work material.
2. **Hot Hardness:** It is the ability of the cutting tool to maintain its hardness and strength at elevated temperatures. This property is more important when the tool is used at higher cutting speeds, for increased productivity.
3. **Toughness:** The tool should have enough toughness to withstand the impact loads that come at the start of the cut to force fluctuations due to imperfections in the work material. This property is needed so that tools do not chip or fracture easily, especially during interrupted cutting operations like milling.
4. **Wear Resistance:** The tool-chip and chip-work interface are exposed to severe conditions that adhesive and abrasive wear takes place very easily. Therefore, wear resistance means the attainment of acceptable tool life before tools need to be replaced.
5. **Low Friction:** The coefficient of friction between the tool and chip should be low. This would lower wear rates and allow better chip flow.
6. **Thermal Characteristics:** As a lot of heat is generated at the cutting zone, the tool material should have higher thermal conductivity to dissipate the heat in shortest possible time, otherwise the tool temperature would become higher and thereby reducing its life.

3.1.7 CUTTING TOOL MATERIALS

The selection of proper cutting tool material depends on the type of service to which the tool will be subjected. The principal cutting tool materials are:

1. **Carbon and Medium Alloy Steels:** These are the oldest of the tool materials dating back hundreds of years. It is a high carbon steel containing about 0.9 to 1.3% carbon. These are inexpensive, easily shaped and sharpened but they do not

have sufficient hardness and wear resistance. Therefore, these are used in the manufacture of tools operating at low cutting speeds (about 12 m/min) and as hand operated tools.

2. **High Speed Steels:** It is the general purpose metal for low and medium cutting speeds owing to its superior hot hardness and resistance to wear. The major difference between high speed tool steel and plain high carbon steel is the addition of alloying elements (manganese, chromium, tungsten, vanadium, molybdenum, cobalt and niobium) to harden and strengthen the steel and make it more resistant to heat (hot hardness). There are three types of high speed steels: ***Tungsten high speed steel (T-series), Molybdenum high speed steel (M-series) and Cobalt high speed steel.***
3. **Cemented Carbides:** They are so named as they are composed principally of carbon mixed with other elements. The basic ingredient is tungsten carbide which is extremely hard. These tools are produced by powder metallurgy. Carbide tools are basically of three types: ***Tungsten carbide (WC), Tantalum carbide (TaC) and Titanium carbide (TiC).***
4. **Stellites:** They contain 40 to 48% cobalt, 30 to 35% chromium and 12 to 19% tungsten. They cannot be forged to shape but are deposited directly on the tool shank through an oxyacetylene flame. They preserve hardness up to 1000°C and can be operated on steels at cutting speeds 2 times higher than for high speed steel. They are used in non-metal cutting application such as rubber, plastics (where loads are gradually applied).
5. **Ceramics:** These are made by composing aluminum oxide powder in a mould at about 280 kg/cm^2. They are made in the form of tips that are clamped on metal shanks. Other materials used to produce ceramic tools include silicon carbide, boron carbide and titanium carbide and titanium boride. They have very low heat conductivity and extremely high compressive strength. They can withstand temperatures up to 1200°C and can be used at cutting speeds 4 times that of cemented carbides and up to 40 times that of high speed cutting tools.
6. **Diamond:** The diamonds used for cutting tools may be industrial grade natural diamonds or synthetic polycrystalline diamonds. It is the hardest known material

and can be run at cutting speeds about 50 times greater than that for high speed steel tool and temperatures up to 1650°C. These are used for cutting very hard materials such as glass, plastics and ceramics and for producing very fine finishes.

3.2 GENETIC ALGORITHMS

Genetic algorithms are the adaptive heuristic search algorithms based on the mechanics of natural selection and natural genetics. They exploit historical information to direct the search into the region of better performance within the search space. This technique was developed by John Holland at the University of Michigan.

3.2.1 INTRODUCTION

Genetic algorithm is a paradigm which tries to mimic the genetic evolution of a species. It simulates the biological processes that allow the consecutive generations in a population to adapt to their environment. This process is applied through genetic inheritance from parents to children and through survival of the fittest. Therefore, GA is a population-based search methodology [19].

3.2.2 GA PRINCIPLE

The genetic algorithm is based on the Darwin's principle of natural selection and survival of the fittest. Therefore, it is a paradigm that tries to mimic genetic evolution of a species.

The Darwin's principle of Natural Selection was:

a. IF there are organisms that reproduce, and
b. IF offsprings inherit traits from their progenitors, and
c. IF there is variability of traits, and
d. IF the environment cannot support all members of a growing population,
e. THEN those members of the population with less-adaptive traits (determined by the environment) will die out, and
f. THEN those members with more-adaptive traits (determined by the environment) will thrive

The result will be the evolution of a new Species.

Therefore, the essentials of Darwinian evolution were:

a. Organisms reproduce in a proportion to their fitness in the environment.
b. Offsprings inherit all traits from their parents.
c. Traits are inherited with some variation through mutation and recombination process.

The following Figure 3.3 shows the flowchart of Darwin's principle of natural selection.

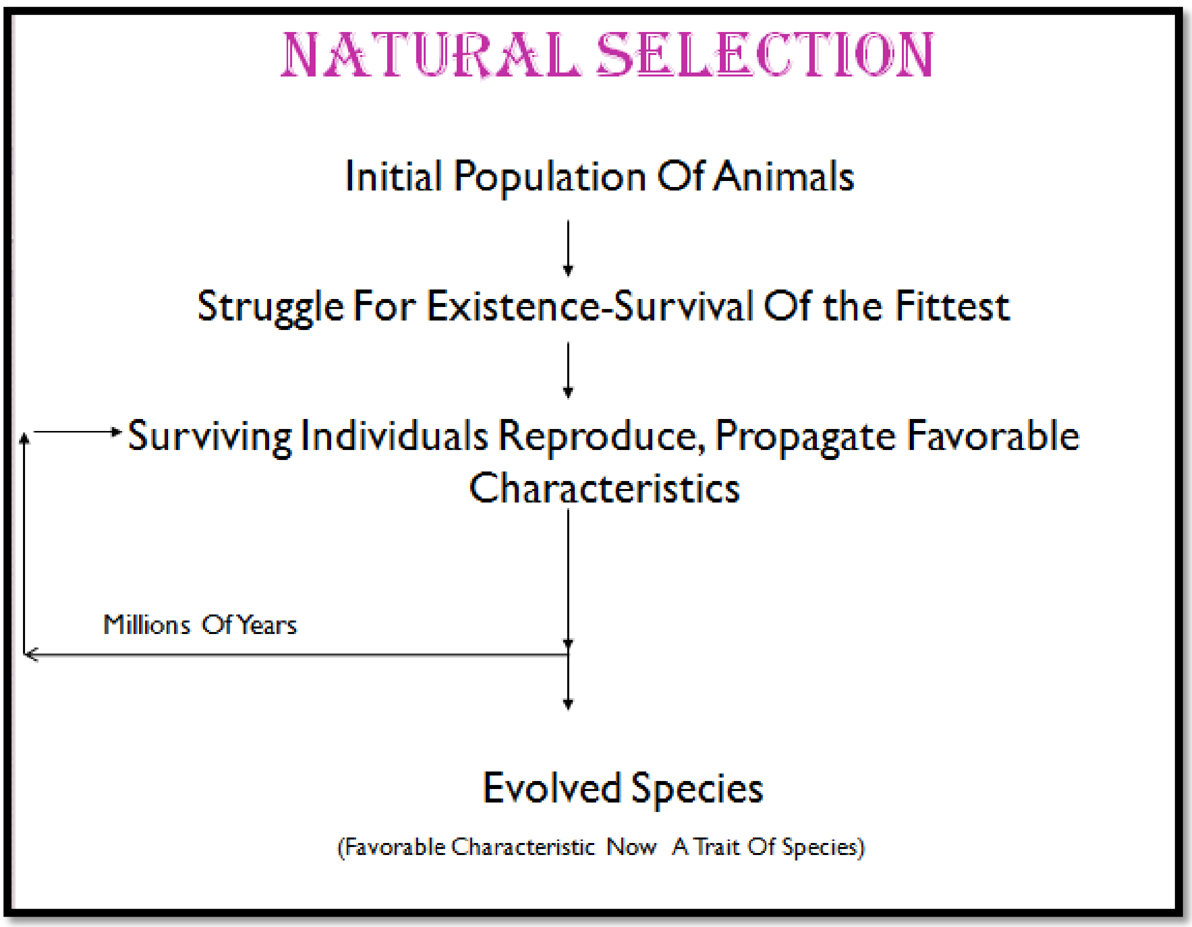


Figure 3.3 Flowchart of Darwin's Principle of Natural Selection (S. N. Deepa)

3.2.3 GA PROCEDURE

The genetic algorithm starts with randomly chosen parent chromosomes from the search space to create a population. They work with chromosome genotype. The population "evolves" towards the better chromosomes by applying genetic operators modeling the genetic processes occurring in the nature-selection, recombination and mutation.

Selection compares the chromosomes in the population aiming to choose these, which will take part in the reproduction process. The selection occurs with a given probability on the base of fitness functions. The recombination is carried out after selection process is finished. It combines, with redefined probability, the features of two selected parent chromosomes forming similar children. After recombination offspring undergoes to mutation. Generally, the mutation refers to the creation of a new chromosome from one and only one individual with predefined probability. After three operators are carried the offspring is inserted into the population, replacing the parent chromosomes in which they were derived from, producing a new generation. This cycle is performed until the optimization criterion is met [37].

3.2.4 GA TERMINOLOGY WITH MATHEMATICAL PROGRAMMING EQUIVALENCE

Table 3.2 Programming terms analogous to genetic terminology (www.aic.nre.navy.mie/galist)

GENETIC TERMINOLOGY	PROGRAMMING EQUIVALENT
Generation	Iteration
Chromosome/ Individual/ Genotype	Coded vector of control variables
Chromosome Phenotype	Vector of real values of control variables
Gene	Coded particular Variable
Morphogenesis/ Growth Function	Decoding function
Population	Set of vectors of control variables
Objective Function	Quality model characteristics for optimization
Fitness Function	Normalized objective function at iteration t

1. INDIVIDUALS

An individual is a single solution. An individual groups together two forms of solution as given below:

a. The chromosome which is the raw “genetic” information (genotype) that the GA deal.
b. The phenotype which is the expressive of the chromosome in the terms of the model.

A chromosome is subdivided into genes. A gene is the GA’s representation of a single factor for a control factor. Each factor in the solution set corresponds to a gene in the chromosome. Figure 3.4 shows the representation of a genotype.

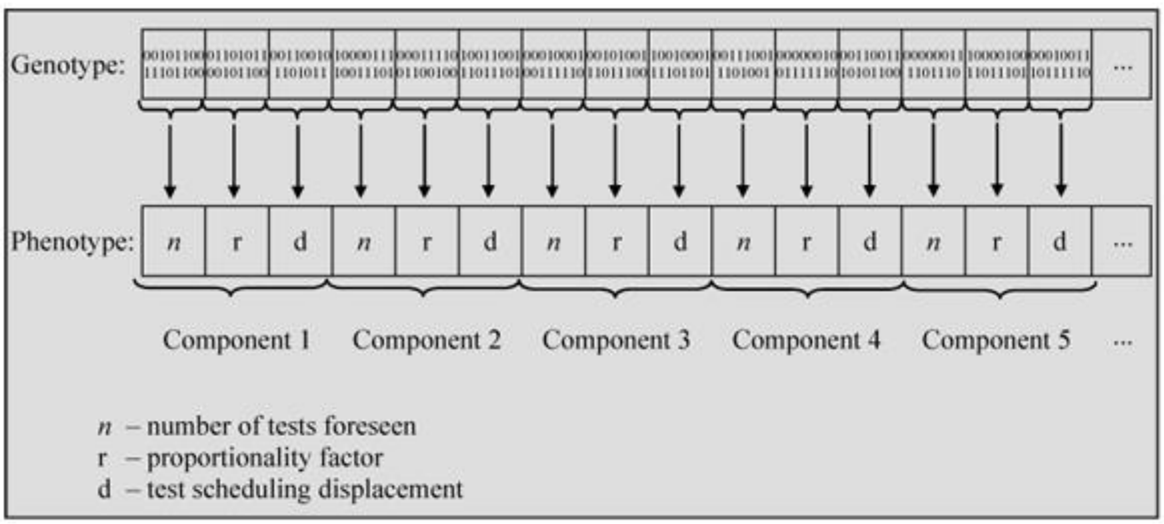


Figure 3.4 Schematic representations of the genotype and phenotype structures [38]

A chromosome should in some way contain information about the solution that it represents. The morphogenesis function associates each genotype with its phenotype as shown in Figure 3.4. It simply means that each chromosome must define one unique solution, but it does not mean that each solution is encoded by exactly one chromosome.

2. GENES

Genes are the basic "instruction" for building a GA. A chromosome is a sequence of genes. Genes may describe a possible solution to a problem, without actually being the solution. A gene is a bit string of arbitrary lengths. The bit string is a binary representation of number of intervals from a lower bound. A gene is the GA's representation of a single factor value for a control factor, where control factor must have an upper bound and a lower bound. This range can be divided into the number of intervals that can be expressed by the gene's bit string. A bit string of length "n" can represent $(2^n - 1)$ intervals. The size of the intervals would be (range) / $(2^n - 1)$. The following Figure 3.5 shows the representation of a gene.

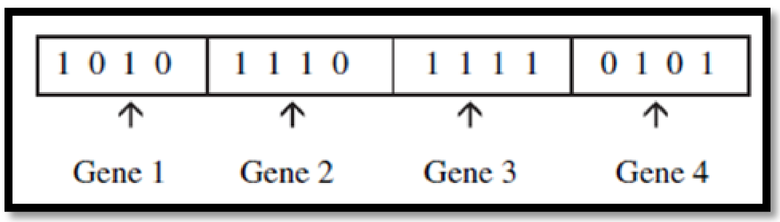


Figure 3.5 Representation of a Gene [39]

3. FITNESS

The fitness of an individual in a GA is the value of an objective function for its type phenotype. For calculating fitness, the chromosome has to be first decoded and the objective function has to be evaluated. The fitness not only indicates how good the solution is, but also corresponds to how close the chromosome is to the optimal one.

4. POPULATION

A population is a collection of individuals. A population consists of a number of individuals being tested, the phenotype parameters defining the individuals and some information about the search space. The two important aspects of population used in GA's are:

a. The initial population generation.
b. The population size.

For each and every problem, the population size will depend on the complexity of the problem. It is often a random initialization of population.

3.2.5 GA OPERATORS

The basic operators in genetic algorithm include:

a. Encoding
b. Selection
c. Recombination
d. Mutation

3.2.5.1 ENCODING

Encoding is a process of representing individual genes. The process can be performed using bits, numbers, trees, arrays, lists, or any other object.

a. BINARY ENCODING

The most common way of encoding is a binary string. Each chromosome encodes a binary (bit) string. Each bit in the string can represent some characteristics of the solution. Every bit string therefore is a solution but not necessarily the best solution. Another possibility is that the whole string can be represent a number. The way bit strings can code differs from problem to problem.

Chromosome 1	1 1 0 1 0 0 0 1 1 0 1 0
Chromosome 2	0 1 1 1 1 1 1 1 1 1 0 0

Figure 3.6 Binary Coding [37]

Binary coded string with 1s and 0s are mostly used. The length of the string depends on the accuracy. In such coding

1. Integers are represented exactly.
2. Finite number of real number can be represented.
3. Numbers of real number represented increases with string length.

b. PERMUTATION ENCODING (REAL NUMBER CODING)

Every chromosome is a string of number, represented in a sequence. Sometime corrections have to be done after genetic operation is complete. In permutation encoding, every chromosome is a string of integers/real values, which represent a number in a sequence. Permutation encoding is only useful for ordering problems.

Chromosome 1	1 5 3 2 6 4 7 9 8
Chromosome 2	8 5 6 7 2 3 1 4 9

Figure 3.7 Real Number Coding [37]

c. VALUE CODING

Every chromosome is a string of values and the values can be anything connected to the problem. This encoding produces best results for some special problems. Direct value encoding can be used in problems, where some complicated values, such as real numbers, are used.

Chromosome A	1.2324 5.3243 0.4556 2.3293 2.4545
Chromosome B	ABDJEIFJDHDIERJFDLDFLFEGT
Chromosome C	(back), (back), (right), (forward), (left)

Figure 3.8 Value Coding [37]

In value encoding (Figure 3.8), every chromosome is a string of some values. Values can be anything connected to problem, form number, real number or characters to some complicated objects.

3.2.5.2 SELECTION

Selection is the process of choosing two parents from the population for crossing. After deciding on an encoding, the next side is to decide how to perform selection, i.e., how to choose individuals in the population that will create offspring for the next generation and how many offspring each will create. The purpose of selection is to emphasize fitter individual in the population to be parents for reproduction. The problem is how to select these chromosomes. According to Darwin's theory of evolution the best ones survive to create new offspring. Figure 15-20 shows the basic the basic selection process.

Selection is a method that randomly picks chromosomes out of the population according to their evaluation function. The higher the fitness function, the better chance that an individual will be selected.

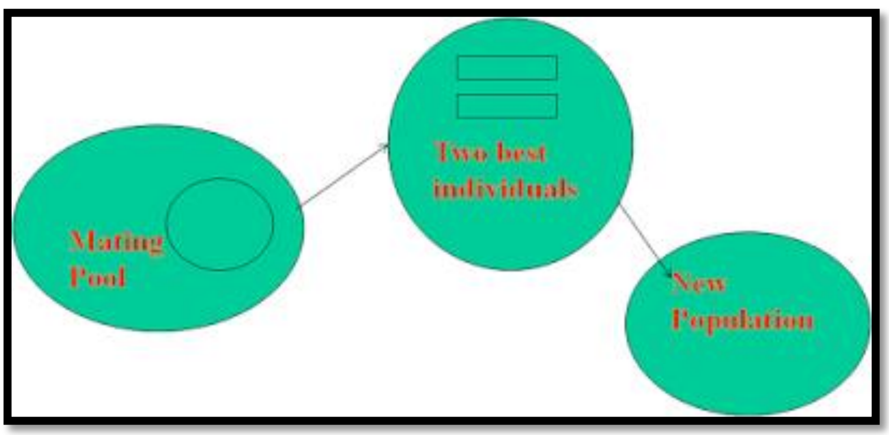


Figure 3.9 Selection process [16]

Selection has to be balanced with variation from crossover and mutation. Too strong selection means sub-optimal highly fit individual will take over the population, reducing the diversity needed for change and progress; too weak selection will result in too slow evolution. The various selection methods are

a. ROULETTE WHEEL SELECTION

Roulette selection is one of the traditional GA selection techniques. The commonly used reproduction operator is the proportionate reproductive operator where a string is selected from the mating pool with the probability proportional to the fitness. The principle of roulette selection is a linear search through a roulette wheel with the slots in the wheel weighted in proportion to the individual's fitness values. A target value is set, which is a random proportion of the sum of the fitness in the population. The population is stepped through until the target value is reached.

The roulette selection can also be explained as follows: Consider the following Figure 3.10.

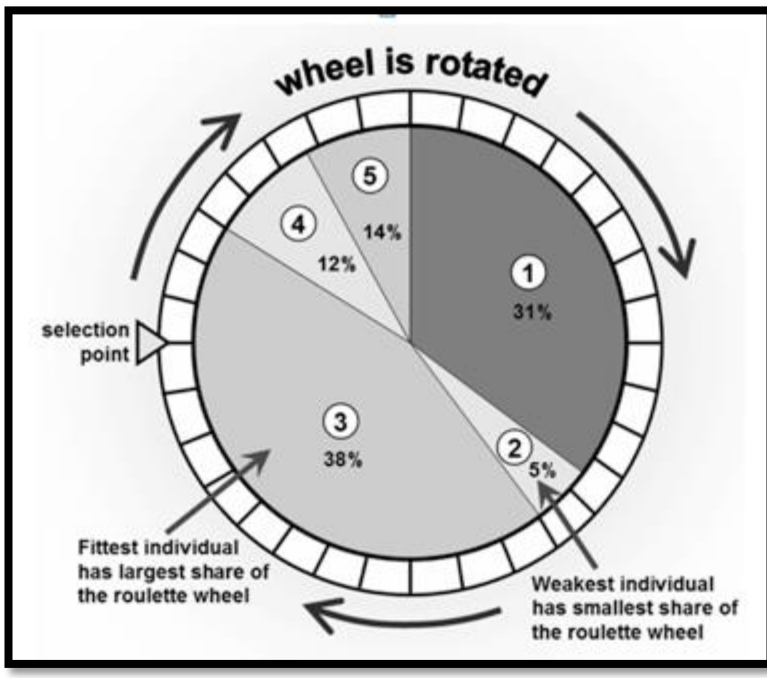


Figure 3.10 Roulette Wheel representation (Newcastle University, CS Resource)

The expected value of an individual is individual's fitness divided by the actual fitness of the population. Each individual is assigned a slice of the Roulette wheel, the size of the slice being proportional to the individual's fitness. The wheel is spun N times, where n is the number of individual in the population. On each spin, the individual under the wheel's marker is selected to be in the pool of parents for the generation. This method is implemented as follows:

1. Sum the total expected value of the individuals in the population. Let it be T.
2. Repeat N times:
   i. Choose a random integer “r” between 0 and T.
   ii. Loop through the individuals in the population, summing the expected values, until the sum is greater than or equal to “r”. The individual whose expected value puts the sum over this limit is the one selected.

Roulette wheel selection is easier to implement but is noisy. The rate of evolution depends upon the variance of fitness’s in the population.

b. RANDOM SELECTION

This technique randomly selects a parent from the population. In terms of disruption of genetic codes, random selection is a little more disruptive, on average, than Roulette wheel selection.

c. RANK SELECTION

The Roulette wheel will have a problem when the fitness values differ very much. If the best chromosome fitness is 90%, its circumference occupies 90% of Roulette wheel, and then other chromosomes have too few chances to be selected. Rank selection ranks the population and every chromosome receive fitness from the ranking. The worst has fitness 1 and the best has fitness N. Its results in slow convergence but prevents too quick convergence. In effect, potential parents are selected and a tournament is held to decide which of the individuals will be parents. There are many ways this can be achieved and two suggestions are:

i. Select a pair of individuals at random. Generate a random number R between 0 and 1. If $R < r$ use the first individual as a parent. If the $R \geq r$ then use the second individual as the parent. This is repeated to select the second parent. The value of r is a parameter to this method.

ii. Select two individual at random. The individual with the highest evaluation becomes the parent. Repeat to find a second parent.

d. TOURNAMENT SELECTION

An ideal selection strategy should be such that it is able to adjust its selective pressure and population diversity so as to fine – tune GA search performance. Unlike, the Roulette wheel selection, the tournament selection strategy provides selective pressure by holding a tournament competition among Nu individuals.

The best individual from the tournament is the one with the highest fitness, who is the winner of Nu. Tournament competition and the winner are then inserted into the mating pool. The tournament competition is repeated until the mating pool for generating new offspring is filled. The mating pool comprising the tournament winner has higher average population fitness. The fitness difference provides the selection pressure, which drives GA to improve the fitness of the succeeding genes. This method is more efficient and leads to an optimal solution.

3.2.5.3 CROSSOVER (RECOMBINATION)

Crossover is the process of taking two parent solutions and producing from them a child. After the selection (reproduction) process, the population is enriched with better individuals. Reproduction makes clones of good string but does not create new ones. Crossover operator is applied to the mating pool with the hope that it creates a better offspring.

Crossover is a recombination operator that proceeds in three steps:

1. The reproduction operator selects at random a pair of two individual strings for the mating.
2. A cross site is selected at random along the string length.
3. Finally, the position values are swapped between the two string following the cross site.

a. SINGLE POINT CROSSOVER

The traditional genetic algorithm uses single- pint crossover, where the two mating chromosomes are cut once at corresponding points and the sections after the cuts exchanged. Here, a cross site or crossover point is selected randomly along the length of the mated strings and bits next to the cross sites are exchanged. If appropriate site is chosen, better children can be obtained by combining good parents, else it severely hampers string quality.

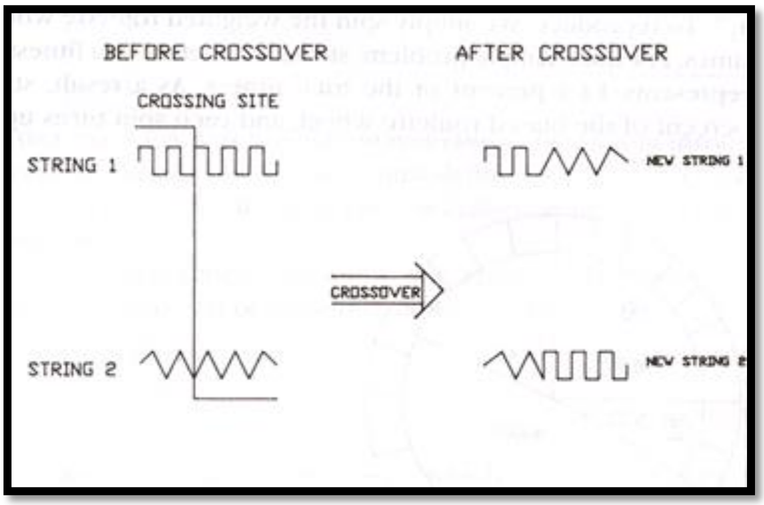


Figure 3.11 Single Point Crossover representation (David E. Goldberg)

b. TWO POINT CROSSOVER

Apart from single – point crossover, many different crossover algorithms have been devised, often involving more than one cut pint. It should be noted that adding further crossover reduces the performance of the GA. The problem with adding additional crossover is that building blocks are more likely to be disrupted. However, an advantage of having more crossover point is that the problem space may be searched more thoroughly.

In two- point crossover, two crossover points are chosen and the contents between these points are exchanged between two mated parents.

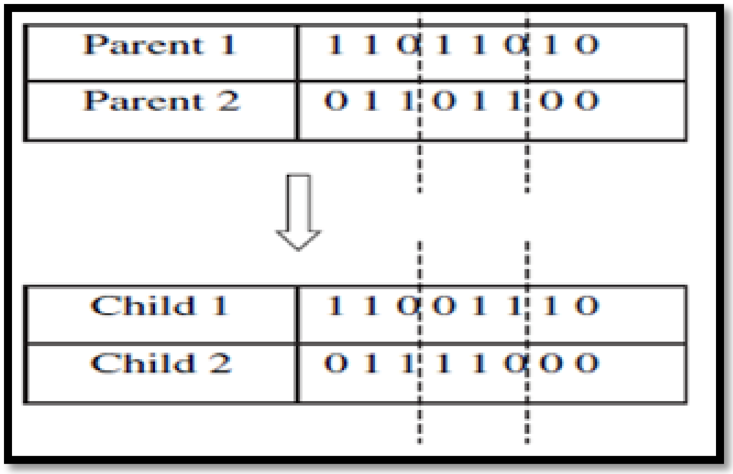


Figure 3.12 Two Point Crossover representation [37]

c. UNIFORM CROSSOVER

Each gene in the offspring is created by copying the corresponding gene from one or the other parent chosen according to a random generated binary crossover mask of the same length as the chromosomes. When there is a 1in the crossover mask, the gene is copied from the first parent, and where there is 0 in the mask the gene copied from the second parent. A new crossover mask is randomly generated for each pair of parents. Offspring, therefore, contain a mixture of genes from each parent. The number of effective crossing point is not fixed, but will average L/2 (where L is the chromosome length).

Parent 1	1 0 1 1 0 0 1 1
Parent 2	0 0 0 1 1 0 1 0
Mask	1 1 0 1 0 1 1 0
Child 1	1 0 0 1 1 0 1 0
Child 2	0 0 1 1 0 0 1 1

Figure 3.13 Uniform Crossover representation [37]

In Figure 3.13, new children are produced using uniform crossover approach. It can be noticed that while producing child 1, when there is 1 in the mask, the gene is copied from the parent 1 else it is copies from the parent 2. On producing child 2, when there is a 1 in the mask, the gene is copied from the parent 2, and when there is a 0 in the mask, the gene is copied from the parent 1.

3.2.5.4 MUTATION

After crossover, the springs are subjected to mutation. Mutation prevents the algorithm to be tapped in a local minimum. Mutation plays a role of recovering the lost genetic materials as well as for randomly distributing genetic information. It is an insurance policy against the irreversible loss of genetic material. Mutation has been traditionally considered as a simple search operator. If crossover is supposed to exploit the current solution to find better ones, mutation is supposed to help for the exploration of the whole search space.

It introduces new genetic structures in the population by randomly modifying some of its building blocks. Mutation helps escape from local minima's trap and maintain diversity in the population. It also keeps gene pool well stocked, thus ensuring ergodicity. A search space is said to be ergodic if there is a non- zero probability of generating any solution from any population state.

There are many different forms of mutation for the different kinds of representation.

a. FLIPPING

Flipping of a bit involves changing 0 to 1 and 1 to 0 based on a mutation chromosome generated. Figure 3.14 explains mutation- flipping concept. A parent is considered and a mutation chromosome is randomly generated. For a 1 in mutation chromosome, the corresponding bit in parent chromosome is flipped (0 to 1and 1 to 0) and child chromosome is produced.

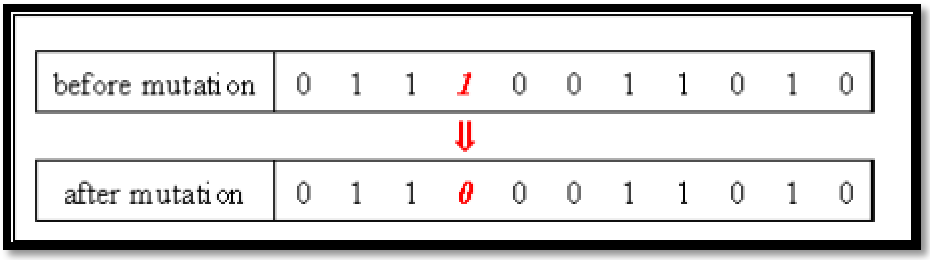


Figure 3.14 Mutation Flipping (S. N. Deepa)

In the case illustrated in Figure 3.14, 1 in red is the place of mutation chromosome, therefore the corresponding bits in parent chromosome are flipped and the child is generated.

b. INTERCHANGING

Two random positions of the string are chosen and the bits corresponding to those positions are interchanged (Figure 3.15).

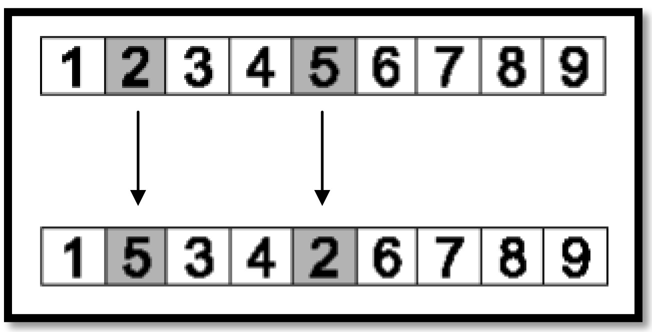


Figure 3.15 Mutation type – Interchanging [40]

c. REVERSING

A random position is chosen and the bits next to that position are reversed and child chromosome is produced.

d. MUTATION PROBALBILITY

An important parameter in the mutation technique is the mutation (P_m). It decides how often parts of chromosome will be mutated. If there is no mutation, offspring are generated immediately after crossover (or directly copied) without any change. If mutation is performed, one or more parts of a chromosome are changed. If mutation probability is 100%, whole chromosome is changed; if it is 0%, nothing is changed. Mutation generally prevents the GA from falling into local extremes. Mutation should occur very often, because then GA will in fact change to random search.

3.2.6 GA SPECIAL CASES

3.2.6.1 ELITISM

It is a method which copies the best chromosome to the new offspring population before crossover and mutation. It is a successful variant of constructing a new population which allows better organisms to be carried to next generation unaltered. This strategy is known as elitist selection.

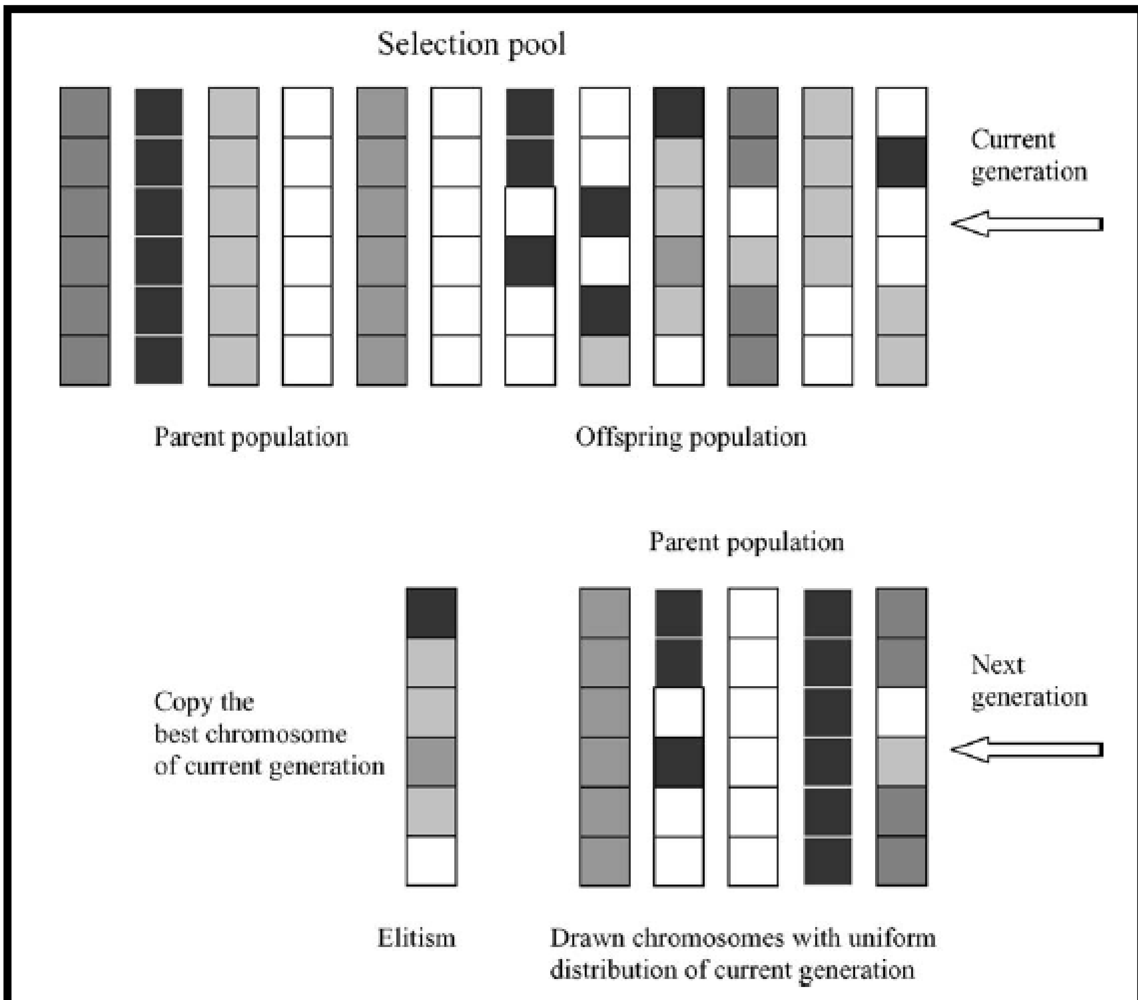


Figure 3.16 Elitist selection and participation in formation of new generation [37]

Consider the Figure 3.16, while creating a new population by crossover or mutation the best chromosome or fittest variable might be lost, in order to preserve it GA copies a small proportion of the best chromosome into the next generation unaltered. This helps in improving the performance as it does not waste time in re-discovering the previously discarded solutions. Therefore, chromosomes preserved unchanged through elitism are eligible for selection when the next generation is generated [40, 41].

3.2.6.2 GENITOR ("DELETE-WORST")

In this strategy the worst chromosome or most unfit variable of the population is replaced. It immediately improves the mean population fitness and may converge prematurely. It is based on rapid takeover policy of using large populations without duplicates [41].

3.2.7 GA WORKING MECHANISM

The understanding of genetic principle, its terminology and the genetic operators viz. selection, crossover (recombination) and mutation including the special cases of elitism and genitor helps in formulating the general working flowchart of GA. The following Figure 3.17 shows the flowchart of the GA mechanism.

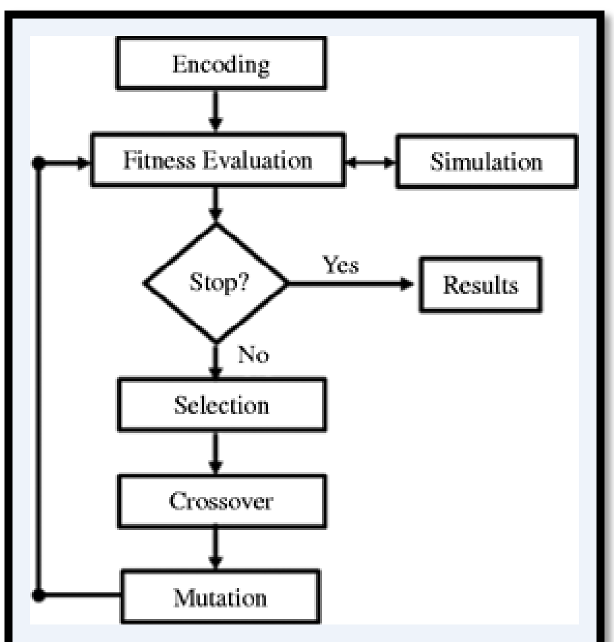


Figure 3.17 Flowchart of Genetic Algorithm [42]

3.2.8 ADVANTAGES OF GENETIC ALGORITHM

GA is created to work with a predetermined constant size of population and to use continuous search space for individuals' representation. The GA genetic operators comprise a great number of selection, recombination and mutation. It provides an opportunity for future extension of its capability by involving of new schemes in its genetic operators [37].

Therefore, GA forms a very advantageous optimization technique. The following list further elaborates on the advantages of GA.

1. GA search parallel from a population of points. Therefore, it has the ability to avoid being trapped in local optimal solution like traditional methods, which search a single point.
2. GA use probabilistic selection rules, not deterministic ones.
3. It works on the chromosome, which is encoded version of potential solutions' parameters, rather the parameters themselves.
4. It uses fitness score, which is obtained from objective functions, without other derivative or auxiliary information.
5. It solves problems with multiple solutions.
6. Since GA execution technique is not dependent on the error surface, one can use it to solve multi-dimensional, non-differential, non-continuous and non-parametrical problems.
7. GA is easily transferred to existing simulations and models.

3.2.9 APPLICATIONS OF GENETIC ALGORITHM

An effective GA representation and meaningful fitness evaluation are the keys of the success in GA applications. The appeal of GA's come from their simplicity and elegance as robust search algorithms as well as from their power to discover good solutions rapidly for difficult high – dimensional problem. GAs have been used for problem – solving and for modeling. GAs are applied to many scientific, engineering problems, in business and entertainment, including *(S. N. Sivanandam & S. N. Deepa)*:

1. ***Optimization:*** GAs have been used in a variety of optimization tasks, including numerical optimization and combinatorial optimization problems such as travelling salesman problem(TSP), circuit design (Louis, 1993), job shop scheduling (Goldstein, 1991) and video & sound quality optimizations.
2. ***Automatic programming:*** GAs have been used to evolve computer programs for specific tasks and to design other computational structures, for example, cellular automata and sorting networks.
3. ***Machine and robot learning:*** GAs have been used for many machine – learning applications, including classifications and prediction, and protein structure prediction. GAs have also been used to design neutral networks, to evolve rules for learning classifier system or symbolic production systems, and to design and control robots.
4. ***Economic models:*** GAs have been used to model processes of innovation, the development of bidding strategies and the emergence of economic markets.
5. ***Immune system models:*** GAs have been used to models various aspects of the natural immune system including somatic mutation during an individual's lifetime and the discovery of multi- gene families during evolutionary time.
6. ***Ecological models:*** GAs have been used to model ecological phenomena such as biological arms races, host- parasite co- evolution, symbiosis and resource flow in ecologies.
7. ***Population genetics models:*** GAs have been used to study questions in population genetics, such as 'under what conditions will be a gene for recombination be evolutionally viable?'
8. ***Interactions between evolution and learning:*** GAs have been used to study how individual learning and species affect one another.
9. ***Models of social systems:*** GAs have been used to study evolutionary aspects of social systems, such as the evolution of cooperation (Chughtai, 1995), the evolution of communication and trail – following behavior in ants.
10. ***Combinatorial Optimization:*** GA is extensively used in problems related to travelling salesman, routing, bin packing, graph coloring and partitioning.

3.3 RESPONSE SURFACE METHODOLOGY

RSM has proved to be a very helpful model in problems of optimization of process parameters. Optimal cutting parameters are determined by RSM method using the grey relational grade as the performance index for a problem of turning process.

In this problem, chip-tool interface temperature, main cutting force, and feed force are important characteristics in turning operations. Using these characteristics, the cutting operations, including cutting velocity, feed rate, depth of cut, and effective tool nose radius, are optimized. A model is developed to correlate the multiple performance characteristic called grey relational grade and turning parameters and a new combination of RSM and grey relational analysis is proposed [43]. Therefore, RSM is a successful modeling technique for determination and analysis of a problem.

3.3.1 INTRODUCTION

Response surface methodology, or RSM, is a collection of mathematical and statistical techniques useful for the modeling and analysis of problems in which a response of interest is influenced by several variables and the objective is to optimize this response. For example, suppose that an engineer wishes to find the levels of temperature (x_1) and pressure (x_2) that maximize the yields (y) of a process. The process yield is a function of the levels of temperature and pressure, say

$$y = f(x_1, x_2) + \epsilon$$

which ϵ represents the noise or error observed y. If we denote the expected response by $E(y) = f(x_1, x_2) = \eta$, then the surface represented by

$$\eta = f(x_1, x_2)$$

is called a response surface. Figure 3.18 shows the three-dimensional response surface showing the expected yield (η) as a function of temperature (x_1) and pressure (x_2) while Figure 3.19 shows the contour plot of the response surface.

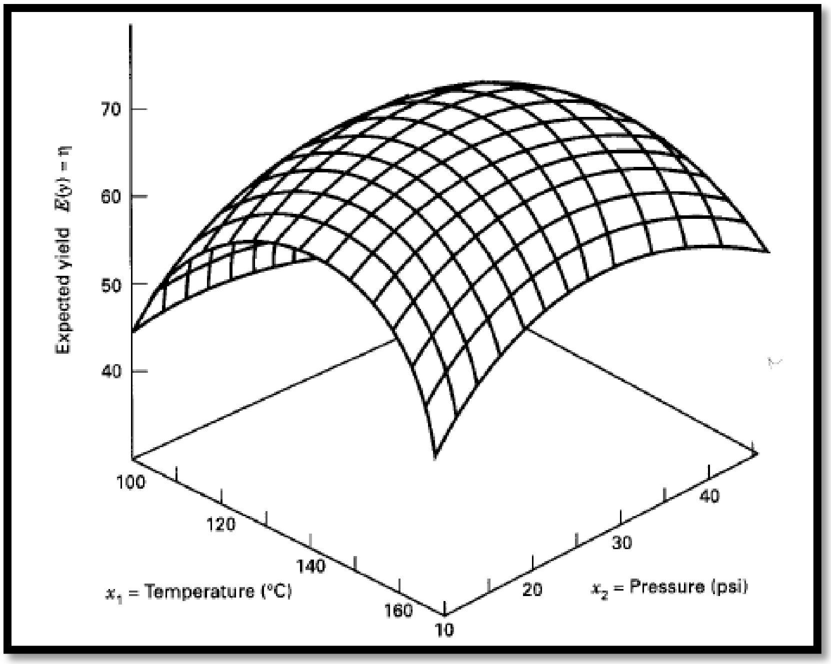


Figure 3.18 A three-dimensional response surface (D. C. Montgomery)

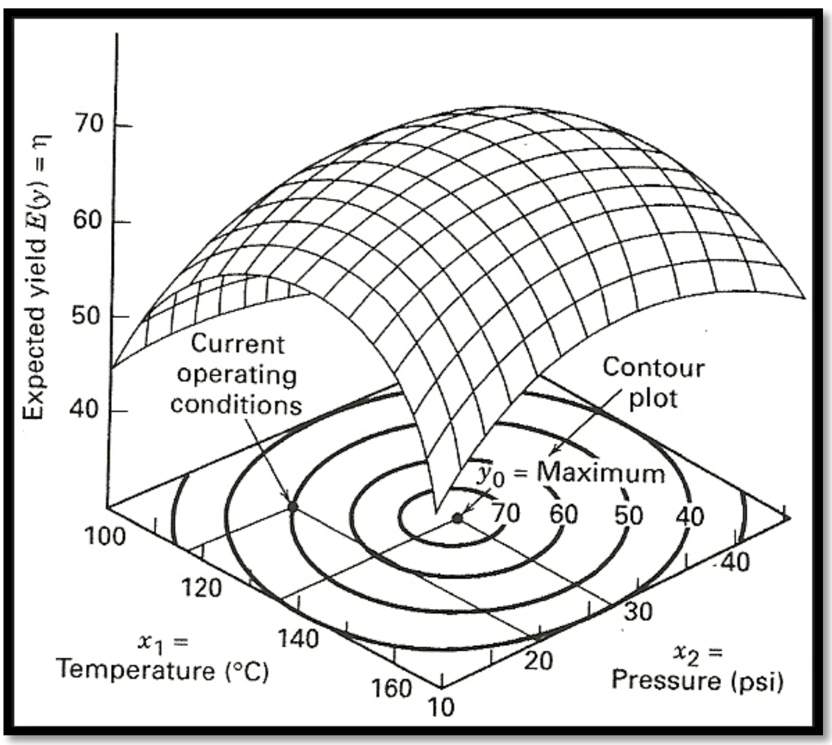


Figure 3.19 A contour plot of a response surface (D. C. Montgomery)

In most RSM problems, the form of the relationship between the response and the independent variables is unknown. Thus, the first step in RSM is to find a suitable approximation for the true functional relationship between y and the set of independent variables. Usually, a low order polynomial in some region of the independent variables is employed.

If the response is well modeled by a linear function of the independent variables, then the approximating function is the first- order model.

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k + \epsilon$$

If there curvature model in the system, then a polynomial of higher degree must be used, such as the second- order model.

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i=1}^{k} \beta_{ii} x_i^2 + \sum\sum_{i<j} \beta_{ij} x_i x_j + \epsilon$$

Almost all RSM problems use one or both of these model.

The method of least square is used to estimate the parameters in the approximating polynomials. The response surface analysis is then performed using the fitted surface. If the fitted surface is an adequate approximation of the true response function, then analysis of the fitted surface will be approximately equivalent to analysis of the actual system. The model parameters can be estimated most effectively if proper experimental designs are used to collect the data. Designs for fitting response surfaces are called response surface designs.

The eventual objective of RSM is to determine the optimum operating conditions for the system or to determine a region of the factor space in which operating requirement are satisfied.

3.3.2 THE METHOD OF STEEPEST ASCENT

The method of steepest ascent is a procedure for moving sequentially in the direction of the maximum increase in the response. Of course, if minimization is desired, then we call this technique the method of steepest descent.

The fitted first- order model is

$$\hat{y} = \hat{\beta}_0 + \sum_{i=1}^{k} \hat{\beta}_i x_i$$

and the first- order response surface, that is, the contours of ŷ, is a series of parallel lines as shown in the Figure 3.20.

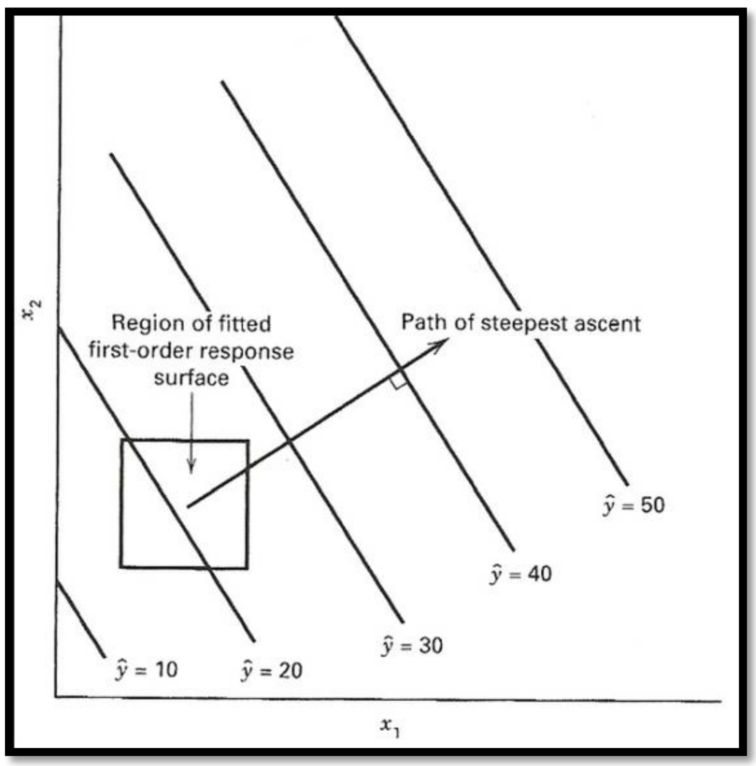


Figure 3.20 First-order response surface and path of steepest ascent (D. C. Montgomery)

Experiments are conducted along the path of steepest ascent until no further increase in response is observed. Then a new first- order model may be fit, a new path of steepest ascent determined, and the procedure continued. Eventually, the experiment will arrive in the vicinity of the optimum. This is usually indicated by lack of fit of a first- order model.

3.4 DESIGN OF EXPERIMENT

The section gives the details of the experimental set-up, the specifications of the work material and tool material and the recording of results. All the data was analyzed on the basis of the literature review done previously and depending on this information the process variables were selected. The main objective of this experiment is to determine the chip-tool interface temperature in orthogonal turning process depending on cutting parameters i.e. cutting speed and depth of cut for different tool and work material combinations.

3.4.1 IDENTIFICATION OF PROCESS CONTROL VARIABLES

Based on the literature review the important process parameters identified for the determination of the chip-tool interface temperature in orthogonal turning process are cutting speed and depth of cut along with different tool material and work material.

3.4.2 WORKING RANGE OF PROCESS CONTROL VARIABLES

Trial runs were conducted to find the upper and lower limits of the process parameters by varying one of the parameter and keeping the rest parameters at constant values. The limits of the process parameters were selected in such a way that the chip-tool interface temperature was minimized. The selected process control variables' working range also depended on the machine tool specification and the literature review. The upper limit of the parameter is coded as HIGH and lower limit as LOW. The process control parameters with their upper and lower limits are tabulated as follows:

Table 3.3 Process control parameters and their

Sl.No	Parameters	Units	Notation	-1	0	+1
1	Cutting Speed	m/min	V	233	340	530
2	Depth of Cut	mm	D	0.5	2.0	4.0

3.4.3 DEVELOPMENT OF DESIGN MATRIX

In the development of the design matrix, two factors namely cutting speed (V) and depth of cut (D) were considered, each at two levels. This design is known as 2^2 factorial design and the four treatment combinations were generated. These treatment combinations are listed below in Table 3.7.

Table 3.4 Design Matrix

Reading no.	Input Parameters		Treatment Combination
	Cutting Speed (V)	Depth of Cut (D)	
1	-1	-1	(1)
2	-1	+1	a
3	+1	-1	b
4	+1	+1	ab

3.4.4 EXPERIMENTAL SET-UP

The investigations were carried out in the laboratory by setting up the mechanism to measure the chip-tool interface temperature. The most widely used method for measuring the average chip-tool interface temperature is the tool-work thermocouple with due care to avoid generation of parasitic emf and electrical short circuit. This method uses the tool and work piece as the elements of a thermocouple. The hot junction is the interface between the tool and the work piece and cold junction is formed by the remote sections of the tool and work piece which must be connected electrically and held at a constant reference temperature as shown in the Figure 3.21[21].

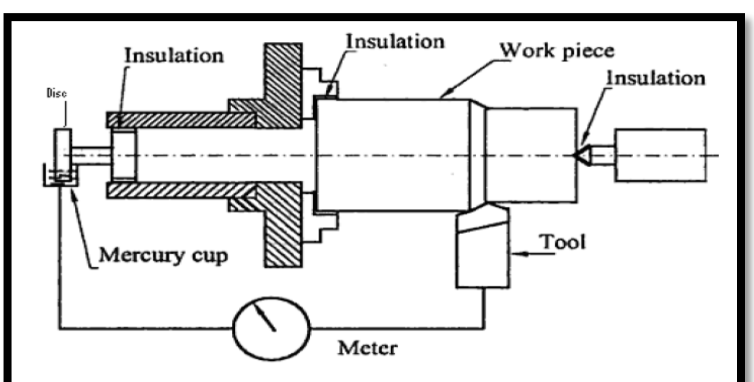


Figure 3.21 Schematic experimental set-up using Tool-Work Thermocouple technique [21]

An experimental set up was designed and fabricated to measure the temperature on cutting tool and work piece junction during metal cutting on lathe machine tool (LMT, heavy duty lathe machine).

An iron rod was screwed to the work piece through special adaptor whose one end was mounted on a three jaw universal chuck while the other end of the rod was attached to a metallic (copper) disc by an arrangement of coupling joint (Figure 3.23). This disc rotated along with the rotation of the chuck and was immersed into the mercury box (Figure 3.24). This mercury box was connected to one of the terminal of the milli voltmeter. The other terminal of milli voltmeter was screwed to the tool insert. The circuit system completed when the tool and work piece came into contact. The following Figure 3.22 shows the experimental set-up for measuring the chip-tool interface temperature.

Figure 3.22 Designed Experimental Set-up

Tool and work piece junction acted as the hot junction, while machining was on and other ends of the work piece and tool at room temperature, acted as cold junction [21].

Nylon insulation was provided to reduce the noise in the thermocouple signals.

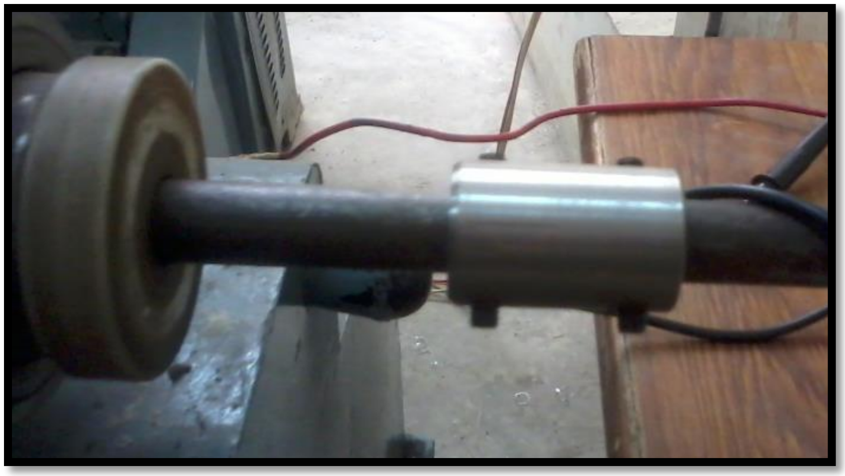


Figure 3.23 Coupling joining the iron rod and the mercury box

Figure 3.24 Mercury box

3.4.5 CALIBRATION OF TOOL-WORK THERMOCOUPLE

The purpose in calibrating the tool- work thermocouple is to develop a thermoelectric relationship between the cutting tool material and the work piece material. Shaw reported a lead bath for the heated junction medium in the calibration of the tool-work thermocouple. After a lead bath is insulated and uniformly heated, both the tool and work piece chip are inserted into the bath with a thermocouple for calibration. Here, the calibration of the tool-work thermocouple was carried out by external flame heating and the tool was calibrated directly with the work piece [21].

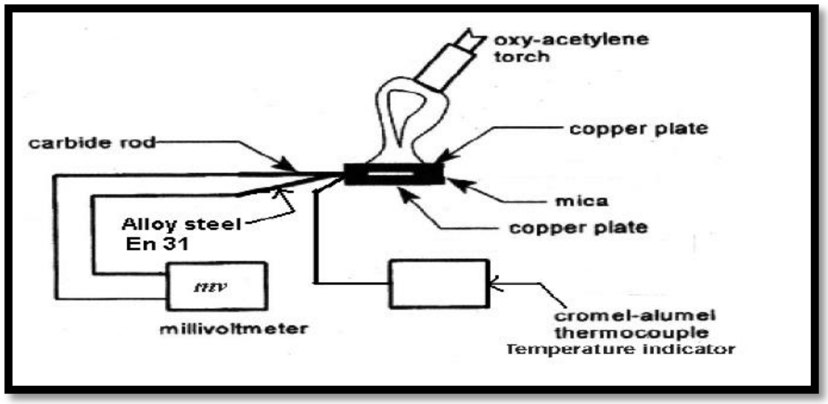


Figure 3.25 Experimental Set-up for calibrating tool-work thermocouple [21]

3.4.6 MATERIAL SPECIFICATION

ALUMINUM SHAFT

Table 3.5 Chemical Composition of Aluminium Shaft

Al	Cu	Mg	Si	Fe	Mn	Ni	Zn	Pb	Sn	Ti	Cr
98.49	0.030	0.602	0.565	0.169	0.093	0.001	0.008	0.002	0.001	0.013	0.004

The above chemical composition conforms to **IS:733 Gr: 63400 (Al 6063 Grade)**

BRASS SHAFT

Table 3.6 Chemical Composition of Brass Shaft

Cu	Sn	Zn	Pb	Fe	Ni	Al	Si	Mn	P	Cr	S
61.13	0.250	35.18	2.57	0.328	0.187	0.051	0.043	0.230	0.003	0.002	0.006

The above chemical composition conforms to **IS:318 Gr ‘2’**

STEEL SHAFT

Table 3.7 Chemical Composition of Steel Shaft

C	Si	Mn	P	S	Cr	Mo	Ni	Al	Cu	Ti	V
0.213	0.196	0.760	0.036	0.037	0.161	0.007	0.094	0.032	0.169	0.003	0.008

The above chemical composition conforms to **IS: 2062**

3.4.7 TOOL MATERIAL

Cutting tools are designed with inserts or replaceable tips. These tools are known as indexable tools. The cutting edge consists of a separate piece of material, either brazed, welded or clamped on to the tool body. Common materials for include tungsten carbide, polycrystalline diamond and cubic boron nitride.

In this experimental work three different tool materials are used namely,

a. High Speed Steel
b. Tungsten Carbide
c. Polycrystalline Diamond

After a complete study of various types of inserts the above materials were selected and the tool inserts used conforms to the "Turning Applications Manual of TaeguTec (Member IMC Group)".

GENERAL PURPOSE HIGH SPEED STEELS							
Type	CHEMICAL	COMPOSITION					
	Carbon	Tungsten	Molybdenum	Chromium	Vanadium	Hardness Rockwell C	Term
M1	.80	1.50	8.00	4.00	1.00	63-65	"HSS"
M2	.85	6.00	5.00	4.00	1.90	63-65	"HSS"
M7	1.00	1.75	8.75	4.00	2.00	63-65	"HSS"
M50	.85	.10	4.25	4.00	1.00	63-65	"HSS"

Figure 3.26 High Speed Steel Cutting Tool Data

Grade		Color	ISO Range (P M K / N S H)	Application						Workpiece Material and Application
				Turning	Milling	T-Clamp	Hole Making	Threading	End Milling / Fine Ball	
Carbide	K10	Metal	K05 - K15	●	●	●	●			General machining of cast iron
			N05 - N15	●	●	●	●			General machining of aluminum alloys and non-ferrous materials
			S05 - S15	●		●	●			General machining of heat-resistant alloy
	P30	Metal	P25 - P35	●	●					General machining of steel
	UF10	Metal	P25 - P35						●	General machining of steel
			M25 - M35						●	General machining of stainless steel
			N25 - N35		●		●		●	General machining of aluminum alloys and non-ferrous materials

Figure 3.27 Carbide Tool Grade Data

PCD	KP500	Black	N01 - N10	●	●	●			●	High Si-Al alloy, hardmetal, metal composite & ceramic composite materials
	KP300	Black	N10 - N20	●	●	●			●	General turning and milling of non-ferrous materials
	KP100	Black	N20 - N30	●	●	●			●	Non-ferrous metals. Good surface finishes

Figure 3.28 PCD Tool Grade Data

3.4.8 RECORDING OF RESPONSES

The experiment was performed with various combinations of tool and work material within the specified working range of the process control parameters. The responses (chip-tool interface temperature) determined by the experiment were recorded as follows:

Table 3.8 Experimental Temperature value with corresponding EMF

TOOL MATERIAL – Tungsten carbide WORK MATERIAL – Mild Steel				
S. NO.	**CUTTING SPEED (m/min)**	**DEPTH OF CUT (mm)**	**EMF GENERATED (mV)**	**CHIP-TOOL INTERFACE TEMPERATURE (°C)**
1	233	0.5	3.763	95.6286
2	233	1.0	4.063	99.1654
3	233	1.5	4.263	104.0056
4	233	2.0	5.063	123.4944
5	233	2.5	5.163	125.9460
6	233	3.0	5.163	125.9460
7	233	3.5	5.163	125.9460
8	233	4.0	5.163	125.9460
9	340	0.5	4.113	100.3744
10	340	1.0	4.663	113.7230
11	340	1.5	5.063	123.4944
12	340	2.0	5.463	133.3207
13	340	2.5	5.563	135.7865
14	340	3.0	5.463	133.3207
15	340	3.5	5.663	138.2549
16	340	4.0	5.663	138.2549
17	530	0.5	4.013	97.9571
18	530	1.0	5.063	123.4944
19	530	1.5	5.463	133.3207
20	530	2.0	5.963	145.6784
21	530	2.5	6.113	149.3998
22	530	3.0	6.013	146.6183
23	530	3.5	6.363	155.6147
24	530	4.0	6.413	156.8594

Table 3.9 Experimental Temperature value with corresponding EMF

TOOL MATERIAL – Tungsten Carbide WORK MATERIAL – Aluminium				
S. NO.	**CUTTING SPEED (m/min)**	**DEPTH OF CUT (mm)**	**EMF GENERATED (mV)**	**CHIP-TOOL INTERFACE TEMPERATURE (°C)**
1	233	0.5	1.413	35.1634
2	233	1.0	1.463	36.3892
3	233	1.5	1.513	37.6137
4	233	2.0	1.413	35.1634
5	233	2.5	1.563	38.8368
6	233	3.0	1.513	37.6137
7	233	3.5	1.663	41.2791
8	233	4.0	1.713	42.4983
9	340	0.5	1.513	37.6137
10	340	1.0	1.613	40.0586
11	340	1.5	1.663	41.2791
12	340	2.0	1.713	42.4983
13	340	2.5	1.813	44.9330
14	340	3.0	1.813	44.9330
15	340	3.5	1.913	47.3631
16	340	4.0	1.963	48.5765
17	530	0.5	1.613	40.0586
18	530	1.0	1.713	42.4983
19	530	1.5	1.763	43.7163
20	530	2.0	1.863	46.1487
21	530	2.5	1.963	48.5765
22	530	3.0	2.063	51.4133
23	530	3.5	1.913	47.3631
24	530	4.0	1.863	46.1487

Table 3.10 Experimental Temperature value with corresponding EMF

TOOL MATERIAL – Tungsten Carbide WORK MATERIAL – Brass				
S. NO.	**CUTTING SPEED (m/min)**	**DEPTH OF CUT (mm)**	**EMF GENERATED (mV)**	**CHIP-TOOL INTERFACE TEMPERATURE (°C)**
1	233	0.5	1.363	33.9362
2	233	1.0	1.413	35.1634
3	233	1.5	1.413	35.1634
4	233	2.0	1.313	32.7075
5	233	2.5	1.363	33.9362
6	233	3.0	1.363	33.9362
7	233	3.5	1.363	33.9362
8	233	4.0	1.363	33.9362
9	340	0.5	1.363	33.9362
10	340	1.0	1.613	40.0586
11	340	1.5	1.613	40.0586
12	340	2.0	1.613	40.0586
13	340	2.5	1.613	40.0586
14	340	3.0	1.613	40.0586
15	340	3.5	1.613	40.0586
16	340	4.0	1.613	40.0586
17	530	0.5	1.613	40.0586
18	530	1.0	1.663	41.2791
19	530	1.5	1.763	43.7163
20	530	2.0	1.663	41.2791
21	530	2.5	1.663	41.2791
22	530	3.0	1.663	41.2791
23	530	3.5	1.663	41.2791
24	530	4.0	1.663	41.2791

Table 3.11 Experimental Temperature value with corresponding EMF

TOOL MATERIAL – Polycrystalline Diamond WORK MATERIAL – Aluminium				
S. NO.	**CUTTING SPEED (m/min)**	**DEPTH OF CUT (mm)**	**EMF GENERATED (mV)**	**CHIP-TOOL INTERFACE TEMPERATURE (°C)**
1	233	0.5	1.763	43.7163
2	233	1.0	1.913	47.3631
3	233	1.5	2.413	59.4555
4	233	2.0	2.263	55.8366
5	233	2.5	2.413	59.4555
6	233	3.0	2.413	59.4555
7	233	3.5	2.363	58.2499
8	233	4.0	2.363	58.2499
9	340	0.5	3.013	73.8881
10	340	1.0	2.563	63.0688
11	340	1.5	2.713	66.6778
12	340	2.0	2.663	65.4804
13	340	2.5	2.663	65.4804
14	340	3.0	2.863	70.2838
15	340	3.5	2.813	69.0821
16	340	4.0	2.763	67.8801
17	530	0.5	2.513	61.8649
18	530	1.0	2.563	63.0688
19	530	1.5	2.263	55.8366
20	530	2.0	2.563	63.0688
21	530	2.5	2.713	66.6778
22	530	3.0	2.813	69.0821
23	530	3.5	2.863	70.2838
24	530	4.0	2.913	71.5560

Table 3.12 Experimental Temperature value with corresponding EMF

TOOL MATERIAL – HSS WORK MATERIAL – Aluminium				
S. NO.	**CUTTING SPEED (m/min)**	**DEPTH OF CUT (mm)**	**EMF GENERATED (mV)**	**CHIP-TOOL INTERFACE TEMPERATURE (°C)**
1	233	0.5	1.363	33.9362
2	233	1.0	1.513	37.6317
3	233	1.5	1.713	42.4983
4	233	2.0	1.813	44.9330
5	233	2.5	1.813	44.9330
6	233	3.0	1.763	43.7163
7	233	3.5	1.863	46.1487
8	233	4.0	1.963	48.5765
9	340	0.5	1.413	35.1634
10	340	1.0	1.413	35.1634
11	340	1.5	1.563	38.8368
12	340	2.0	1.863	46.1487
13	340	2.5	1.963	48.5765
14	340	3.0	1.813	44.9330
15	340	3.5	2.063	51.4133
16	340	4.0	2.113	52.2111
17	530	0.5	1.613	40.0586
18	530	1.0	1.763	43.7163
19	530	1.5	1.813	44.9330
20	530	2.0	1.913	47.3631
21	530	2.5	1.963	48.5765
22	530	3.0	2.013	49.7889
23	530	3.5	2.463	60.6605
24	530	4.0	2.513	61.8649

Table 3.13 Experimental Temperature value with corresponding EMF

TOOL MATERIAL – HSS WORK MATERIAL – Brass				
S. NO.	**CUTTING SPEED (m/min)**	**DEPTH OF CUT (mm)**	**EMF GENERATED (mV)**	**CHIP-TOOL INTERFACE TEMPERATURE (°C)**
1	233	0.5	1.613	40.0586
2	233	1.0	2.113	52.2111
3	233	1.5	2.113	52.2111
4	233	2.0	2.113	52.2111
5	233	2.5	2.113	52.2111
6	233	3.0	2.113	52.2111
7	233	3.5	2.013	49.7889
8	233	4.0	2.013	49.7889
9	340	0.5	1.463	36.3892
10	340	1.0	2.213	54.6288
11	340	1.5	2.213	54.6288
12	340	2.0	2.213	54.6288
13	340	2.5	2.213	54.6288
14	340	3.0	2.213	54.6288
15	340	3.5	2.263	55.8366
16	340	4.0	2.263	55.8366
17	530	0.5	1.313	32.7075
18	530	1.0	2.463	60.6605
19	530	1.5	2.513	61.8649
20	530	2.0	2.513	61.8649
21	530	2.5	2.513	61.8649
22	530	3.0	2.513	61.8649
23	530	3.5	2.513	61.8649
24	530	4.0	2.513	61.8649

Table 3.14 Experimental Temperature value with corresponding EMF

TOOL MATERIAL – Polycrystalline Diamond WORK MATERIAL – Brass				
S. NO.	**CUTTING SPEED (m/min)**	**DEPTH OF CUT (mm)**	**EMF GENERATED (mV)**	**CHIP-TOOL INTERFACE TEMPERATURE (°C)**
1	233	0.5	2.113	52.2111
2	233	1.0	2.413	59.4555
3	233	1.5	2.413	59.4555
4	233	2.0	2.413	59.4555
5	233	2.5	2.413	59.4555
6	233	3.0	2.413	59.4555
7	233	3.5	2.413	59.4555
8	233	4.0	2.413	59.4555
9	340	0.5	2.063	51.4133
10	340	1.0	2.363	58.2499
11	340	1.5	2.363	58.2499
12	340	2.0	2.713	66.6778
13	340	2.5	2.713	66.6778
14	340	3.0	2.813	69.0821
15	340	3.5	2.913	71.5560
16	340	4.0	2.963	72.6868
17	530	0.5	2.513	61.8649
18	530	1.0	2.713	66.6778
19	530	1.5	2.613	64.2722
20	530	2.0	2.163	53.4201
21	530	2.5	2.813	69.0821
22	530	3.0	3.013	73.8881
23	530	3.5	2.913	71.5560
24	530	4.0	2.913	71.5560

Chapter 4

DEVELOPMENT OF MATHEMATICAL MODEL USING REGRESSION ANALYSIS

4.1 INTRODUCTION

In many problems two or more variables are related, and it is of interest to model and explore this relationship. For example, in a chemical process the yield of product is related to the operating temperature. The engineer may want to build a model relating yields to temperature and then use the model for prediction, process optimization, or process control.

In general, suppose that there is a single dependent variable or response y that depends on k independent or regressor variables, for example, x_1, x_2, ……., x_k. The relationship between these variables is characterized by a mathematical model called regression model. The regression model is fit to a set of sample data.

There is a strong interplay between design of experiment and regression analysis. The emphasis is on the importance of expressing the result of an experiment quantitatively, in terms of an empirical model, to facilitate understanding, interpretation, and implementation. Regression models are the basis for this.

4.2 LINEAR REGRESSION MODELS

Consider an example to develop an empirical model relating the viscosity of a polymer to the temperature and the catalysts feed rate. A model that might describe this relationship is

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \varepsilon \qquad (4.1)$$

where y represents the viscosity, x_1 represents the temperature, and x_2 represents the catalysts feed rate. This is a multiple linear regression model with two independent variables. The independent variables are also known as predictor variables or regressors.

The term linear is used because the equation is a linear function of the unknown parameters β_0, β_1, and β_2. The model describes a plane in the two- dimensional x_1, x_2 space. The parameter β_0 defines the intercept of the plane and β_1 and β_2 are partial regression coefficients because β_1 measures the expected change in y per unit change in x_1 when x_2 is held constant and β_2 measures the expected change in y per unit change in x_2 when x_1 is held constant.

In general, the response variable y may be related to k regressor variables. The model with general equation

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots\ldots + \beta_k x_k + \varepsilon \qquad (4.2)$$

is called a multiple linear regression model with k regressor variables. The parameters β_j, j=0, 1 ….. , k are called the regression coefficients. This model describes a hyperplane in the k- dimensional space of the regressor variables $\{x_j\}$. The parameters β_j represents the expected change in response y per unit change in x_j when all the remaining independent variables x_i (i=j) are held constant.

Models that are more complex in appearance than equation may often still be analyzed by multiple linear regression techniques. For example, consider adding an interaction term to the first- order model in two variables,

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_{12} x_1 x_2 + \varepsilon \qquad (4.3)$$

if $x_3 = x_1 x_2$ and $\beta_3 = \beta_{12}$, then equation can be written as

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \varepsilon \qquad (4.4)$$

which is a standard multiple linear regression model with three regressors.

Consider the second- order response surface model in two variables:

$$y = \beta_0 + \beta_i x_1 + \beta_2 x_2 + \beta_{11} x_1^2 + \beta_{22} x_2^2 + \beta_{12} x_1 x_2 + \varepsilon \qquad (4.5)$$

If $x_3 = x_1^2$, $x_4 = x_2^2$, $x_5 = x_1 x_2$, $\beta_3 = \beta_{11}$, $\beta_4 = \beta_{22}$ and $\beta_5 = \beta_{12}$, then this becomes

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \varepsilon \qquad (4.6)$$

which is a linear regression model.

Therefore, in general any regression model that is linear in the parameters (the β's) is a linear regression model, regardless of the shape of the response surface that it generates. The methods of estimating the parameters in multiple linear regression models is called model fitting.

4.3 ESTIMATION OF THE PARAMETERS IN LINEAR REGRESSION MODEL

The method of least square is typically used to estimate the regression coefficients in a multiple linear regression model. Suppose that n > k observations on the response variable are available, say $y_1, y_2, \ldots, y_n$. Along with each observed response y_i, there will be an observation on each regressor variable and let x_{ij} denote the *i*th observation or level of variable x_j. The data will appear as in table 4.1. A assumption is made that the error term ε in the model has E (x) = 0 and V (ε) = σ^2 and that the $\{\varepsilon_i\}$ are uncorrelated random variable.

Therefore the model equation (equation 4.2) can be written in terms of the observation in table 4.1 as

$$\begin{aligned} y_i &= \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_k x_{ik} + \epsilon_i \\ &= \beta_0 + \sum_{j=1}^{k} \beta_j x_{ij} + \epsilon_i \qquad i = 1, 2, \ldots, n \end{aligned} \tag{4.7}$$

Table 4.1 Data for Multiple Linear Regression (D. C. Montgomery)

y	x_1	x_2	$\cdots$	x_k
y_1	x_{11}	x_{12}	$\cdots$	x_{1k}
y_2	x_{21}	x_{22}	$\cdots$	x_{2k}
$\vdots$	$\vdots$	$\vdots$		$\vdots$
y_n	x_{n1}	x_{n2}	$\cdots$	x_{nk}

The method of least square chooses the β's in equation 4.7 so that the sum of the square of the errors, ε_i, is minimized. The least squares function is

$$L = \sum_{i=1}^{n} \epsilon_i^2 = \sum_{i=1}^{n} \left(y_i - \beta_0 - \sum_{j=1}^{k} \beta_j x_{ij} \right)^2 \tag{4.8}$$

The function L is to be minimized with respect to $\beta_0, \beta_1, \ldots\ldots, \beta_k$. the least square estimators, say $\beta_0, \beta_1, \ldots.., \beta_k$, must satisfy

$$\left.\frac{\partial L}{\partial \beta_0}\right|_{\hat{\beta}_0, \hat{\beta}_1, \ldots, \hat{\beta}_k} = -2 \sum_{i=1}^{n} \left(y_i - \hat{\beta}_0 - \sum_{j=1}^{k} \hat{\beta}_j x_{ij} \right) = 0$$

and

$$\left.\frac{\partial L}{\partial \beta_j}\right|_{\hat{\beta}_0, \hat{\beta}_1, \ldots, \hat{\beta}_k} = -2 \sum_{i=1}^{n} \left(y_i - \hat{\beta}_0 - \sum_{j=1}^{k} \hat{\beta}_j x_{ij} \right) x_{ij} = 0 \qquad j = 1, 2, \ldots, k \tag{4.9a, 4.9b}$$

Simplifying equation 4.9, then

$$\begin{array}{l}
n\hat{\beta}_0 + \hat{\beta}_1 \sum_{i=1}^{n} x_{i1} + \hat{\beta}_2 \sum_{i=1}^{n} x_{i2} + \cdots + \hat{\beta}_k \sum_{i=1}^{n} x_{ik} = \sum_{i=1}^{n} y_i \\
\hat{\beta}_0 \sum_{i=1}^{n} x_{i1} + \hat{\beta}_1 \sum_{i=1}^{n} x_{i1}^2 + \hat{\beta}_2 \sum_{i=1}^{n} x_{i1}x_{i2} + \cdots + \hat{\beta}_k \sum_{i=1}^{n} x_{i1}x_{ik} = \sum_{i=1}^{n} x_{i1}y_i \\
\vdots \\
\hat{\beta}_0 \sum_{i=1}^{n} x_{ik} + \hat{\beta}_i \sum_{i=1}^{n} x_{ik}x_{i1} + \hat{\beta}_2 \sum_{i=1}^{n} x_{ik}x_{i2} + \cdots + \hat{\beta}_k \sum_{i=1}^{n} x_{ik}^2 = \sum_{i=1}^{n} x_{ik}y_i
\end{array} \tag{4.10}$$

These equation are called the least square normal equations. Note that there are p= k + 1 normal equations, one for each of the unknown regression coefficients. The solutions to the normal equations will be the least squares estimators of the regression coefficient β_0, $\beta_1, \ldots\ldots, \beta_k$.

It is simpler to solve the normal equations if they are expressed in matrix notation as given below.

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\epsilon} \tag{4.11}$$

where

$$\mathbf{y} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}, \qquad \mathbf{X} = \begin{bmatrix} 1 & x_{11} & x_{12} & \cdots & x_{1k} \\ 1 & x_{21} & x_{22} & \cdots & x_{2k} \\ \vdots & \vdots & \vdots & & \vdots \\ 1 & x_{n1} & x_{n2} & \cdots & x_{nk} \end{bmatrix},$$

$$\boldsymbol{\beta} = \begin{bmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_k \end{bmatrix} \quad \text{and} \quad \boldsymbol{\epsilon} = \begin{bmatrix} \epsilon_1 \\ \epsilon_2 \\ \vdots \\ \epsilon_n \end{bmatrix}$$

The fitted regression model is

$$\hat{\mathbf{y}} = \mathbf{X}\hat{\boldsymbol{\beta}}$$

In scalar notation, the fitted model is

$$\hat{y}_i = \hat{\beta}_0 + \sum_{i=1}^{k} \hat{\beta}_j x_{ij} \qquad i = 1, 2, \ldots, n$$

The difference between the actual observation y_i and the corresponding fitted value $\hat{y}_i$, is the residual, say $e_i = y_i - \hat{y}_i$. Then (n*1) vector of residual is denoted by

$$\mathbf{e} = \mathbf{y} - \hat{\mathbf{y}}$$

4.4 DESIGN OF MATHEMATICAL MODEL W.R.T. EXPERIMENT

A mathematical model can be proposed to develop a relationship between the process variables (dependent variables) and the output variable (response) which will further help in predicting the response. This model can be used as input in the computer to predict the response for various combinations of input parameters. The experimental data was used to develop the model and the analysis of the model was carried out by the ANOVA (ANalysis Of VAriance) and surface plots. The software used for this model development and analysis was MINITAB 16.

4.4.1 DEVELOPMENT OF MODEL

The response function can be expressed as: **Y = Φ (V, D)**

where Y = Response (chip-tool interface temperature); V = Cutting speed (m/min); D = Depth of cut (mm)

Using the equation 4.3, the regression equation can be formulated as

$$\mathbf{Y = \beta_0 + \beta_1 V + \beta_2 D + \beta_{12} V{*}D} \tag{4.12}$$

where β_0 is constant while β_1, β_2, and β_{12} are partial regression coefficients of the model.

4.4.2 EVALUATION OF THE COEFFICIENTS OF MODEL

The values of the coefficient of the response surface were calculated using the regression analysis. The calculations were carried out using the software package Minitab 16 and the values are given in the tabular form:

Table 4.2 Description of tool and work material with combination number

COMBINATION NO.	TOOL MATERIAL	WORKPIECE MATERIAL
1	Tungsten Carbide	Mild Steel
2	Tungsten Carbide	Aluminium
3	Tungsten Carbide	Brass
4	Poly-Crystalline Diamond	Aluminium
5	High Speed Steel	Aluminium
6	High Speed Steel	Brass
7	Poly-Crystalline Diamond	Brass

Table 4.3 Values of coefficients obtained from Minitab 16 software for various tool-work material combinations

COMBINATION NO.	VALUE OF β_0	VALUE OF β_1	VALUE OF β_2	VALUE OF β_{12}
1	87.8528	0.0364173	5.19486	0.0171856
2	28.5064	0.0233002	2.21404	0.000423852
3	29.1979	0.0229529	0.248613	0.0000901811
4	47.9813	0.025205	1.95918	0.00127404
5	32.1399	0.00603885	2.05817	0.00785572
6	46.2108	0.000272313	1.13838	0.0119095
7	49.8266	0.0150567	1.80926	0.00447773

4.4.3 FORMULATION OF REGRESSION EQUATIONS

Using the equation 4.12, the regression equations are formed for various tool-work material combinations. These equations are given as follows:

COMBINATION NO. 1:

Cutting Temperature (T) = 87.8528 + 0.0364173*V + 5.19486*D + 0.0171856*V*D

COMBINATION NO. 2:

Cutting Temperature (T) = 28.5064 + 0.0233002*V + 2.21404*D + 0.000423852*V*D

COMBINATION NO. 3:

Cutting Temperature (T) = 29.1979 + 0.0229529*V + 0.248613*D +0.0000901811*V*D

COMBINATION NO. 4:

Cutting Temperature (T) = 47.9813 + 0.025205*V + 1.95918*D + 0.00127404*V*D

COMBINATION NO. 5:

Cutting Temperature (T) = 32.1399 + 0.00603885*V + 2.05817*D + 0.00785572*V*D

COMBINATION NO. 6:

Cutting Temperature (T) = 46.2108 + 0.000272313*V + 1.13838*D + 0.0119095*V*D

COMBINATION NO. 7:

Cutting Temperature (T) = 49.8266 + 0.0150567*V + 1.80926*D + 0.00447773*V*D

4.4.4 MINITAB OUTPUT OF REGRESSION EQUATIONS

The following results were obtained from the software Minitab 16 by giving raw input to the software:

COMBINATION NO. 1:

```
Regression Equation

Temperature  =  87.8528 + 0.0364173 Cutting Speed + 5.19486 Depth of Cut +
                0.0171856 Speed.Depth of Cut


Coefficients
```

Term	Coef	SE Coef	T	P
Constant	87.8528	10.5130	8.35662	0.000
Cutting Speed	0.0364	0.0271	1.34279	0.194
Depth of Cut	5.1949	4.1638	1.24764	0.227
Speed.Depth of Cut	0.0172	0.0107	1.59995	0.125

COMBINATION NO. 2:

```
Regression Equation

Temperature  =  28.5064 + 0.0233002 Cutting Speed + 2.21404 Depth of Cut +
                0.000423852 Speed.Depth of Cut


Coefficients
```

Term	Coef	SE Coef	T	P
Constant	28.5064	3.09980	9.19619	0.000
Cutting Speed	0.0233	0.00800	2.91374	0.009
Depth of Cut	2.2140	1.22770	1.80340	0.086
Speed.Depth of Cut	0.0004	0.00317	0.13383	0.895

COMBINATION NO. 3:

```
Regression Equation

Temperature  =  29.1979 + 0.0229529 Cutting Speed + 0.248613 Depth of Cut +
                9.01811e-005 Speed.Depth of Cut


Coefficients
```

Term	Coef	SE Coef	T	P
Constant	29.1979	2.76594	10.5562	0.000
Cutting Speed	0.0230	0.00714	3.2168	0.004
Depth of Cut	0.2486	1.09548	0.2269	0.823
Speed.Depth of Cut	0.0001	0.00283	0.0319	0.975

COMBINATION NO. 4:

Regression Equation

```
Temperature  =  47.9813 + 0.025205 Cutting Speed + 1.95918 Depth of Cut +
                0.00127404 Speed.Depth of Cut
```

Coefficients

Term	Coef	SE Coef	T	P
Constant	47.9813	8.77833	5.46588	0.000
Cutting Speed	0.0252	0.02265	1.11301	0.279
Depth of Cut	1.9592	3.47674	0.56351	0.579
Speed.Depth of Cut	0.0013	0.00897	0.14205	0.888

COMBINATION NO. 5:

Regression Equation

```
Temperature  =  32.1399 + 0.00603885 Cutting Speed + 2.05817 Depth of Cut +
                0.00785572 Speed.Depth of Cut
```

Coefficients

Term	Coef	SE Coef	T	P
Constant	32.1399	3.55503	9.04069	0.000
Cutting Speed	0.0060	0.00917	0.65847	0.518
Depth of Cut	2.0582	1.40800	1.46177	0.159
Speed.Depth of Cut	0.0079	0.00363	2.16276	0.043

COMBINATION NO. 6:

Regression Equation

```
Temperature  =  46.2108 + 0.000272313 Cutting Speed - 1.13838 Depth of Cut +
                0.0119095 Speed.Depth of Cut
```

Coefficients

Term	Coef	SE Coef	T	P
Constant	46.2108	8.78903	5.25779	0.000
Cutting Speed	0.0003	0.02267	0.01201	0.991
Depth of Cut	-1.1384	3.48097	-0.32703	0.747
Speed.Depth of Cut	0.0119	0.00898	1.32623	0.200

COMBINATION NO. 7:

Regression Equation

```
Temperature  =  49.8266 + 0.0150567 Cutting Speed + 1.80926 Depth of Cut +
                0.00447773 Speed.Depth of Cut
```

Coefficients

Term	Coef	SE Coef	T	P
Constant	49.8266	6.43040	7.74860	0.000
Cutting Speed	0.0151	0.01659	0.90765	0.375
Depth of Cut	1.8093	2.54682	0.71040	0.486
Speed.Depth of Cut	0.0045	0.00657	0.68153	0.503

4.4.5 ANALYSIS OF ADEQUACY OF THE MODEL

A one-way analysis of variance (ANOVA) tests the hypothesis that the means of several populations are equal. The method is an extension of the two-sample t-test, specifically for the case where the population variances are assumed to be equal. A one-way analysis of variance requires the following:

a. A response or measurement taken from the units sampled.
b. A factor or discrete variable that is altered systematically. The different values chosen for the factor variable are called levels of the factor. Each level of the factor in the analysis corresponds to a larger population with its own mean. The sample mean is an estimate of the level mean for the whole population.

ANOVA software was used to check the adequacy of the developed models based on the following rules:

a. The F-ratio of the developed model is calculated and is compared with the standard tabulated value of F-ratio for a specific level of confidence.
b. If calculated value of F-ratio does not exceed the tabulated value, then with the corresponding confidence probability the model may be considered adequate. For this analysis, the confidence interval is taken as 95%.

4.4.6 ANOVA OUTPUT FOR ADEQUACY OF MODEL

The following results were obtained by the ANOVA software by giving the raw input to the software:

COMBINATION NO. 1:

Source	DF	SS	MS	F	P
Cutting Speed	2	2090.01	1045.01	43.15	0.000
Depth of Cut	7	5024.28	717.75	29.64	0.000
Error	14	339.08	24.22		
Total	23	7453.37			

S = 4.921   R-Sq = 95.45%   R-Sq(adj) = 92.53%

COMBINATION NO. 2:

Source	DF	SS	MS	F	P
Cutting Speed	2	247.394	123.697	33.21	0.000
Depth of Cut	7	185.745	26.535	7.12	0.001
Error	14	52.144	3.725		
Total	23	485.282			

S = 1.930   R-Sq = 89.25%   R-Sq(adj) = 82.35%

COMBINATION NO. 3:

Source	DF	SS	MS	F	P
Cutting Speed	2	228.141	114.071	74.33	0.000
Depth of Cut	7	22.889	3.270	2.13	0.108
Error	14	21.484	1.535		
Total	23	272.514			

S = 1.239   R-Sq = 92.12%   R-Sq(adj) = 87.05%

COMBINATION NO. 4:

Source	DF	SS	MS	F	P
Cutting Speed	2	698.89	349.446	15.24	0.000
Depth of Cut	7	216.25	30.893	1.35	0.300
Error	14	321.01	22.929		
Total	23	1236.15			

S = 4.788   R-Sq = 74.03%   R-Sq(adj) = 57.34%

COMBINATION NO. 5:

Source	DF	SS	MS	F	P
Cutting Speed	2	211.05	105.523	14.44	0.000
Depth of Cut	7	815.69	116.527	15.95	0.000
Error	14	102.28	7.306		
Total	23	1129.01			

S = 2.703   R-Sq = 90.94%   R-Sq(adj) = 85.12%

COMBINATION NO. 6:

Source	DF	SS	MS	F	P
Cutting Speed	2	265.76	132.882	12.67	0.001
Depth of Cut	7	1017.16	145.308	13.86	0.000
Error	14	146.80	10.486		
Total	23	1429.72			

S = 3.238   R-Sq = 89.73%   R-Sq(adj) = 83.13%

COMBINATION NO. 7:

Source	DF	SS	MS	F	P
Cutting Speed	2	272.24	136.118	6.17	0.012
Depth of Cut	7	443.43	63.348	2.87	0.044
Error	14	308.86	22.062		
Total	23	1024.53			

S = 4.697   R-Sq = 69.85%   R-Sq(adj) = 50.47%

4.5 ANALYSIS AND DISCUSSION OF RESULTS

4.5.1 RESULTS OF THE MATHEMATICAL MODEL

The results obtained from the mathematical models depending on the regression equations are tabulated for different tool-work material combinations as follows:

Table 4.4 Predicted temperature for tungsten carbide (tool) and mild steel (work)

READING NO.	CUTTING SPEED (m/min)	DEPTH OF CUT (mm)	CHIP-TOOL INTERFACE TEMPERATURE (°C)
1	233	0.5	100.9375824
2	233	1.0	105.5371348
3	233	1.5	110.1366872
4	233	2.0	114.7362396
5	233	2.5	119.335792
6	233	3.0	123.9353444
7	233	3.5	128.5348968
8	233	4.0	133.1344492
9	340	0.5	105.753664
10	340	1.0	111.272646
11	340	1.5	116.791628
12	340	2.0	122.31061
13	340	2.5	127.289592
14	340	3.0	133.348574
15	340	3.5	138.867556
16	340	4.0	144.386538
17	530	0.5	114.305583
18	530	1.0	121.457197
19	530	1.5	128.608811
20	530	2.0	135.760425
21	530	2.5	142.912039
22	530	3.0	150.063653
23	530	3.5	157.215267
24	530	4.0	164.366881

Table 4.5 Predicted temperature for tungsten carbide (tool) and aluminium (work)

READING NO.	**CUTTING SPEED (m/min)**	**DEPTH OF CUT (mm)**	**CHIP-TOOL INTERFACE TEMPERATURE (°C)**
1	233	0.5	35.09174536
2	233	1.0	36.24814412
3	233	1.5	37.40454287
4	233	2.0	38.56094163
5	233	2.5	39.71763845
6	233	3.0	40.87373915
7	233	3.5	42.03013791
8	233	4.0	43.18653666
9	340	0.5	37.60754284
10	340	1.0	38.78636048
11	340	1.5	39.96569252
12	340	2.0	41.14476736
13	340	2.5	42.3238422
14	340	3.0	43.50291704
15	340	3.5	44.68229188
16	340	4.0	45.8610652
17	530	0.5	42.074484678
18	530	1.0	43.29418756
19	530	1.5	44.51352834
20	530	2.0	45.73286912
21	530	2.5	46.9522099
22	530	3.0	48.17155068
23	530	3.5	49.39089146
24	530	4.0	50.61023224

Table 4.6 Predicted temperature for tungsten carbide (tool) and brass (work)

READING NO.	CUTTING SPEED (m/min)	DEPTH OF CUT (mm)	CHIP-TOOL INTERFACE TEMPERATURE (°C)
1	233	0.5	34.68073318
2	233	1.0	34.8155509
3	233	1.5	34.95036349
4	233	2.0	35.08527609
5	233	2.5	35.22005869
6	233	3.0	35.35480129
7	233	3.5	35.49019076
8	233	4.0	35.62442649
9	340	0.5	37.14152329
10	340	1.0	37.28116057
11	340	1.5	37.42079786
12	340	2.0	37.56043515
13	340	2.5	37.70007244
14	340	3.0	37.83970972
15	340	3.5	37.97934701
16	340	4.0	38.1189843
17	530	0.5	41.51114149
18	530	1.0	41.65934598
19	530	1.5	41.80755047
20	530	2.0	41.95575497
21	530	2.5	42.10395946
22	530	3.0	42.25216395
23	530	3.5	42.40036844
24	530	4.0	42.54857272

Table 4.7 Predicted temperature for PCD (tool) and aluminium (work)

READING NO.	CUTTING SPEED (m/min)	DEPTH OF CUT (mm)	CHIP-TOOL INTERFACE TEMPERATURE (°C)
1	233	0.5	54.98208066
2	233	1.0	56.11009632
3	233	1.5	57.23811198
4	233	2.0	58.36612764
5	233	2.5	59.4941433
6	233	3.0	60.62215896
7	233	3.5	61.75012962
8	233	4.0	62.8748378
9	340	0.5	57.7471768
10	340	1.0	59.0033536
11	340	1.5	60.1395304
12	340	2.0	61.3357072
13	340	2.5	62.531884
14	340	3.0	63.7280608
15	340	3.5	64.9242376
16	340	4.0	66.1204144
17	530	0.5	62.6271606
18	530	1.0	63.9743712
19	530	1.5	65.2915818
20	530	2.0	66.6087924
21	530	2.5	67.926003
22	530	3.0	69.2432166
23	530	3.5	70.5604242
24	530	4.0	71.87766348

Table 4.8 Predicted temperature for high speed steel (tool) and aluminium(work)

READING NO.	CUTTING SPEED (m/min)	DEPTH OF CUT (mm)	CHIP-TOOL INTERFACE TEMPERATURE (°C)
1	233	0.5	35.49122638
2	233	1.0	37.43550276
3	233	1.5	39.37977914
4	233	2.0	41.32405552
5	233	2.5	43.2683319
6	233	3.0	45.21260828
7	233	3.5	47.15688466
8	233	4.0	49.10116104
9	340	0.5	36.5576664
10	340	1.0	38.9222238
11	340	1.5	41.2867812
12	340	2.0	43.6513386
13	340	2.5	46.015896
14	340	3.0	48.3804534
15	340	3.5	50.7450108
16	340	4.0	53.1095682
17	530	0.5	38.4513413
18	530	1.0	41.5621921
19	530	1.5	44.6730429
20	530	2.0	47.7838937
21	530	2.5	50.8947445
22	530	3.0	54.0055953
23	530	3.5	57.1164461
24	530	4.0	60.2272969

Table 4.9 Predicted temperature for high speed steel (tool) and brass (work)

READING NO.	CUTTING SPEED (m/min)	DEPTH OF CUT (mm)	CHIP-TOOL INTERFACE TEMPERATURE (°C)
1	233	0.5	47.1024755
2	233	1.0	47.9107815
3	233	1.5	48.72904825
4	233	2.0	49.547315
5	233	2.5	50.36558175
6	233	3.0	50.614513
7	233	3.5	52.00211525
8	233	4.0	52.820382
9	340	0.5	47.7588114
10	340	1.0	49.2142364
11	340	1.5	50.6696614
12	340	2.0	52.1250864
13	340	2.5	53.5805114
14	340	3.0	55.0359364
15	340	3.5	56.4914614
16	340	4.0	57.9467864
17	530	0.5	48.94195339
18	530	1.0	51.52878089
19	530	1.5	54.11560839
20	530	2.0	56.70243589
21	530	2.5	59.28916339
22	530	3.0	61.30690089
23	530	3.5	64.46291839
24	530	4.0	67.04974589

Table 4.10 Predicted temperature for PCD (tool) and brass (work)

READING NO.	CUTTING SPEED (m/min)	DEPTH OF CUT (mm)	CHIP-TOOL INTERFACE TEMPERATURE (°C)
1	233	0.5	54.76109665
2	233	1.0	56.18738219
3	233	1.5	57.61366774
4	233	2.0	59.03995328
5	233	2.5	60.46623883
6	233	3.0	61.89252437
7	233	3.5	63.31880992
8	233	4.0	64.74509546
9	340	0.5	56.6117221
10	340	1.0	58.2775662
11	340	1.5	59.9434103
12	340	2.0	61.6092544
13	340	2.5	63.2750985
14	340	3.0	64.9409426
15	340	3.5	66.6067867
16	340	4.0	68.2726308
17	530	0.5	59.89787943
18	530	1.0	61.9891079
19	530	1.5	64.08033635
20	530	2.0	66.1715648
21	530	2.5	68.26279325
22	530	3.0	70.3540217
23	530	3.5	72.44525015
24	530	4.0	74.5364786

4.5.2 GRAPHICAL OUTPUT OF MATHEMATICAL MODEL

The results obtained from the mathematical models depending on the regression equations for different tool-work material combinations are plotted showing the main effects and interaction of the cutting parameters on the response variable i.e. chip tool interface temperature. These are explained as follows:

COMBINATION NO. 1:

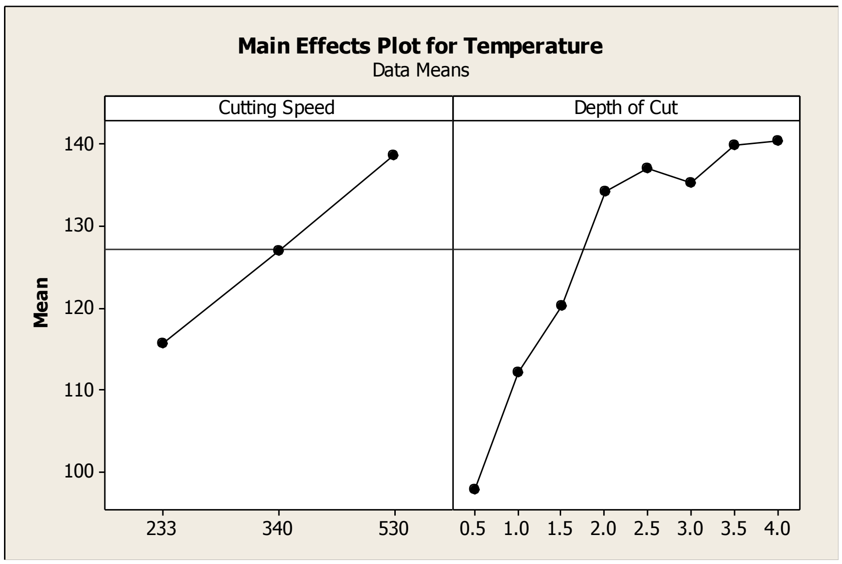


Figure 4.1 Main Effects Plot for Temperature

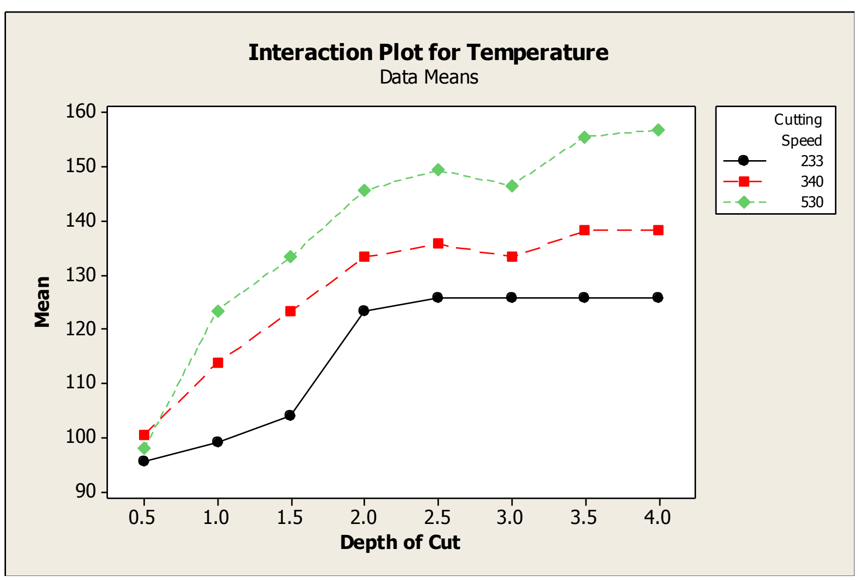


Figure 4.2 Interaction Plot for Temperature

The plot of main effects for tungsten carbide tool and mild steel work shows that when cutting speed increases from 233 m/min to 340 m/min and further to 530 m/min, the chip tool interface temperature increases. While when depth of cut increases the temperature reaches its maximum value at 2.5 mm of DOC and then decreases and further increases as DOC is increased.

The interaction plot shows how the chip-tool interface temperature varies at different cutting speeds between 0.5 to 4.0 mm DOC range.

COMBINATION NO. 2:

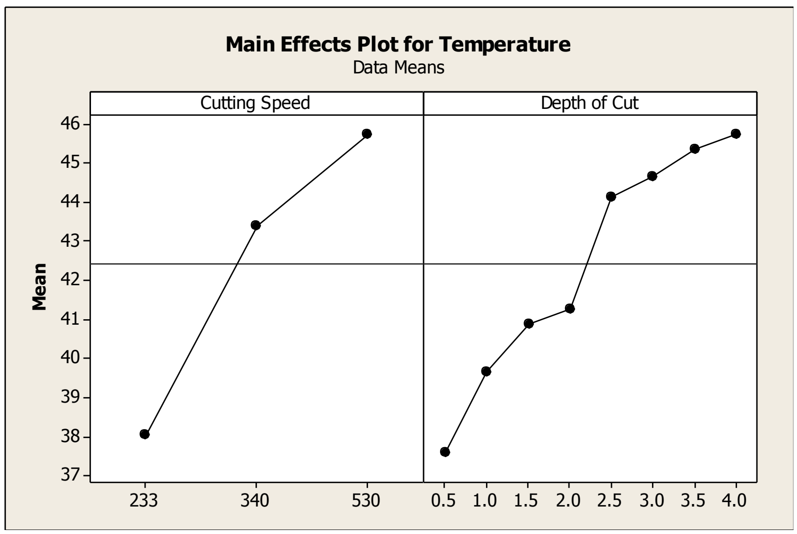


Figure 4.3 Main Effects Plot for Temperature

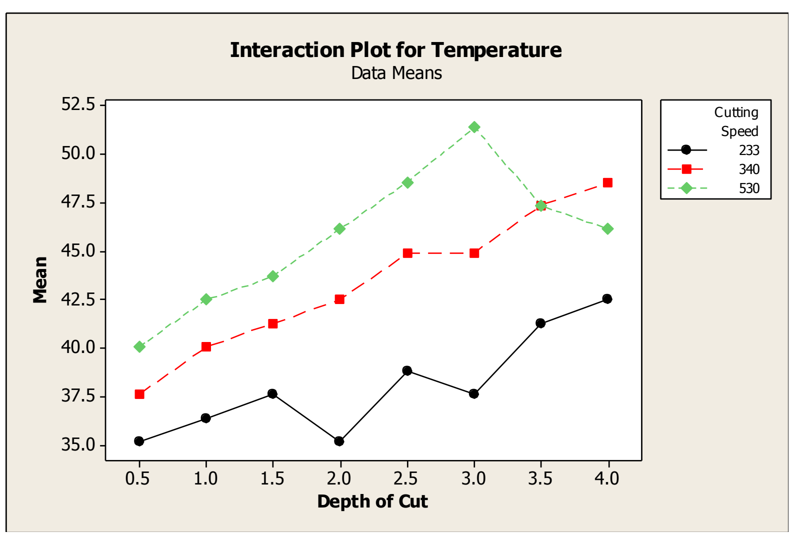


Figure 4.4 Interaction Plot for Temperature

The plot of main effects for tungsten carbide tool and aluminium work shows that when cutting speed increases from 233 m/min to 340 m/min and further to 530 m/min, the chip tool interface temperature increases. While when depth of cut increases the temperature also increases.

The interaction plot shows how the chip-tool interface temperature varies at different cutting speeds between 0.5 to 4.0 mm DOC range. At 530 m/min cutting speed the temperature decreases when the DOC is increased from 3.0 mm to 3.5 mm and further while in other cases it increases.

COMBINATION NO. 3:

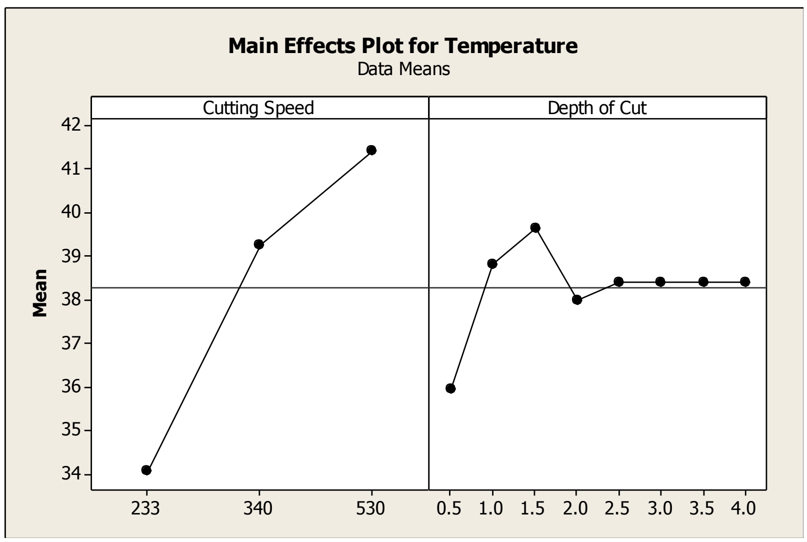


Figure 4.5 Main Effects Plot for Temperature

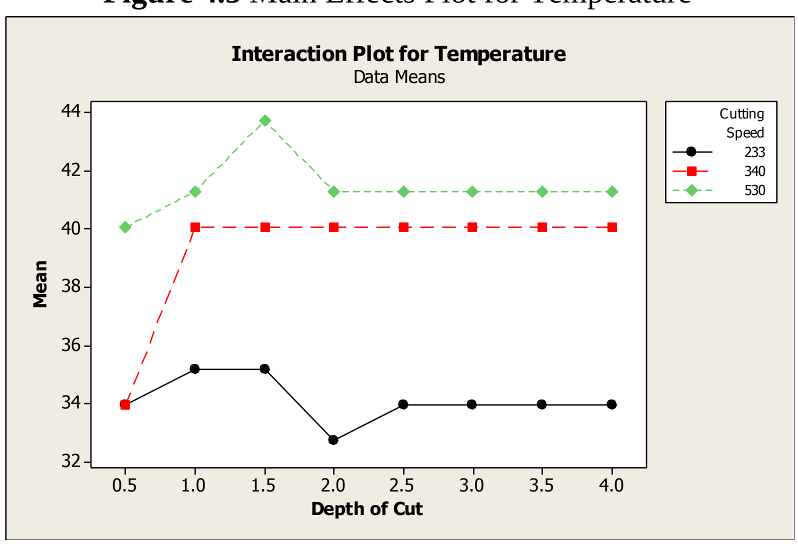


Figure 4.6 Interaction Plot for Temperature

The plot of main effects for tungsten carbide tool and brass work shows that when cutting speed increases from 233 m/min to 340 m/min and further to 530 m/min, the chip tool interface temperature increases. While when depth of cut increases the temperature reaches its maximum value at 1.5 mm DOC after which it decreases and nearly becomes constant after 2.55 mm DOC.

The interaction plot shows how the chip-tool interface temperature varies at different cutting speeds between 0.5 to 4.0 mm DOC range. At 530 m/min cutting speed the temperature decreases when the DOC is increased from 1.5 mm to 2.0 mm after which it becomes constant and in other cases after a slight increase it becomes constant.

COMBINATION NO. 4:

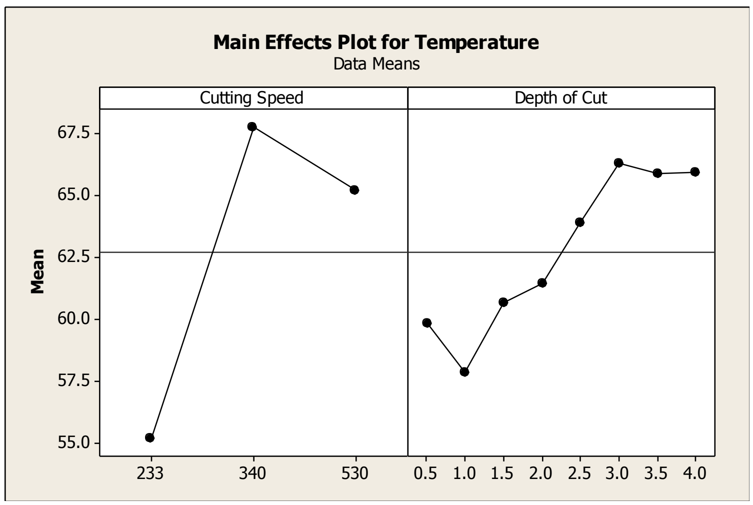


Figure 4.7 Main Effects Plot for Temperature

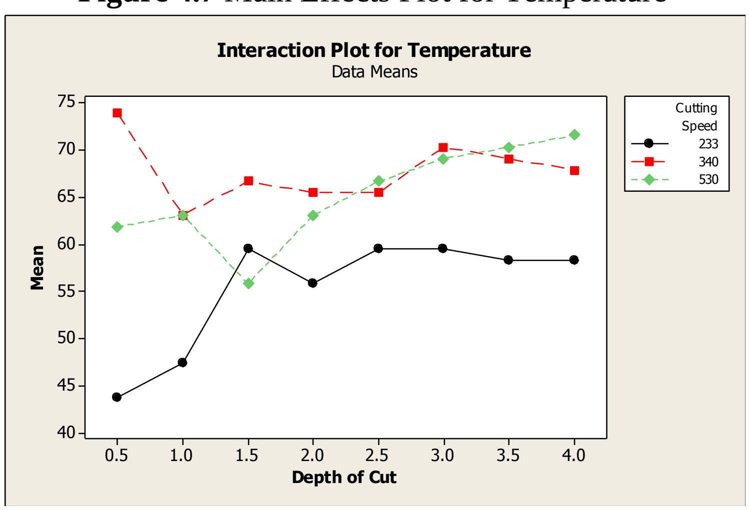


Figure 4.8 Interaction Plot for Temperature

The plot of main effects for PCD tool and aluminium work shows that when cutting speed increases from 233 m/min to 340 m/min the chip tool interface temperature increases and further increase of cutting speed to 530 m/min decreases the temperature. While when depth of cut increases the temperature increases after initial dip at the value at 1.0 mm DOC.

The interaction plot shows how the chip-tool interface temperature varies at different cutting speeds between 0.5 to 4.0 mm DOC range. At 530 m/min cutting speed the temperature decreases in the entire DOC as compared to the temperature values at cutting speed 233 m/min and 340 m/min.

COMBINATION NO. 5:

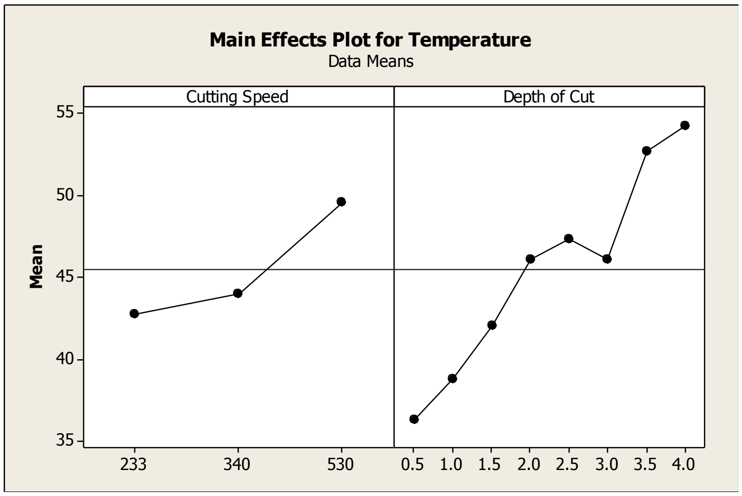


Figure 4.9 Main Effects Plot for Temperature

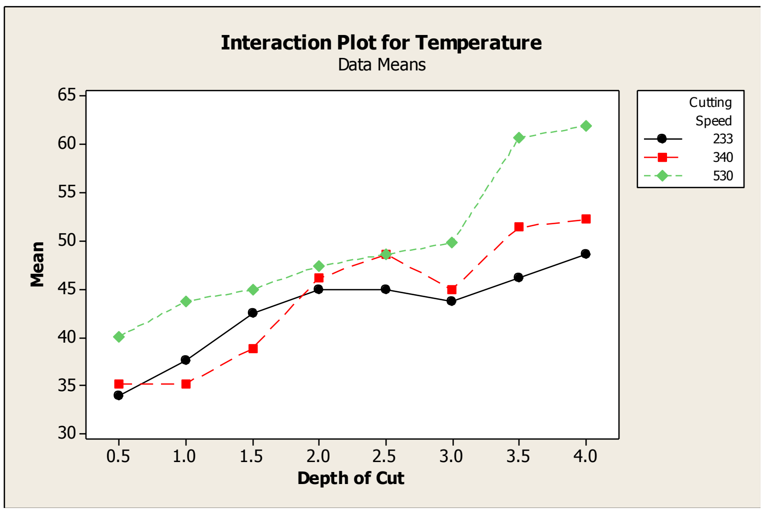


Figure 4.10 Interaction Plot for Temperature

The plot of main effects for HSS tool and aluminium work shows that when cutting speed increases from 233 m/min to 340 m/min and further to 530 m/min the chip tool interface temperature increases. While when depth of cut increases the temperature increases to a maximum value at 2.5 mm DOC after which it decreases and further increase on increase in DOC values.

The interaction plot shows how the chip-tool interface temperature varies at different cutting speeds between 0.5 to 4.0 mm DOC range.

COMBINATION NO. 6:

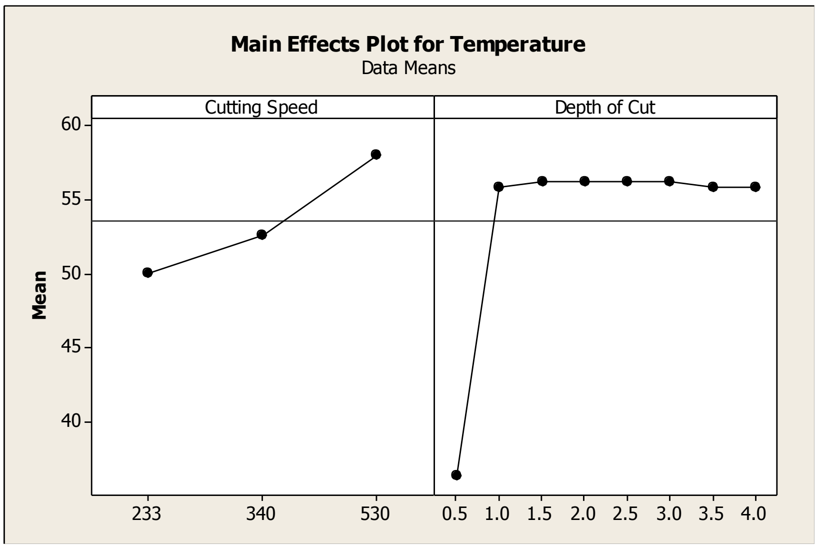


Figure 4.11 Main Effects Plot for Temperature

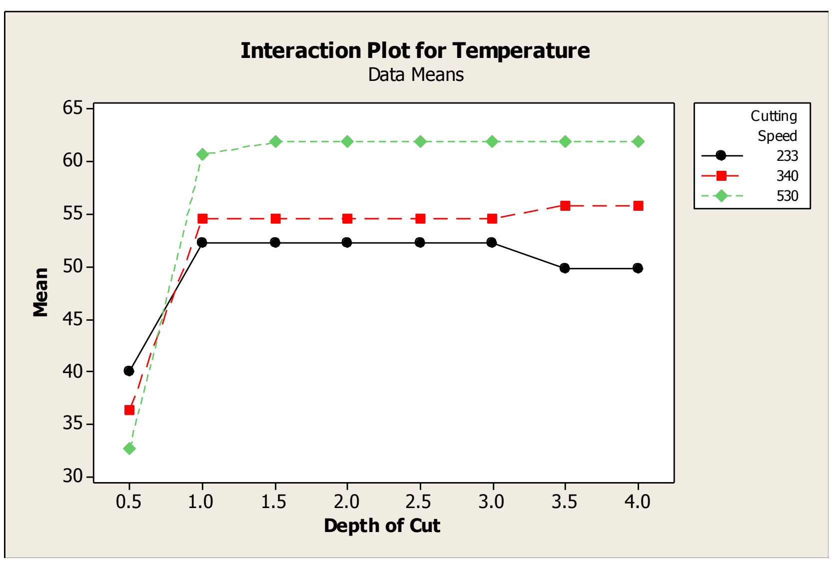


Figure 4.12 Interaction Plot for Temperature

The plot of main effects for HSS tool and brass work shows that when cutting speed increases from 233 m/min to 340 m/min and further to 530 m/min the chip tool interface temperature increases. While when depth of cut increases the temperature increases steeply to a maximum value at 1.0 mm DOC after which it becomes constant for further in DOC values.

The interaction plot shows how the chip-tool interface temperature varies at different cutting speeds between 0.5 to 4.0 mm DOC range. At various cutting speeds the temperature remains nearly constant when DOC values are increased.

COMBINATION NO. 7:

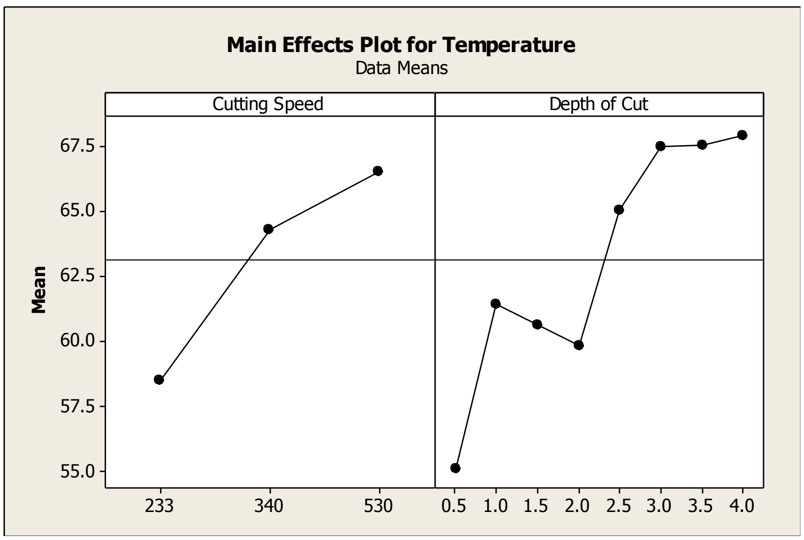


Figure 4.13 Main Effects Plot for Temperature

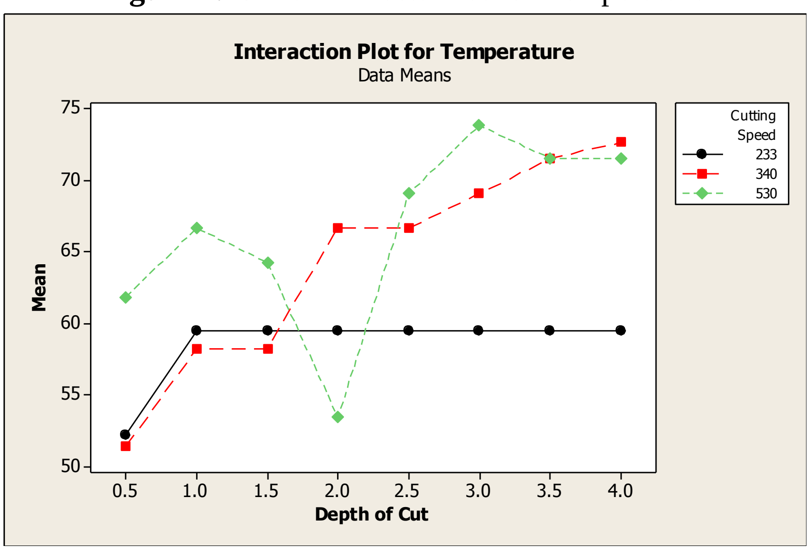


Figure 4.14 Interaction Plot for Temperature

The plot of main effects for PCD tool and brass work shows that when cutting speed increases from 233 m/min to 340 m/min and further to 530 m/min the chip tool interface temperature increases. While when depth of cut increases the temperature increases steeply to a maximum value at 1.0 mm DOC after which it decreases and further increases as the DOC values are increased.

The interaction plot shows how the chip-tool interface temperature varies at different cutting speeds between 0.5 to 4.0 mm DOC range. At 233 m/min cutting speed the temperature remains nearly constant while at cutting speed of 340 m/min it increases gradually and at 530 m/min it initially increases, then falls to a minimum value at 2.0 mm DOC value, after which it further increases as DOC values are increased.

Chapter 5

DEVELOPMENT OF MODEL USING GENETIC ALGORITHM

5.1 IMPORTANCE OF GENETIC ALGORITHM

Genetic algorithms (GAs) are an appealing tool to solve optimization problems [44]. This approach is selected as diversity is considered as the variety and the difference is considered at the gene, chromosome and population level [45].

GAs have the ability to create an initial population of the feasible solutions, and then recombine them in a way to guide their search to only the most promising areas of the state space [46].

5.2 FLOWCHART FOR MODELLING OPTIMIZATION MODEL

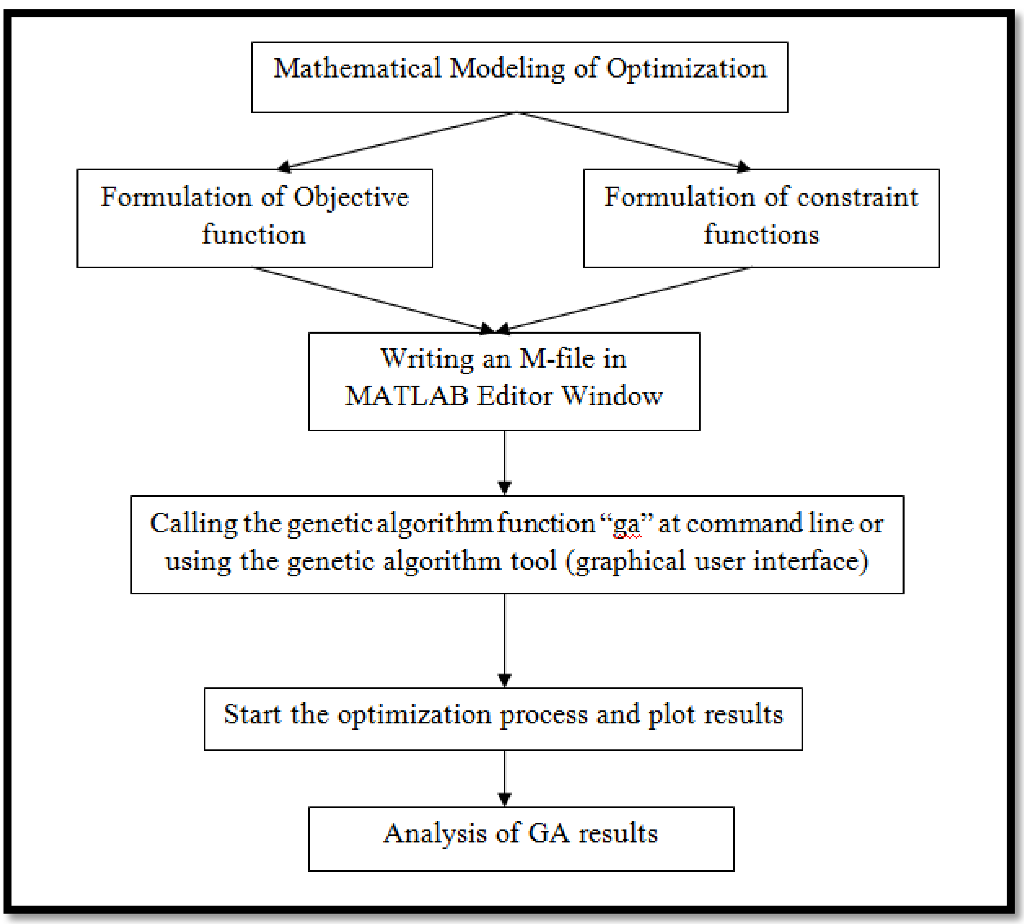


Figure 5.1 Steps involved in optimization of the experimental model

5.3 MATHEMATICAL MODELLING OF OPTIMIZATION

Machining optimization provides optimal or near-optimal solutions in actual metal cutting process. The optimization procedure has two phases. First phase is mathematical modeling of the machining process (cutting performances) where an objective multivariable function should be defined. In that phase, all constraints and bounds of the variables, by using equalities and (or) inequalities should also be defined. Second phase is searching for a global minimum of objective function, under all defined limitations [20].

The mathematical model of optimization consists of the objective function and constraints, as follows:

Objective Function:

$$\text{Min } f(x)$$

Constraint Functions:

$A^* x \leq b$	(Linear Inequalities)
$A_{eq} * x = b_{eq}$	(Linear Equalities)
$C_i(x) \leq 0, i = 1,...,m$	(Nonlinear Inequalities)
$C_{eqi}(x) = 0, i = m+1,...,m+t$	(Nonlinear Equalities)
$L_b \leq x \leq U_b$	(Bounds of Variables)

The objective function of the optimization model is to minimize the chip tool interface temperature in orthogonal cutting process. The chip tool interface temperature is directly related to the cutting speed and depth of cut by response surface methodology, and is defined by the equation:

$$T = C^*V^{x1}*D^{x2}$$

Where T = chip tool interface temperature (°C)

C = Constant

V = Cutting speed (m/min)

D = Depth of cut (mm)

5.4 FORMULATION OF OBJECTIVE FUNCTION FOR OPTIMIZATION

Objective function:

Min T = 32.17*V^0.213733*D^0.179545	(COMBINATION NO. 1)
Min T = 10.9611*V^0.21971*D^0.0975696	(COMBINATION NO. 2)
Min T = 9.5671*V^0.234031*D^0.0205877	(COMBINATION NO. 3)
Min T = 18.79968*V^0.196905*D^0.0718086	(COMBINATION NO. 4)
Min T = 14.1413*V^0.177342*D^0.188984	(COMBINATION NO. 5)
Min T = 18.4561*V^0.162331*D^0.16477	(COMBINATION NO. 6)
Min T = 24.7043*V^0.148959*D^0.0969805	(COMBINATION NO. 7)

Constraint functions:

$V \geq 233$

$V \leq 530$

$D \geq 0.5$

$D \leq 4.0$

5.5 METHODOLOGY OF AN M-FILE

The Genetic Algorithm Toolbox is a collection of functions that extend the capabilities of the Optimization Toolbox and the MATLAB numeric computing environment. All the toolbox functions are MATLAB M-files, made up of MATLAB statements that implement specialized optimization algorithms. To use this toolbox first an M-file is created which computes the function to be optimized. The M-file should accept a row vector, whose length is the number of independent variables for the objective function and return a scalar.

5.5.1 STEPS OF WRITING AN M-FILE

The objective of this experiment is to minimize the chip-tool interface temperature. The M-file which computes this function must accept a row vector x of length 2, corresponding to the variables x_1(cutting speed) and x_2(depth of cut), and return a scalar equal to the value of the function at x. the following steps are involved in writing the M-file:

1. Select New in the MATLAB File menu.
2. Select M-File. This opens a new M-file in the editor.
3. In the M-file, enter the following two lines of code:

   ```
   function T = cutting_temperature(x)
   T = 32.17*x(1)^0.213733*x(2)^0.179545;
   end
   ```

4. Save the M-file in a directory on the MATLAB path.
5. To check that the M-file returns the correct value, enter in the command window

   ```
   cutting_temperature ([233 0.5])
   ans =
   91.0720
   ```

5.5.2 M-FILE WRITING AND CHECKING IN MATLAB

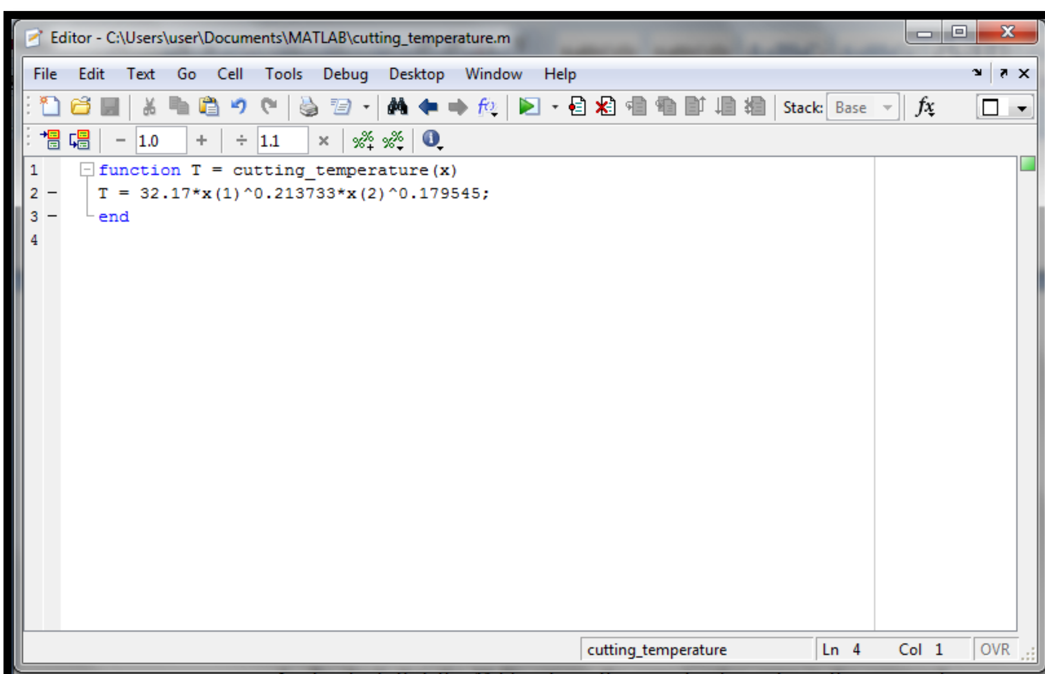


Figure 5.2 M-File in the MATLAB Editor

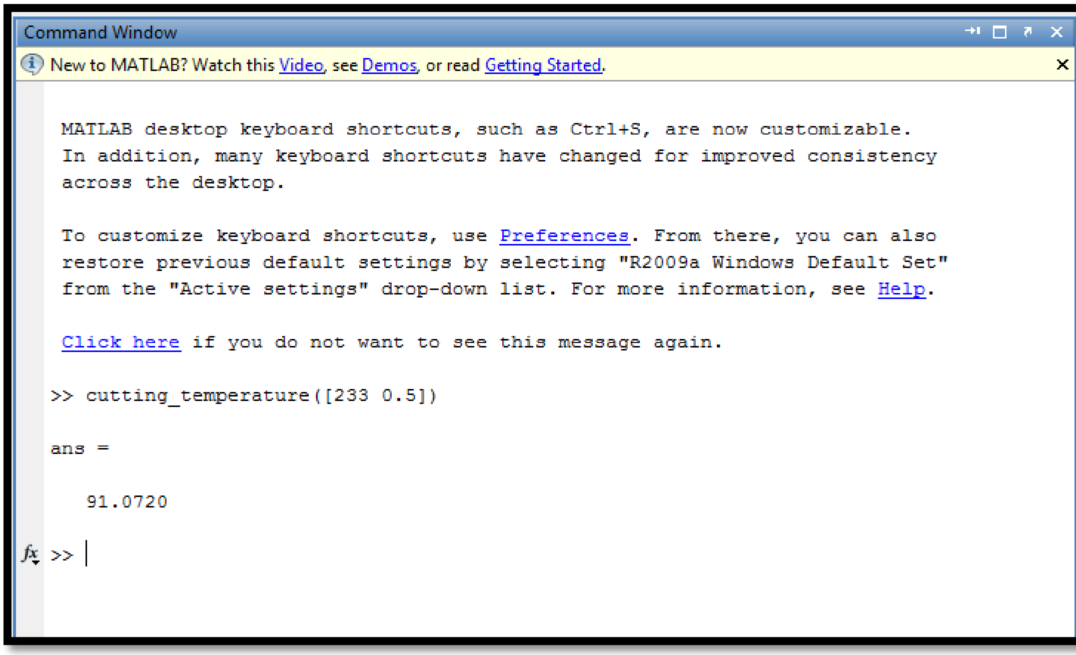


Figure 5.3 Checking the M-File in the Command Window

5.6 USING THE GENETIC ALGORITHM

There are two ways by which the genetic algorithm with the toolbox can be used:

1. Calling the genetic algorithm function ga at the command line.
2. Using the Genetic Algorithm Tool, a graphical interface to the genetic algorithm.

5.6.1 CALLING FUNCTION ga AT COMMAND LINE

To use the genetic algorithm at the command line, the genetic algorithm function ga is called by the syntax

[x fval] = ga(@fitnessfun, nvars, options)

where @fitnessfun is a handle to the fitness function.

nvars is the number of independent variables for the fitness function.

options is a structure containing options for the genetic algorithm.

The results are given by fval – Final value of the fitness function.

x – Point at which the final value is attained.

5.6.2 USING THE GENETIC ALGORITHM TOOL

The Genetic Algorithm Tool is a graphical user interface which enables the use the genetic algorithm without working at the command line. To open this tool, enter at the command window

gatool

This opens the tool as shown below:

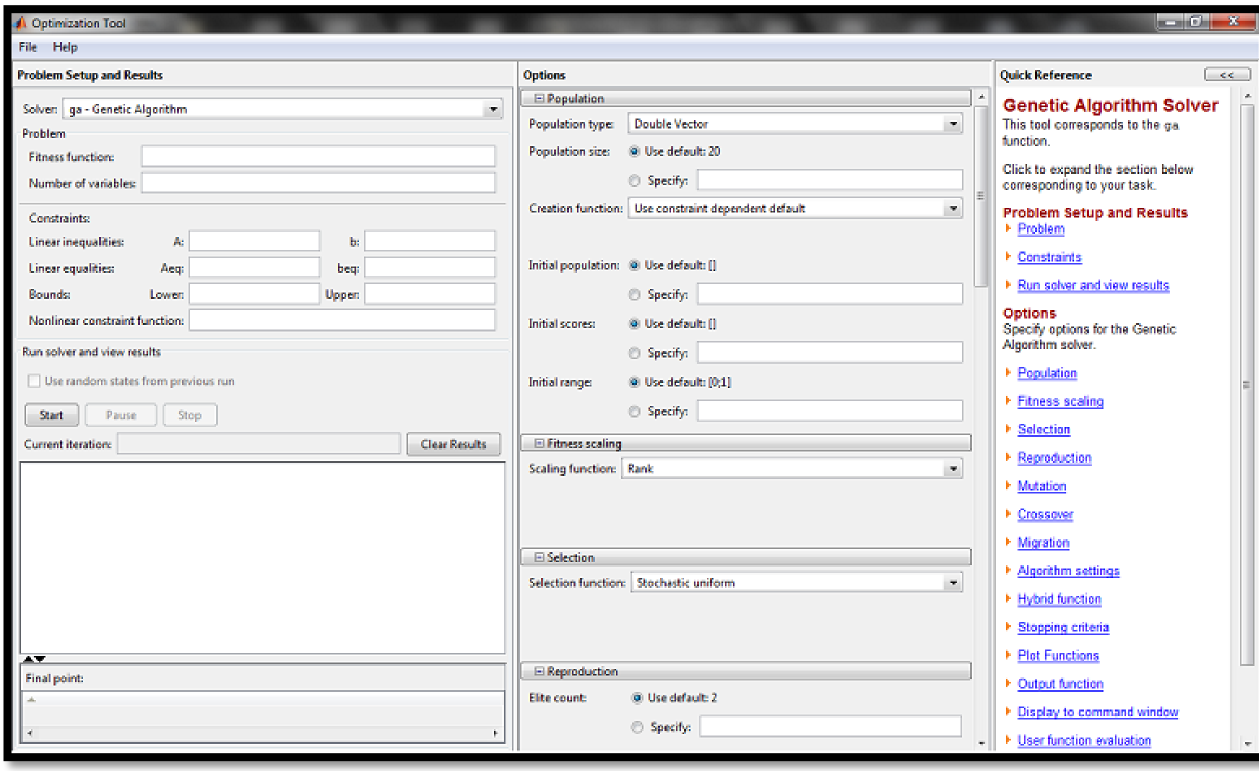


Figure 5.4 GA Optimization Tool window

To use the above tool, following information is required:

1. **Fitness function** – the objective function which is to be minimized. Enter the fitness function in the form @cutting_temperature, where cutting_temperature.m is an M-file computing the fitness function. The @ sign creates a function handle to cutting_temperature.
2. **Number of Variables** – the length of the input vector to the fitness function i.e. cutting_temperature.

To run the genetic algorithm, click the Start button. The tool displays the results of the optimization in the Status and Results pane.

5.7 USING GENETIC ALGORITHM FOR OPTIMISING THE FORMULATED MODEL

Considering the objective functions and constraint functions formulated in Section 5.4, the GA Optimization Tool is used by calling the already saved M-file in the Editor window. The M-file is written as follows:

```
function T = cutting_temperature(x)
T = 32.17*x(1)^0.213733*x(2)^0.179545;
end
```

This M-file is formulated for the readings of COMBINATION NO. 1. Similarly, remaining six M-files are also written following the same rules. These objective functions are subjected to four constraint functions which are already discussed in Section 5.4. The following figure 5.5 shows the optimized result for COMBINATION NO. 1 readings.

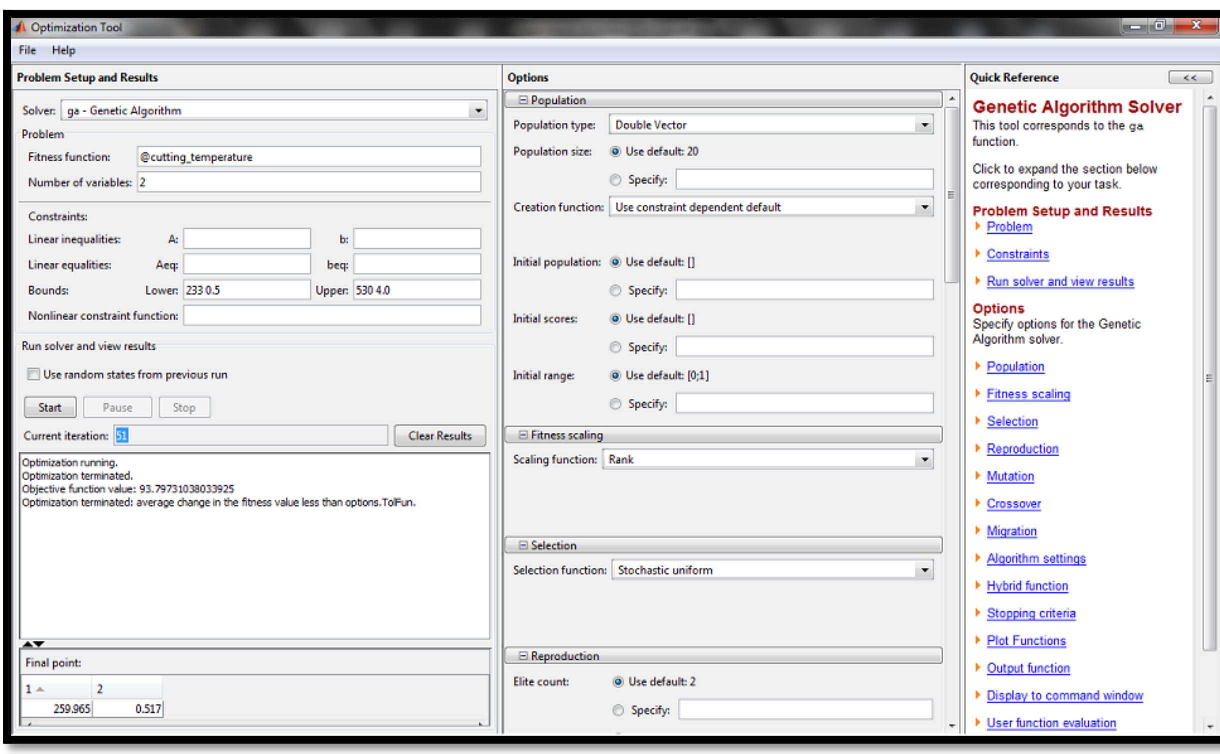


Figure 5.5 GA Optimization Tool window for fitness function “cutting_temperature”

The various options available in the GA Optimization Tool were set as follows:

1. **Population:**

   Population type: Double vector

   Population size: 100

   Creation fcn: use constraint dependent default

   Initial population: []

   Initial scores: []

2. **Fitness Scaling:**

   Fitness scaling fcn: fitscalingrank

3. **Selection:**

   Selection fcn: Stochastic uniform

4. **Reproduction:**

   Elite count: 2

   Crossover fraction: 0.8

5. **Mutation:**

   Mutation fcn: use constraint dependent default

6. **Crossover:**

   Crossover fcn: Scattered

7. **Migration:**

   Migration direction: forward

   Migration interval: 20

   Migration fraction: 0.2

8. **Algorithm Settings:**

   Initial penalty: 10

   Penalty factor: 100

9. **Hybrid function:**

   Hybrid fcn: []

10. **Stopping Criteria:**

    Generations:100

Time limit: Inf

Fitness limit: -Inf

Stall gen limit: 50

Stall time limit: Inf

Tol fun:1.0000e-015

Tol con: 1.0000e-015

11. Plot functions:

Plot interval: 1

Plot fcns: @gaplotbestf@gaplotbestindiv

12. Output function:

Output fcns: [] @gatooloutput

13. Display to Command window:

Display: iterative

14. User evaluation function:

Vectorised: off

Use parallel: never

Diagnostic information

Fitness function = @cutting_temperature

Number of variables = 2

0 Inequality constraints

0 Equality constraints

0 Total number of linear constraints

5.8 RESULTS OF THE GENETIC ALGORITHM MODEL

The results obtained from the GA model depending on the empirical relationship between chip-tool interface temperature and the cutting parameters i.e. cutting speed and depth of cut for different tool-work material combinations are tabulated as follows:

Table 5.1 Temperature predicted by GA for tungsten carbide (tool) and mild steel (work)

READING NO.	CUTTING SPEED (m/min)	DEPTH OF CUT (mm)	CHIP-TOOL INTERFACE TEMPERATURE (°C)
1	233	0.5	91.0720
2	233	1.0	103.1414
3	233	1.5	110.9301
4	233	2.0	116.8104
5	233	2.5	121.5854
6	233	3.0	125.6313
7	233	3.5	129.1570
8	233	4.0	132.2909
9	340	0.5	98.7332
10	340	1.0	111.8180
11	340	1.5	120.2619
12	340	2.0	126.6368
13	340	2.5	131.8135
14	340	3.0	136.1998
15	340	3.5	140.0220
16	340	4.0	143.4196
17	530	0.5	108.5601
18	530	1.0	122.9472
19	530	1.5	132.2315
20	530	2.0	139.2410
21	530	2.5	144.9329
22	530	3.0	149.7557
23	530	3.5	153.9584
24	530	4.0	157.6941

Table 5.2 Temperature predicted by GA for tungsten carbide (tool) and aluminium (work)

READING NO.	CUTTING SPEED (m/min)	DEPTH OF CUT (mm)	CHIP-TOOL INTERFACE TEMPERATURE (°C)
1	233	0.5	33.9324
2	233	1.0	36.3066
3	233	1.5	37.7717
4	233	2.0	38.8470
5	233	2.5	39.7020
6	233	3.0	40.4146
7	233	3.5	41.0271
8	233	4.0	41.5651
9	340	0.5	36.8701
10	340	1.0	39.4499
11	340	1.5	41.0418
12	340	2.0	42.2101
13	340	2.5	43.1392
14	340	3.0	43.9135
15	340	3.5	44.5790
16	340	4.0	45.1636
17	530	0.5	40.6475
18	530	1.0	43.4915
19	530	1.5	45.2466
20	530	2.0	46.5346
21	530	2.5	47.5589
22	530	3.0	48.4125
23	530	3.5	49.1461
24	530	4.0	49.7906

Table 5.3 Temperature predicted by GA for tungsten carbide (tool) and brass (work)

READING NO.	CUTTING SPEED (m/min)	DEPTH OF CUT (mm)	CHIP-TOOL INTERFACE TEMPERATURE (°C)
1	233	0.5	33.7767
2	233	1.0	34.2622
3	233	1.5	34.5494
4	233	2.0	34.7546
5	233	2.5	34.9146
6	233	3.0	35.0459
7	233	3.5	35.1573
8	233	4.0	35.2541
9	340	0.5	36.9001
10	340	1.0	37.4304
11	340	1.5	37.7442
12	340	2.0	37.9684
13	340	2.5	38.1432
14	340	3.0	38.2867
15	340	3.5	38.4084
16	340	4.0	38.5141
17	530	0.5	40.9400
18	530	1.0	41.5284
19	530	1.5	41.8765
20	530	2.0	42.1253
21	530	2.5	42.3193
22	530	3.0	42.4784
23	530	3.5	42.6134
24	530	4.0	42.7307

Table 5.4 Temperature predicted by GA for PCD (tool) and aluminium (work)

READING NO.	CUTTING SPEED (m/min)	DEPTH OF CUT (mm)	CHIP-TOOL INTERFACE TEMPERATURE (°C)
1	233	0.5	52.3213
2	233	1.0	54.9914
3	233	1.5	56.6160
4	233	2.0	57.7978
5	233	2.5	58.7314
6	233	3.0	59.5054
7	233	3.5	60.1677
8	233	4.0	60.7474
9	340	0.5	56.3631
10	340	1.0	59.2395
11	340	1.5	60.9897
12	340	2.0	62.2627
13	340	2.5	63.2684
14	340	3.0	64.1022
15	340	3.5	64.8157
16	340	4.0	65.4402
17	530	0.5	61.5117
18	530	1.0	64.6508
19	530	1.5	66.5609
20	530	2.0	67.9502
21	530	2.5	69.0477
22	530	3.0	69.9577
23	530	3.5	70.7364
24	530	4.0	71.4179

Table 5.5 Temperature predicted by GA for high speed steel (tool) and aluminium (work)

READING NO.	CUTTING SPEED (m/min)	DEPTH OF CUT (mm)	CHIP-TOOL INTERFACE TEMPERATURE (°C)
1	233	0.5	32.6160
2	233	1.0	37.1810
3	233	1.5	40.1420
4	233	2.0	42.3849
5	233	2.5	44.2105
6	233	3.0	45.7603
7	233	3.5	47.1130
8	233	4.0	48.3171
9	340	0.5	34.8768
10	340	1.0	39.7582
11	340	1.5	42.9245
12	340	2.0	45.3228
13	340	2.5	47.2750
14	340	3.0	48.9322
15	340	3.5	50.3787
16	340	4.0	51.6662
17	530	0.5	37.7336
18	530	1.0	43.0148
19	530	1.5	46.4404
20	530	2.0	49.0352
21	530	2.5	51.1472
22	530	3.0	52.9403
23	530	3.5	54.5052
24	530	4.0	55.8982

Table 5.6 Temperature predicted by GA for high speed steel (tool) and brass (work)

READING NO.	CUTTING SPEED (m/min)	DEPTH OF CUT (mm)	CHIP-TOOL INTERFACE TEMPERATURE (°C)
1	233	0.5	39.8873
2	233	1.0	44.7173
3	233	1.5	47.8024
4	233	2.0	50.1229
5	233	2.5	52.0001
6	233	3.0	53.5859
7	233	3.5	54.9644
8	233	4.0	56.1871
9	340	0.5	42.4108
10	340	1.0	47.5420
11	340	1.5	50.8267
12	340	2.0	53.2940
13	340	2.5	55.2899
14	340	3.0	56.9791
15	340	3.5	58.4418
16	340	4.0	59.7419
17	530	0.5	45.5799
18	530	1.0	51.0944
19	530	1.5	54.6247
20	530	2.0	57.2763
21	530	2.5	59.1214
22	530	3.0	61.2336
23	530	3.5	62.8088
24	530	4.0	64.2060

Table 5.7 Temperature predicted by GA for PCD (tool) and brass (work)

READING NO.	CUTTING SPEED (m/min)	DEPTH OF CUT (mm)	CHIP-TOOL INTERFACE TEMPERATURE (°C)
1	233	0.5	52.0256
2	233	1.0	55.6431
3	233	1.5	57.8747
4	233	2.0	59.5121
5	233	2.5	60.8141
6	233	3.0	61.8989
7	233	3.5	62.8312
8	233	4.0	63.6508
9	340	0.5	55.0383
10	340	1.0	58.8653
11	340	1.5	61.2261
12	340	2.0	62.9583
13	340	2.5	64.3356
14	340	3.0	65.4833
15	340	3.5	66.4696
16	340	4.0	67.3360
17	530	0.5	58.8009
18	530	1.0	62.8895
19	530	1.5	65.4117
20	530	2.0	67.2622
21	530	2.5	68.7338
22	530	3.0	69.9599
23	530	3.5	71.0137
24	530	4.0	71.9393

5.9 GRAPHICAL OUTPUT OF FORMULATED GA MODEL

The results obtained from the formulated GA model depending on the equations generated by the response surface methodology for different tool-work material combinations are plotted showing the effects of the cutting parameters on the response variable i.e. chip tool interface temperature as shown below:

COMBINATION NO. 1:

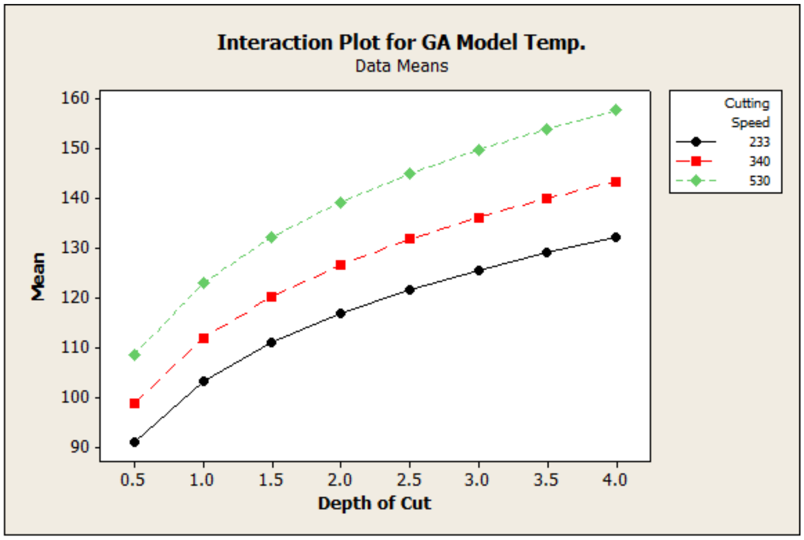


Figure 5.6 Plot for temperature obtained by GA Model

COMBINATION NO. 2:

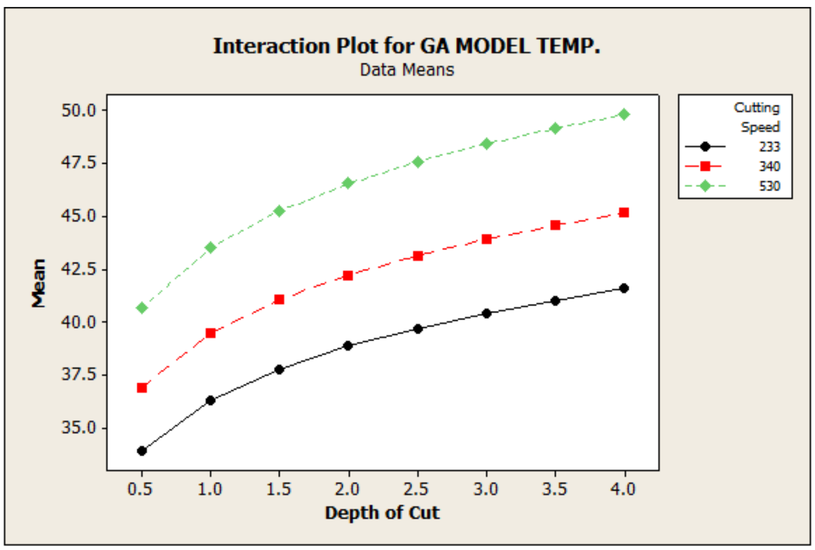


Figure 5.7 Plot for temperature obtained by GA Model

COMBINATION NO. 3:

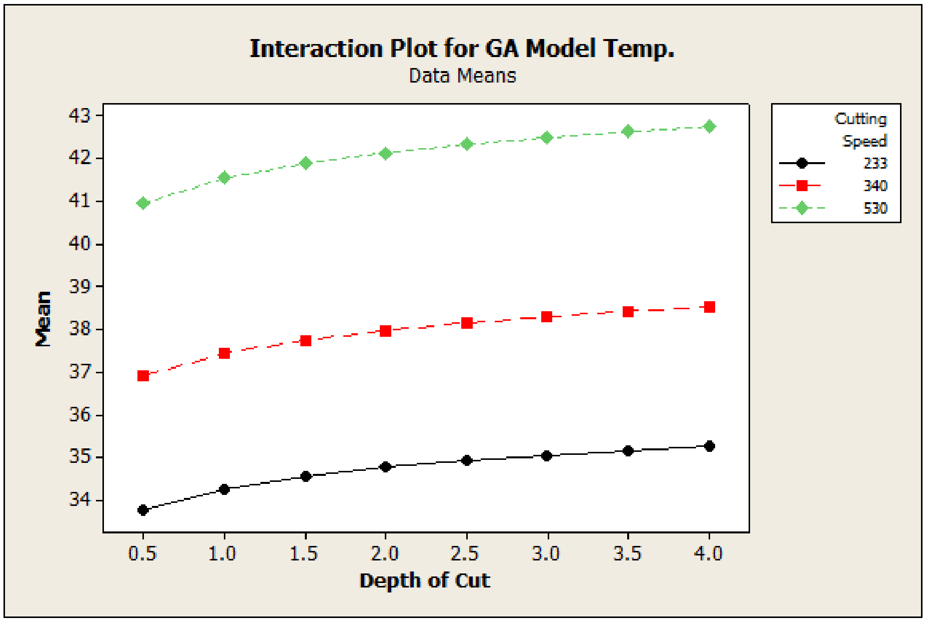


Figure 5.8 Plot for temperature obtained by GA Model

COMBINATION NO. 4:

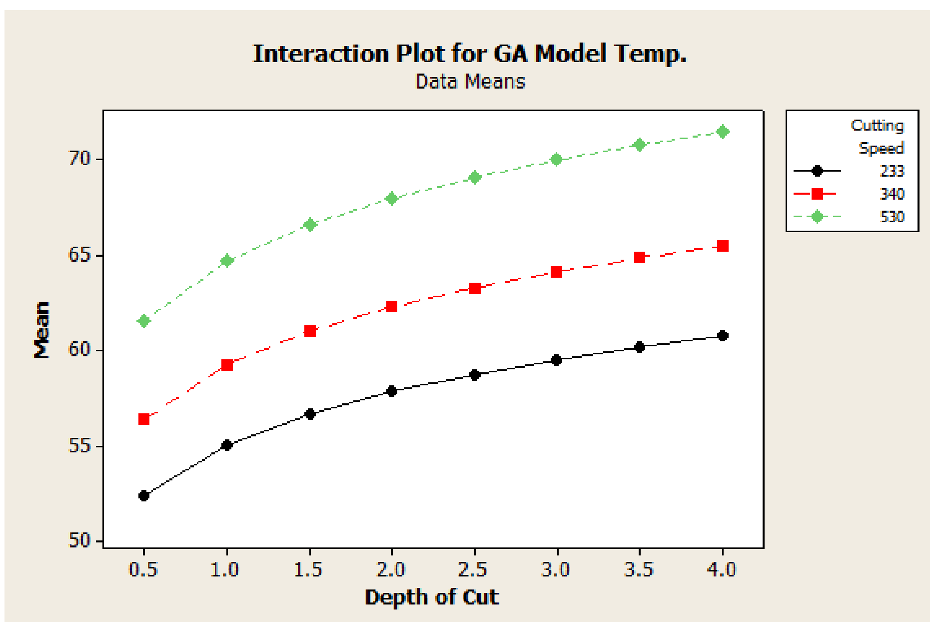


Figure 5.9 Plot for temperature obtained by GA Model

COMBINATION NO. 5:

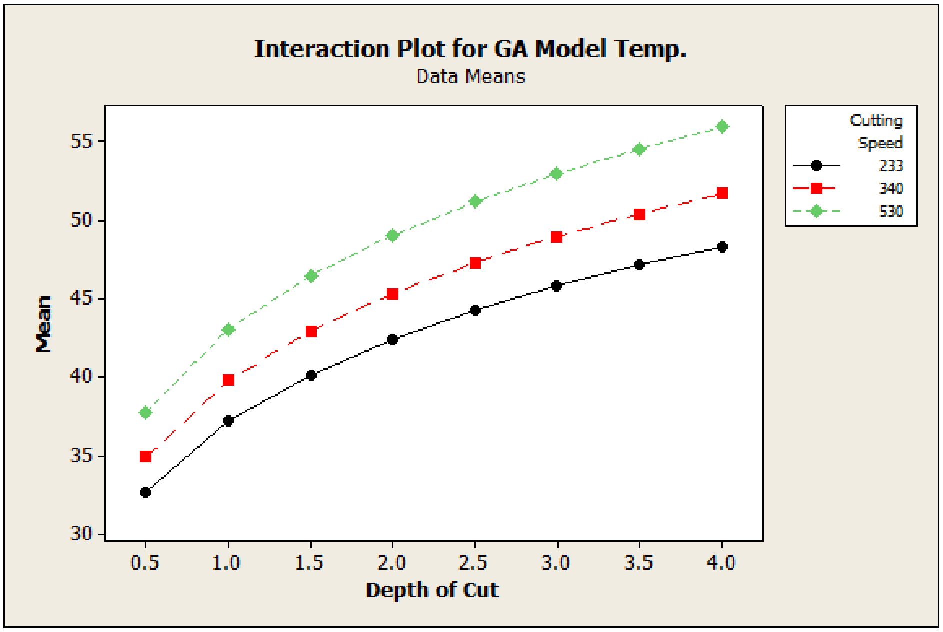


Figure 5.10 Plot for temperature obtained by GA Model

COMBINATION NO. 6:

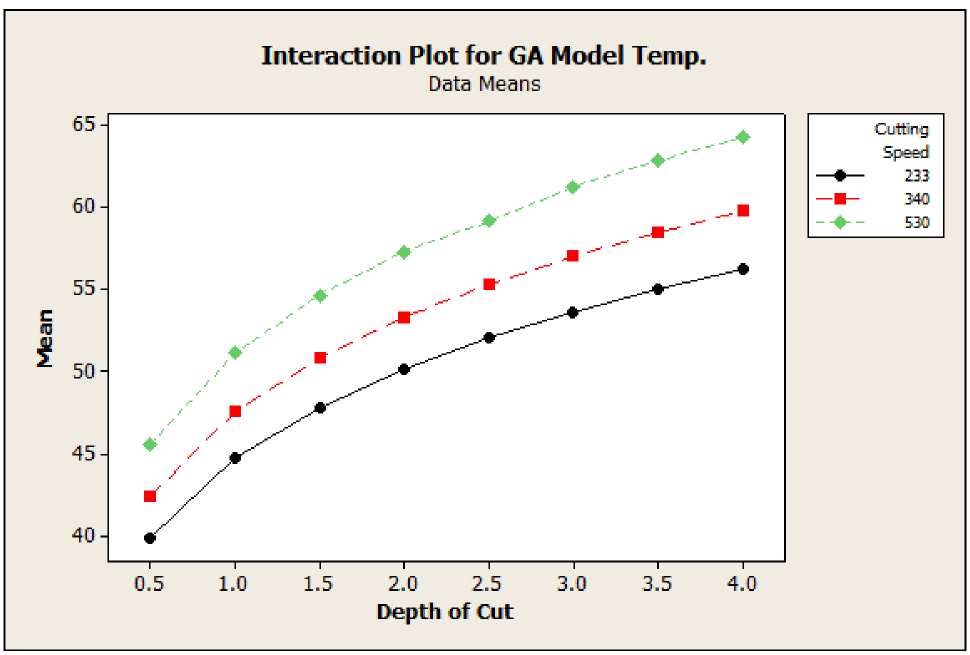


Figure 5.11 Plot for temperature obtained by GA Model

COMBINATION NO. 7:

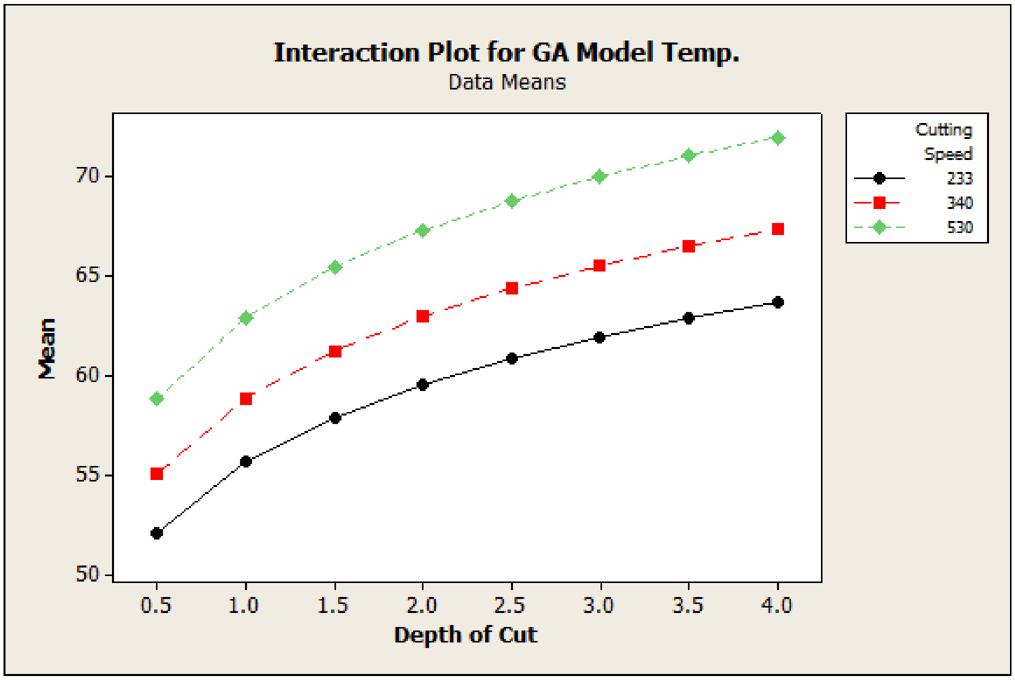


Figure 5.12 Plot for temperature obtained by GA Model

It can be interpret from the above graphs that on increasing the cutting speed a significant increase is observed in the chip-tool interface temperature. Similarly, an increase in the depth of cut increases the chip-tool interface temperature but the increase is small as compared to cutting speed. Therefore, the chip-tool interface temperature largely varies with cutting speed and then depth of cut.

Chapter 6

OPTIMIZATION OF PROCESS PARAMETERS

6.1 OPTIMIZATION: AN INTRODUCTION

In mathematics, computer science or management science, mathematical optimization is the selection of a best element (with regard to certain criteria) from a set of available alternatives.

An optimization problem consists of maximizing or minimizing a real function by systematically choosing input values from within an allowed set and computing the value of the function. The generalization of optimization theory and techniques to other formulations comprises a large area of applied mathematics. Optimization includes finding "best available" values of some objective function given a defined domain (or set of constraints) including a variety of different types of objective functions and different types of domains.

6.2 OPTIMIZATION PROBLEM

An optimization problem in general form can be represented as:

Given: a function $f: A \longrightarrow R$ from some set A to the real numbers

Sought: an element x_0 in A such that $f(x_0) \leq f(x)$ for all x in A (minimization) or such that $f(x_0) \geq f(x)$ for all x in A (maximization)

Such a formulation is known as an "optimization problem". The function f is called, an objective function, a **loss function** or **cost function** (minimization), **indirect utility function** (minimization), **a utility function** (maximization), or **a fitness function** (maximization). A feasible solution that minimizes (or maximizes) the objective function is called an optimal solution.

6.3 OPTIMIZATION TECHNIQUES

There are many techniques which are being used for optimizing problem in various fields of engineering. The following Table 6.1 presents a list of these techniques:

Table 6.1 Methods of Operation Research [47]

Mathematical Programming Techniques	Stochastic Process Techniques	Statistical Methods
Calculus methods	Statistical decision theory	Regression analysis
Calculus of variations	Markov processes	Cluster analysis, pattern recognition
Nonlinear programming	Queueing theory	Design of experiments
Geometric programming	Renewal theory	Discriminate analysis (factor analysis)
Quadratic programming	Simulation methods	
Linear programming	Reliability theory	
Dynamic programming		
Integer programming		
Stochastic programming		
Separable programming		
Multiobjective programming		
Network methods: CPM and PERT		
Game theory		
Simulated annealing		
Genetic algorithms		
Neural networks		

The technique GA, which is being used in the present investigation, is one of the evolutionary algorithms which is based on the mechanics of biological evolution. GA is one of the efficient and effective techniques of optimization that is being used today in business, scientific and engineering circles. It is a heuristic algorithm which can be easily applied to determine approximate solutions to the optimization problems. Following Figure 6.1 shows another classification based on the search techniques.

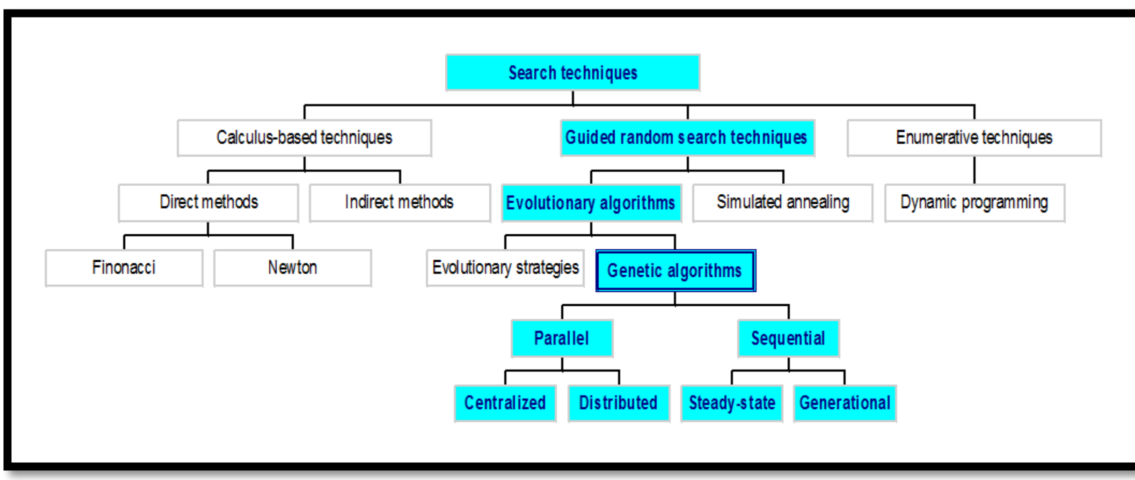


Figure 6.1 Classification based on Search techniques [48]

6.4 OPTIMAL RESULTS FOR DIFFERENT TOOL-WORK COMBINATIONS USING GENETIC ALGORITHM

The genetic algorithm minimized the chip-tool interface temperature depending on the cutting speed and depth of cut for various too-work combinations. The results obtained are given as follows:

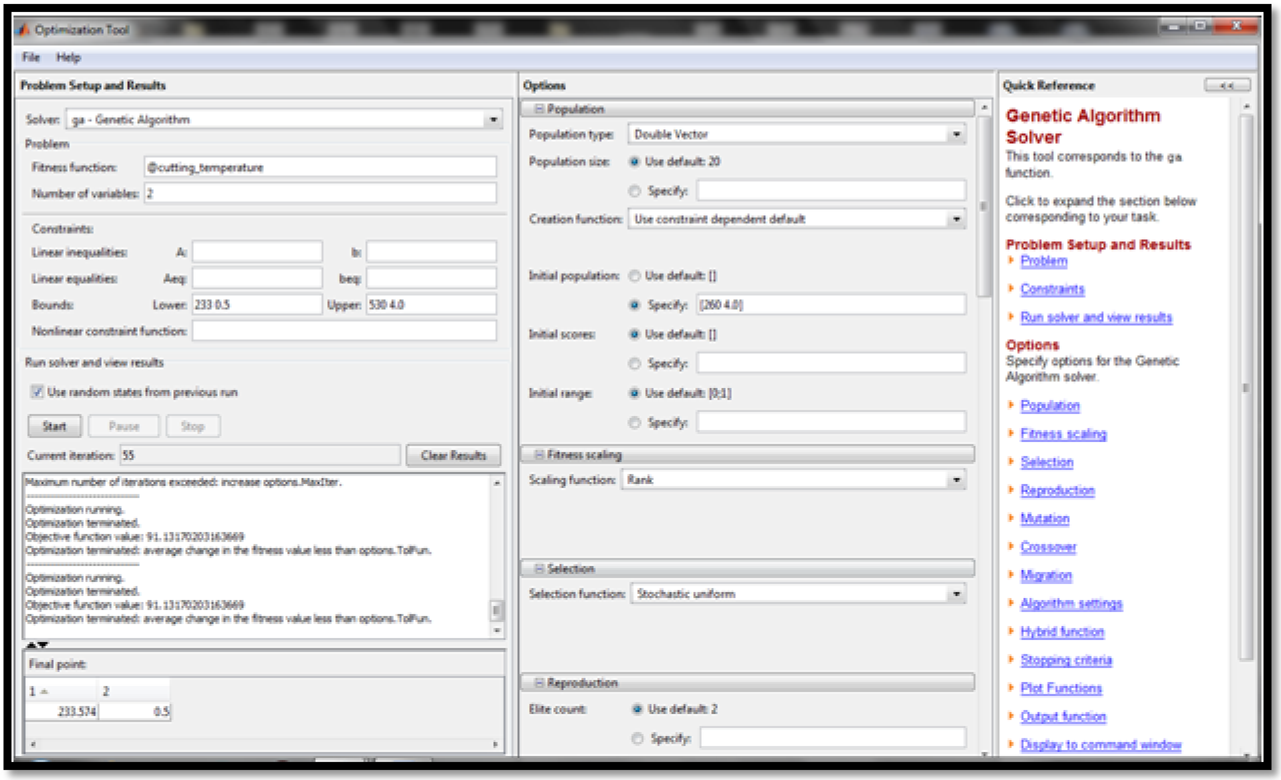


Figure 6.2 GA Optimal result window for tungsten carbide (tool) and mild steel (work)

OPTIMIZED RESULT

Minimized chip-tool interface temperature – **91.13170203163669 °C**

Cutting Speed – **233.574 m/min**

Depth of cut – **0.5 mm**

MATLAB ITERATIONS

Diagnostic information.

Fitness function = @cutting_temperature

Number of variables = 2

0 Inequality constraints

0 Equality constraints

0 Total number of linear constraints

Modified options:

options.InitialPopulation = [260 4]

options.Display = 'diagnose'

options.PlotFcns = { @gaplotbestf @gaplotdistance @gaplotexpectation @gaplotgenealogy @gaplotrange @gaplotselection }

options.OutputFcns = { [] @gatooloutput }

End of diagnostic information.

		Best	Mean	Stall
Generation	f-count	f(x)	f(x)	Generations
1	40	94.99	104.6	0
2	60	94.74	102	0
3	80	94.66	99.88	0
4	100	94.66	100.6	1
5	120	94.57	98.88	0
6	140	94.57	97.61	1
7	160	94.57	97.56	2
8	180	94.49	96.03	0
9	200	94.44	96.86	0
10	220	94.44	98.35	1
11	240	94.4	95.43	0

12	260	94.36	94.5	0
13	280	94.36	94.45	1
14	300	94.32	94.95	0
15	320	94.32	96.19	1
16	340	94.32	95.58	2
17	360	94.3	94.66	0
18	380	94.27	95.49	0
19	400	94.23	94.61	0
20	420	94.23	95.51	1
21	440	94.23	97.65	2
22	460	94.23	97.46	3
23	480	94.22	97.21	0
24	500	94.22	97.1	1
25	520	94.22	95.9	2
26	540	92.49	94.4	0
27	560	92.38	94.29	0
28	580	92.38	94.41	1
29	600	92.37	93.98	0
30	620	92.37	94.24	1

		Best	Mean	Stall
Generation	f-count	f(x)	f(x)	Generations
31	640	92.37	93.75	2
32	660	91.4	93.61	0
33	680	91.38	93.21	0

34	700	91.38	92.77	1
35	720	91.38	92.54	2
36	740	91.37	92.14	0
37	760	91.36	91.65	0
38	780	91.34	92.21	0
39	800	91.34	93.76	1
40	820	91.34	91.7	2
41	840	91.34	91.93	3
42	860	91.33	91.95	0
43	880	91.33	91.95	1
44	900	91.33	91.7	2
45	920	91.33	91.67	3
46	940	91.33	91.41	0
47	960	91.33	91.42	1
48	980	91.15	91.38	0
49	1000	91.15	91.4	1
50	1020	91.14	91.3	0
51	1040	91.14	91.27	1
52	1060	91.13	91.22	0
53	1080	91.13	91.17	1
54	1100	91.13	91.16	0
55	1120	91.13	91.16	1

Optimization terminated: average change in the fitness value less than options.TolFun.

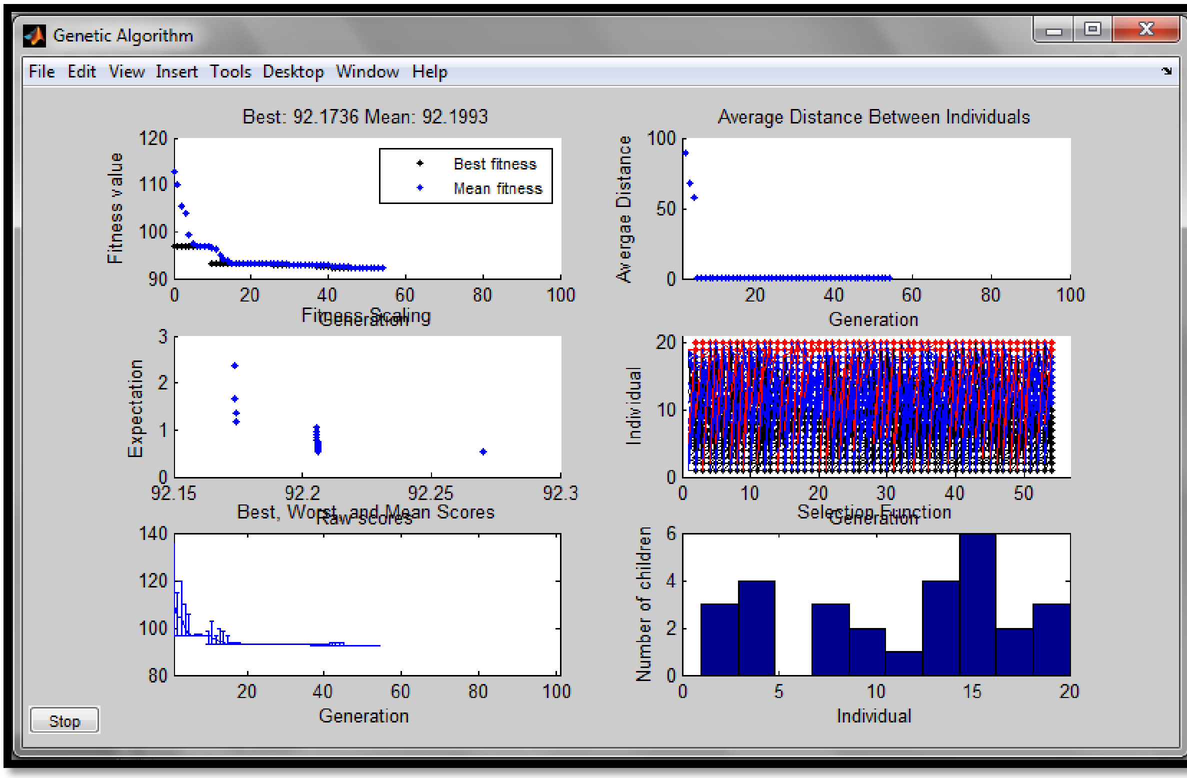


Figure 6.3 Graphical representation of fitness value for tungsten carbide (tool) and mild steel (work)

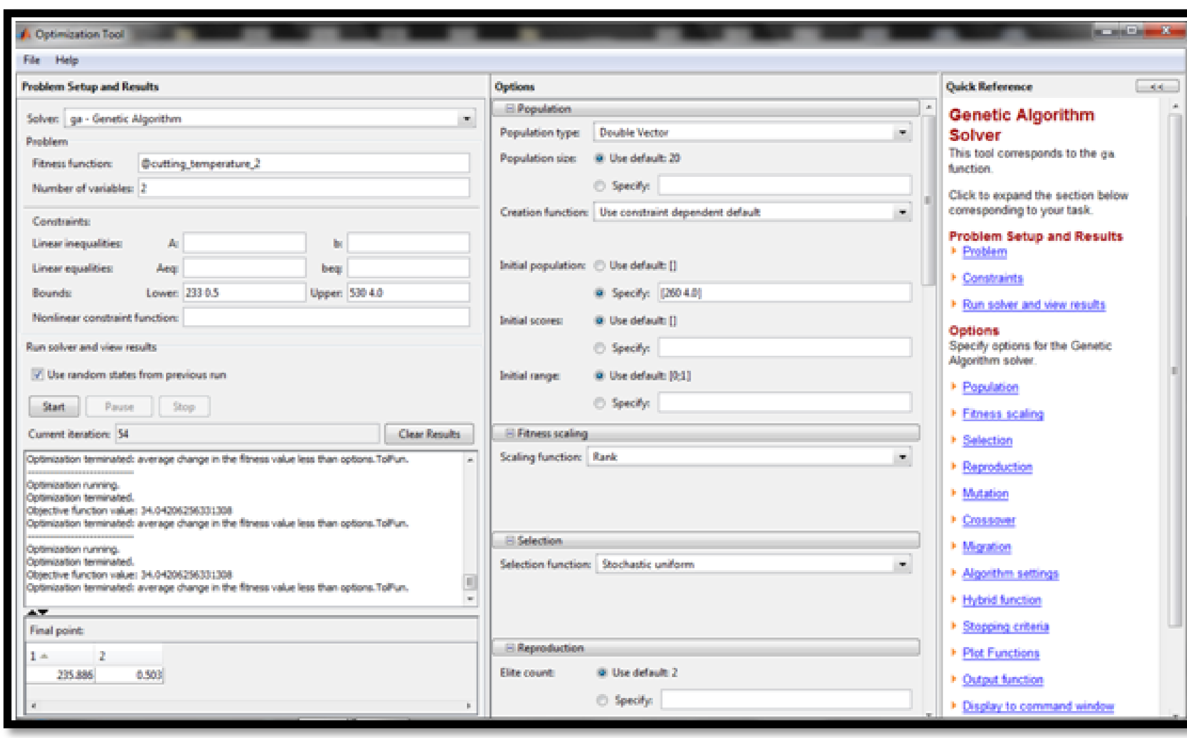


Figure 6.4 GA Optimal result window for tungsten carbide (tool) and aluminium (work)

OPTIMIZED RESULT

Minimized chip-tool interface temperature – **34.04206256331308 °C**

Cutting Speed – **235.886 m/min**

Depth of cut – **0.530 mm**

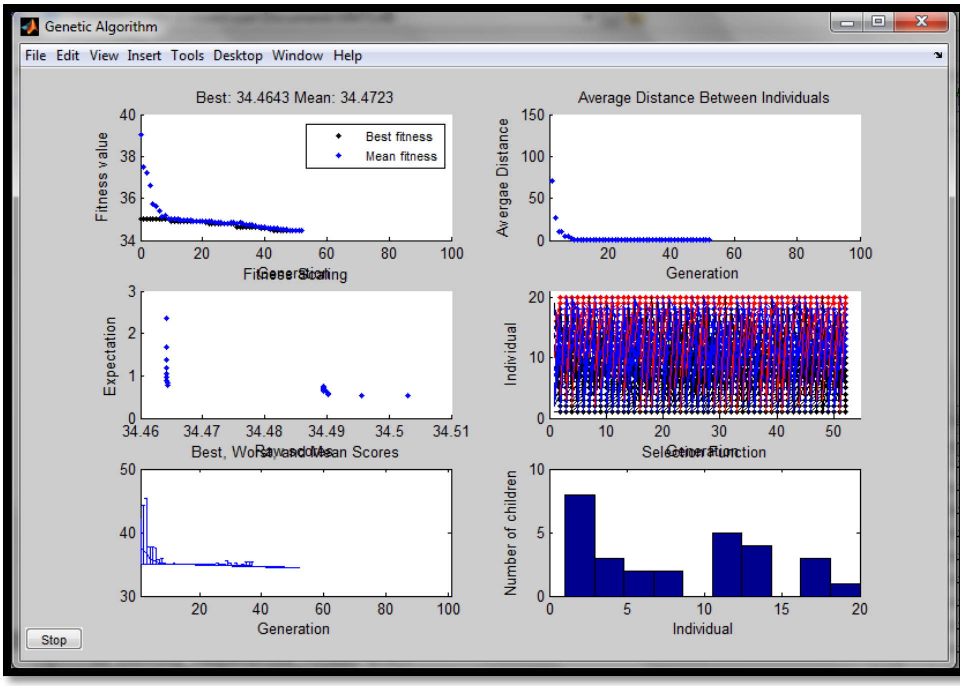


Figure 6.5 Graphical representation of fitness value for tungsten carbide (tool) and aluminium (work)

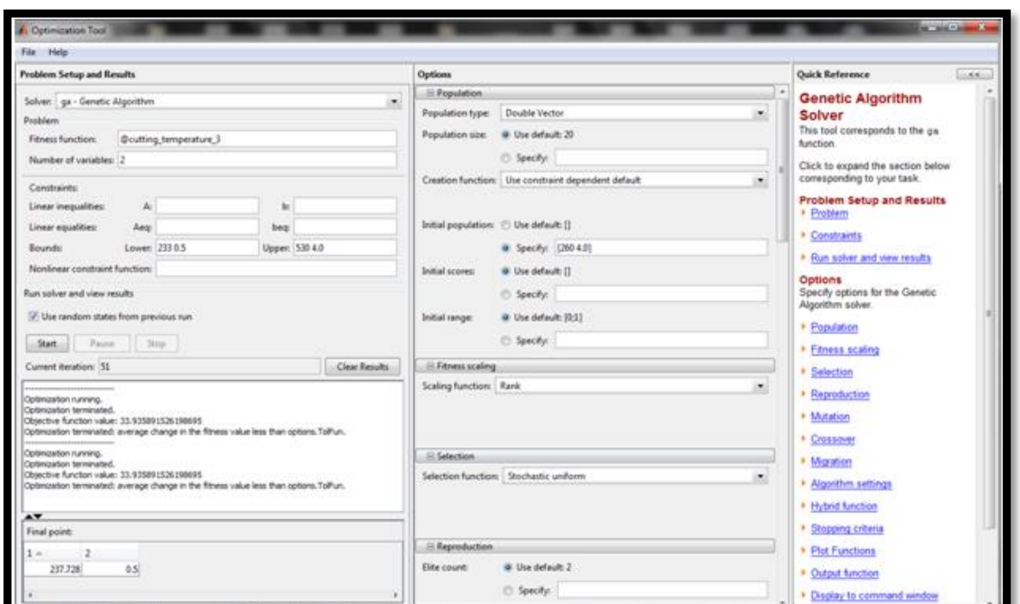


Figure 6.6 GA Optimal result window for tungsten carbide (tool) and brass (work)

OPTIMIZED RESULT

Minimized chip-tool interface temperature – **33.935891526198695 °C**

Cutting Speed – **237.728 m/min**

Depth of cut – **0.5 mm**

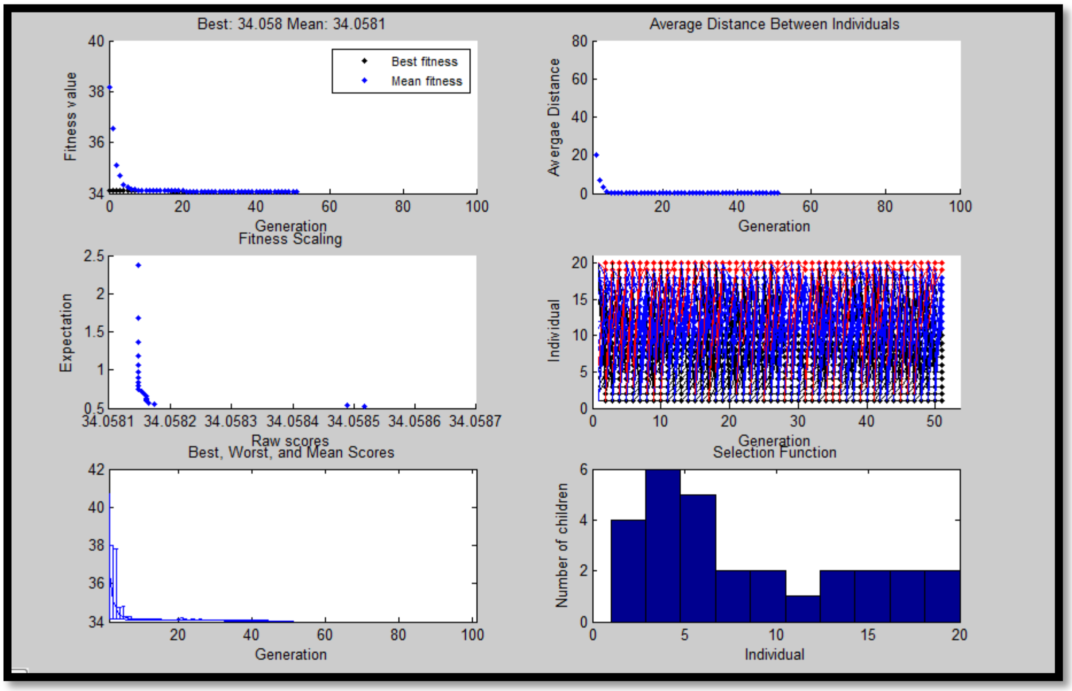


Figure 6.7 Graphical representation of fitness value for tungsten carbide (tool) and brass (work)

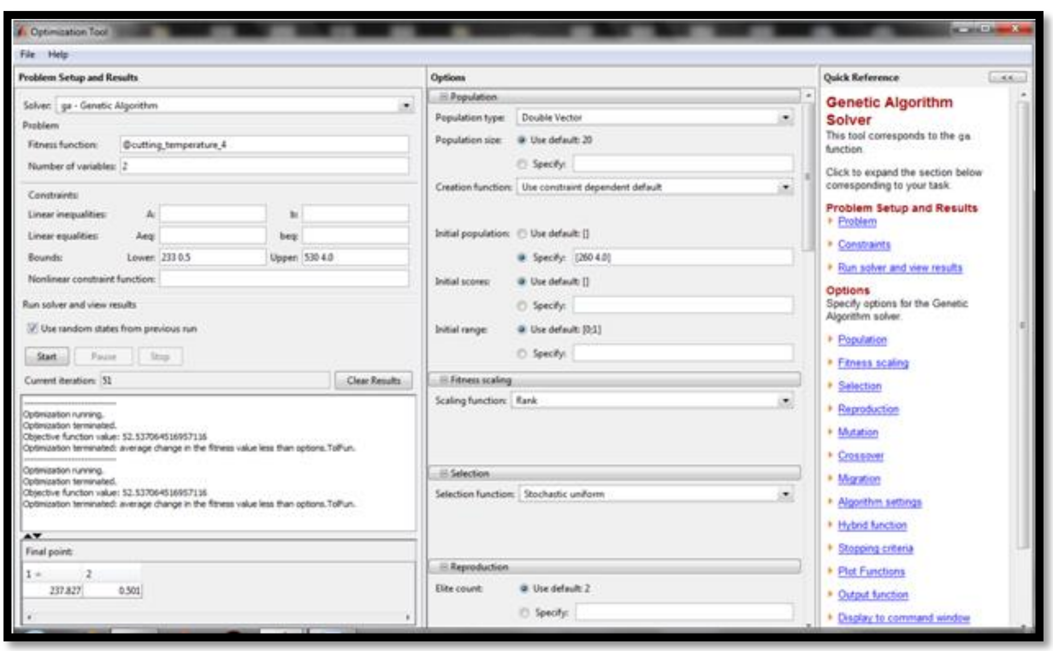


Figure 6.8 GA Optimal result window for PCD (tool) and aluminium (work)

OPTIMIZED RESULT

Minimized chip-tool interface temperature – **52.537064516957116 °C**

Cutting Speed – **237.827 m/min**

Depth of cut – **0.501 mm**

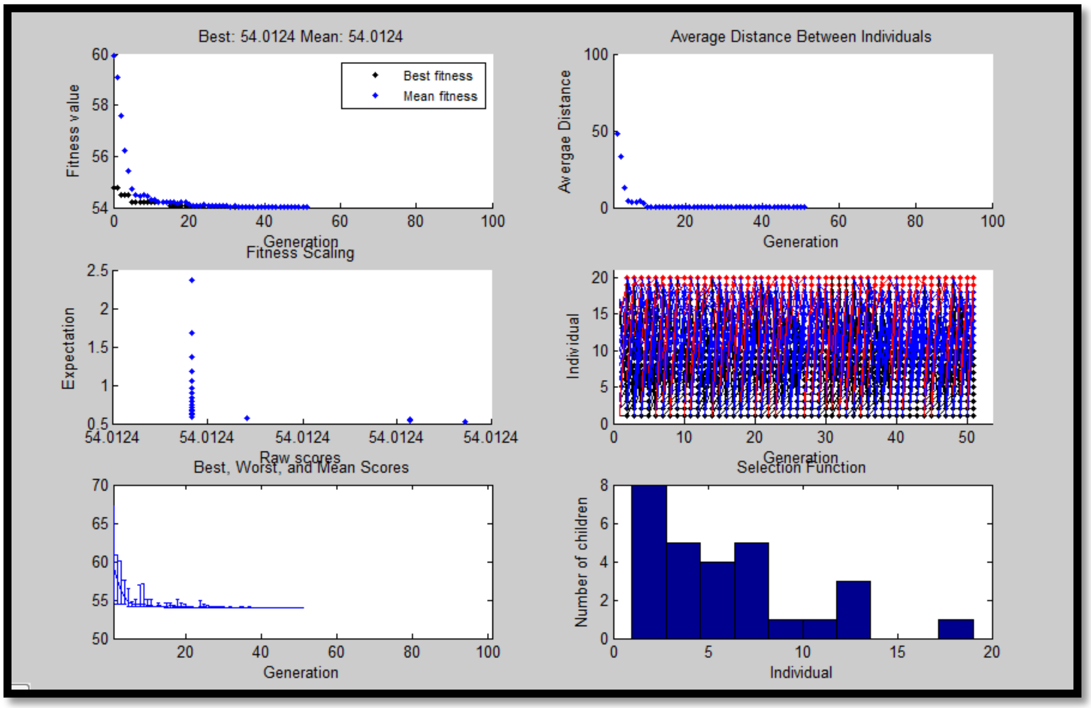


Figure 6.9 Graphical representation of fitness value for PCD (tool) and aluminium (work)

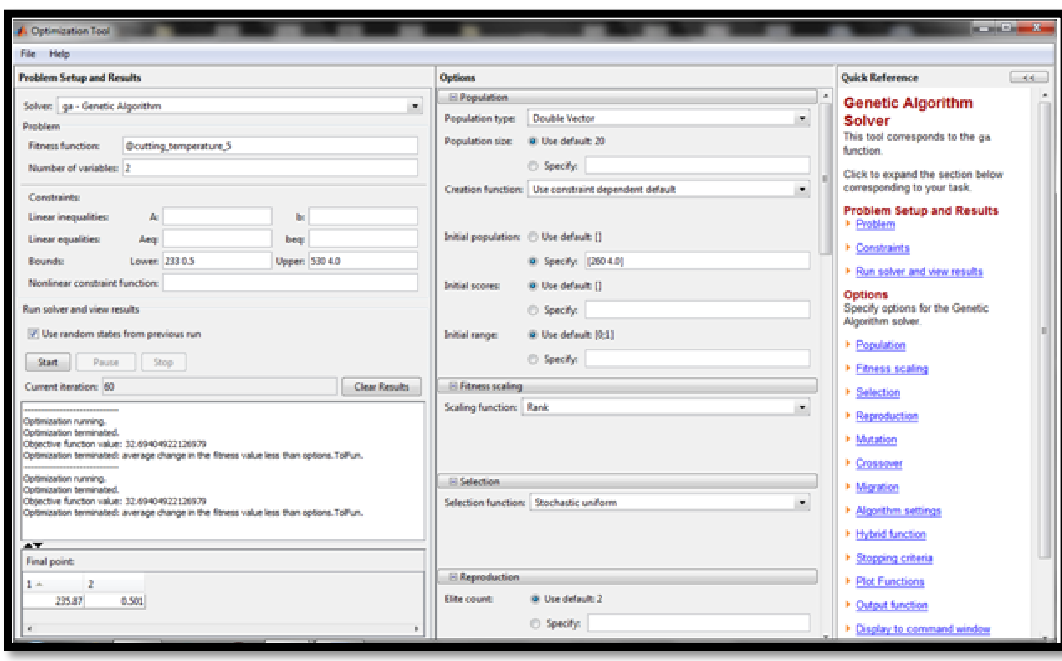


Figure 6.10 GA Optimal result window for high speed steel (tool) and aluminium(work)

OPTIMIZED RESULT

Minimized chip-tool interface temperature – **32.69404922126979 °C**

Cutting Speed – **235.87 m/min**

Depth of cut – **0.501 mm**

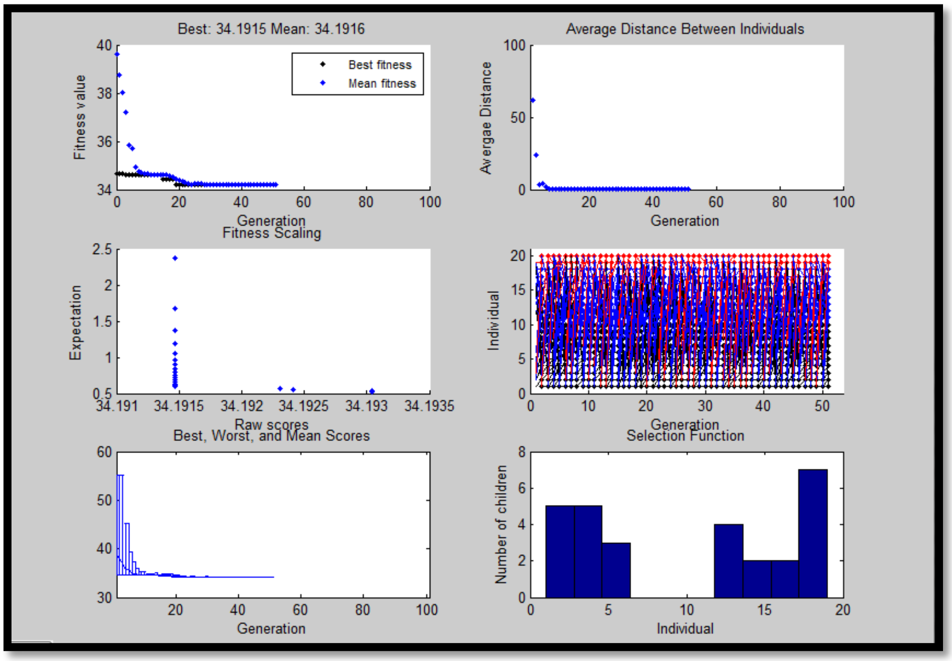


Figure 6.11 Graphical representation of fitness value for high speed steel (tool) and aluminium(work)

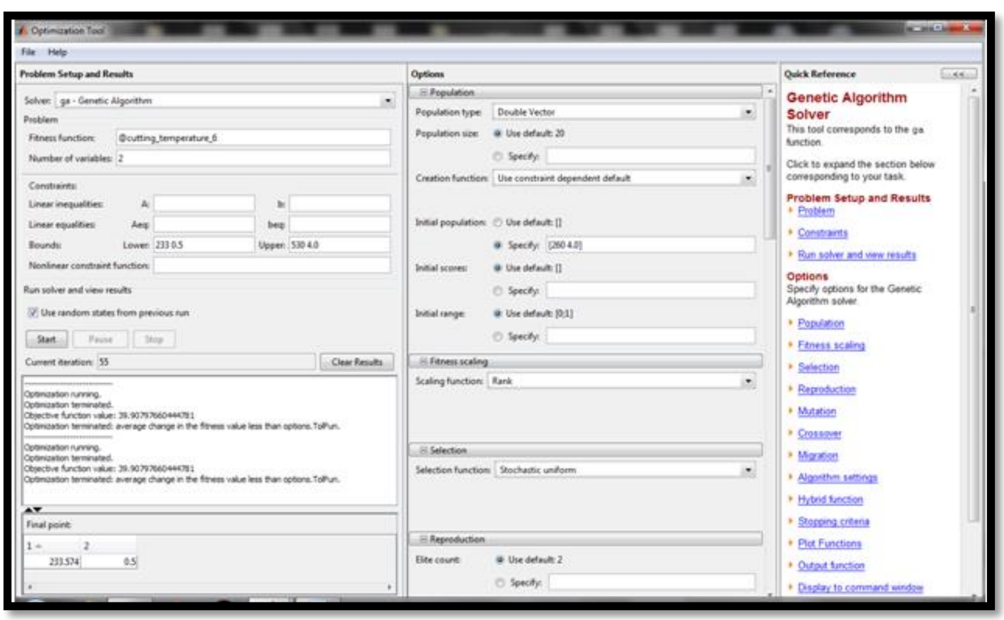


Figure 6.12 GA Optimal result window for high speed steel (tool) and brass (work)

OPTIMIZED RESULT

Minimized chip-tool interface temperature – **39.90797660444781 °C**

Cutting Speed – **233.574 m/min**

Depth of cut – **0.5 mm**

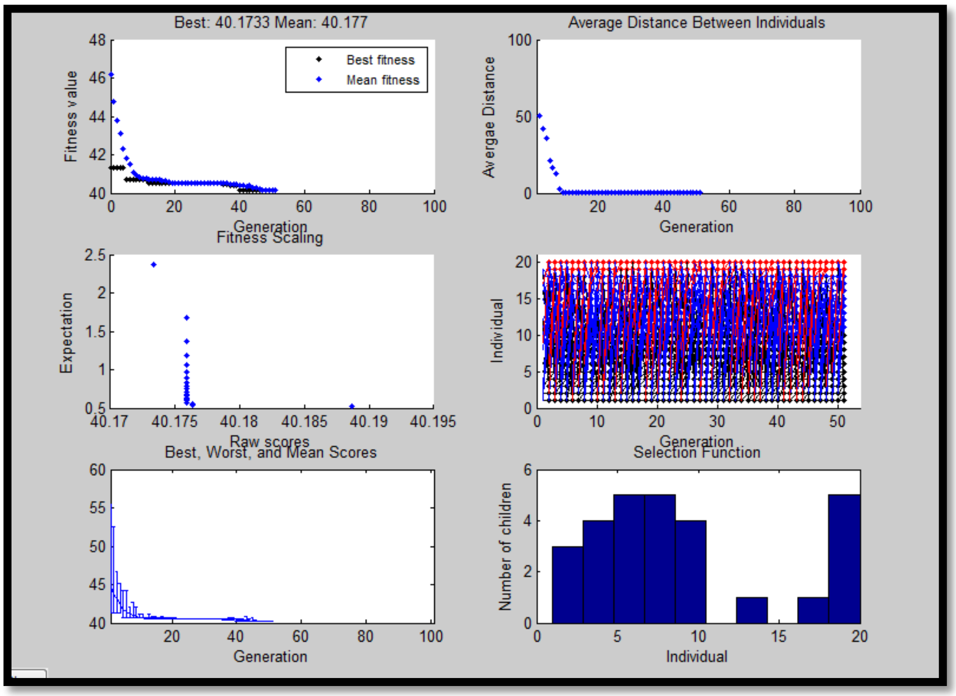


Figure 6.13 Graphical representation of fitness value for high speed steel (tool) and brass (work)

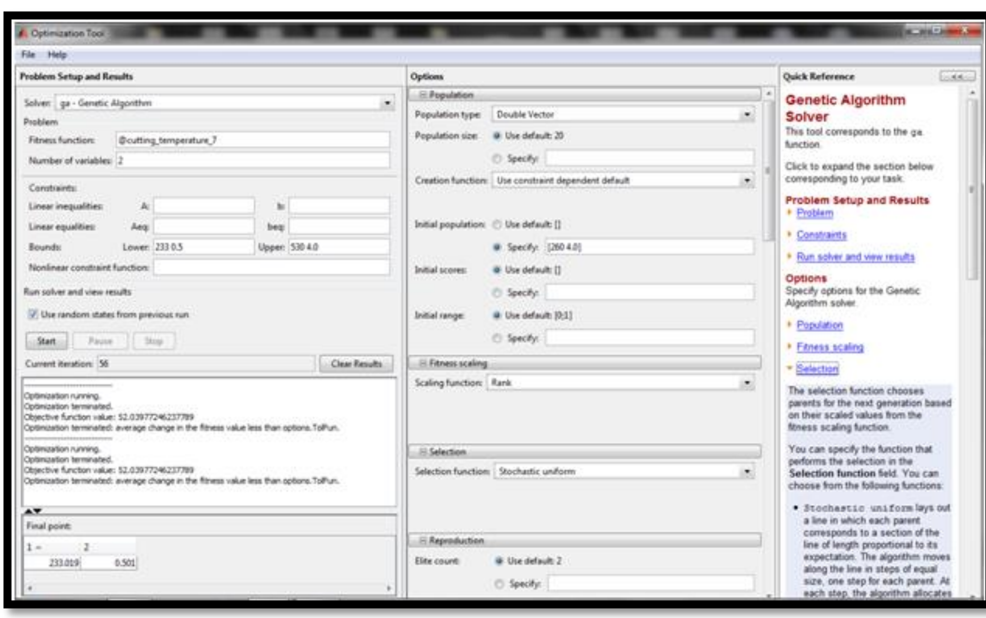


Figure 6.14 GA Optimal result window for PCD (tool) and brass (work)

OPTIMIZED RESULT

Minimized chip-tool interface temperature – **52.03977246237789 °C**

Cutting Speed – **233.019 m/min**

Depth of cut – **0.501 mm**

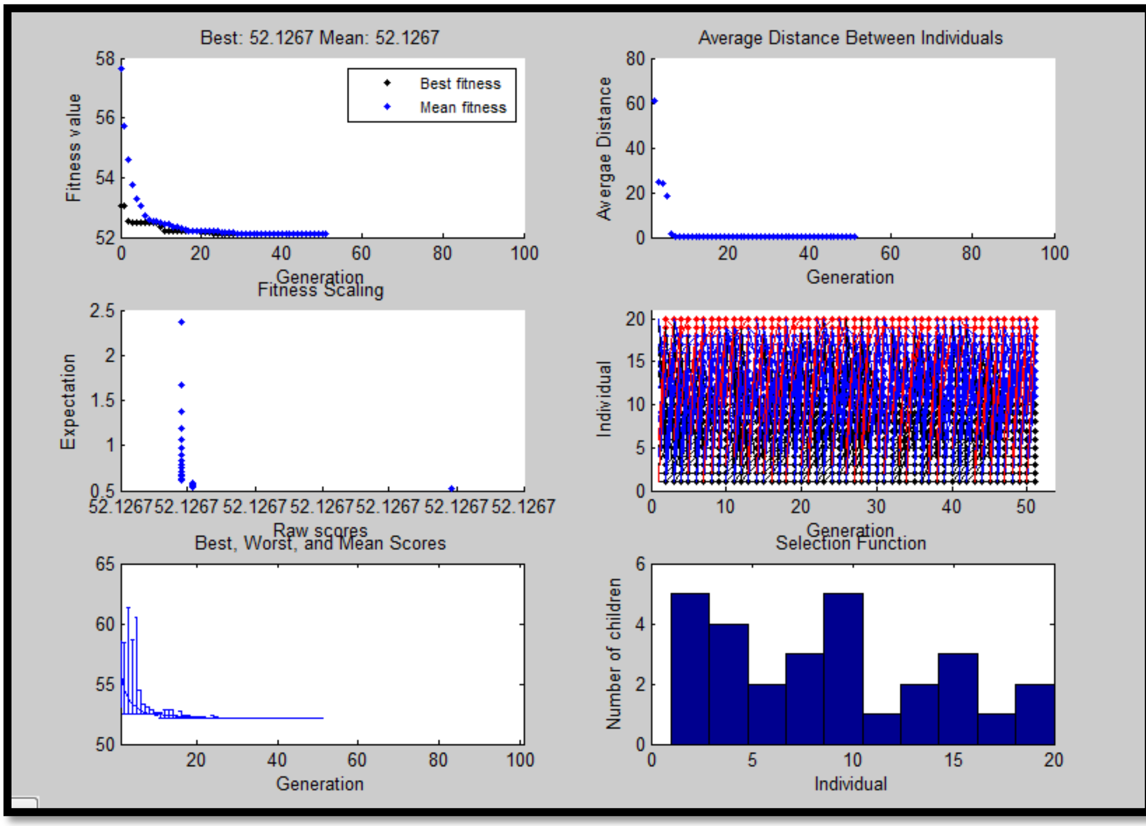


Figure 6.15 Graphical representation of fitness value for PCD (tool) and brass (work)

Chapter 7

RESULTS AND DISCUSSIONS

7.1 COMPARATIVE ANALYSIS OF CHIP-TOOL INTERFACE TEMPERATURES

A comparative analysis is carried out for the chip-tool interface temperature obtained from the three models. The percentage error is also calculated between experimental and predicted results which are tabulated as follows:

Table 7.1 Temperature analysis with % error for tungsten carbide and mild steel

READING NO.	CUTTING SPEED (m/min)	DEPTH OF CUT (mm)	CHIP-TOOL INTERFACE TEMPERATURE (°C)			
			EXPERIMENTAL TEMP.	PREDICTED TEMP.	PERCENTAGE ERROR (%)	GA MODEL TEMP.
1	233	0.5	95.6286	100.9375824	5.2595	91.0720
2	233	1.0	99.1654	105.5371348	6.0374	103.1414
3	233	1.5	104.0056	110.1366872	5.5667	110.9301
4	233	2.0	123.4944	114.7362396	-7.633	116.8104
5	233	2.5	125.9460	119.335792	-5.5391	121.5854
6	233	3.0	125.9460	123.9353444	-1.6223	125.6313
7	233	3.5	125.9460	128.5348968	2.0141	129.1570
8	233	4.0	125.9460	133.1344492	5.3993	132.2909
9	340	0.5	100.3744	105.753664	5.0611	98.7332
10	340	1.0	113.7230	111.272646	-2.2021	111.8180
11	340	1.5	123.4944	116.791628	-5.7391	120.2619
12	340	2.0	133.3207	122.31061	-9.0018	126.6368
13	340	2.5	135.7865	127.289592	-6.6752	131.8135
14	340	3.0	133.3207	133.348574	0.0208	136.1998
15	340	3.5	138.2549	138.867556	0.4411	140.0220
16	340	4.0	138.2549	144.386538	4.2466	143.4196
17	530	0.5	97.9571	114.305583	14.3024	108.5601
18	530	1.0	123.4944	121.457197	-1.6773	122.9472
19	530	1.5	133.3207	128.608811	-3.6637	132.2315
20	530	2.0	145.6784	135.760425	-7.3055	139.2410
21	530	2.5	149.3998	142.912039	-4.6926	144.9329
22	530	3.0	146.6183	150.063653	2.2958	149.7557
23	530	3.5	155.6147	157.215267	1.0180	153.9584
24	530	4.0	156.8594	164.366881	4.5674	157.6941

Table 7.2 Temperature analysis with % error for tungsten carbide and aluminium

READING NO.	CUTTING SPEED (m/min)	DEPTH OF CUT (mm)	CHIP-TOOL INTERFACE TEMPERATURE (°C)			
			EXPERIMENTAL TEMP.	PREDICTED TEMP.	PERCENTAGE ERROR (%)	GA MODEL TEMP.
1	233	0.5	35.1634	35.09174536	-0.2043	33.9324
2	233	1.0	36.3892	36.24814412	-0.3893	36.3066
3	233	1.5	37.6137	37.40454287	-0.5593	37.7717
4	233	2.0	35.1634	38.56094163	8.8107	38.8470
5	233	2.5	38.8368	39.71763845	2.2176	39.7020
6	233	3.0	37.6137	40.87373915	7.9757	40.4146
7	233	3.5	41.2791	42.03013791	1.7868	41.0271
8	233	4.0	42.4983	43.18653666	1.5935	41.5651
9	340	0.5	37.6137	37.60754284	-1.6497	36.8701
10	340	1.0	40.0586	38.78636048	-3.2802	39.4499
11	340	1.5	41.2791	39.96569252	-3.2864	41.0418
12	340	2.0	42.4983	41.14476736	-3.2897	42.2101
13	340	2.5	44.9330	42.3238422	-6.1649	43.1392
14	340	3.0	44.9330	43.50291704	-3.2875	43.9135
15	340	3.5	47.3631	44.68229188	-5.9999	44.5790
16	340	4.0	48.5765	45.8610652	-5.9212	45.1636
17	530	0.5	40.0586	42.074484678	4.7911	40.6475
18	530	1.0	42.4983	43.29418756	1.8382	43.4915
19	530	1.5	43.7163	44.51352834	1.8313	45.2466
20	530	2.0	46.1487	45.73286912	-0.9092	46.5346
21	530	2.5	48.5765	46.9522099	-3.4596	47.5589
22	530	3.0	51.4133	48.17155068	-6.7295	48.4125
23	530	3.5	47.3631	49.39089146	4.1054	49.1461
24	530	4.0	46.1487	50.61023224	8.8154	49.7906

Table 7.3 Temperature analysis with % error for tungsten carbide (tool) and brass (work)

READING NO.	CUTTING SPEED (m/min)	DEPTH OF CUT (mm)	CHIP-TOOL INTERFACE TEMPERATURE (°C)			
			EXPERIMENTAL TEMP.	PREDICTED TEMP.	PERCENTAGE ERROR (%)	GA MODEL TEMP.
1	233	0.5	33.9362	34.68073318	2.1468	33.7767
2	233	1.0	35.1634	34.8155509	-0.9992	34.2622
3	233	1.5	35.1634	34.95036349	0.6096	34.5494
4	233	2.0	32.7075	35.08527609	6.7769	34.7546
5	233	2.5	33.9362	35.22005869	3.6452	34.9146
6	233	3.0	33.9362	35.35480129	4.0124	35.0459
7	233	3.5	33.9362	35.49019076	4.3786	35.1573
8	233	4.0	33.9362	35.62442649	4.7389	35.2541
9	340	0.5	33.9362	37.14152329	8.6300	36.9001
10	340	1.0	40.0586	37.28116057	-7.4500	37.4304
11	340	1.5	40.0586	37.42079786	-7.0491	37.7442
12	340	2.0	40.0586	37.56043515	-6.6511	37.9684
13	340	2.5	40.0586	37.70007244	-6.2561	38.1432
14	340	3.0	40.0586	37.83970972	-5.8640	38.2867
15	340	3.5	40.0586	37.97934701	-5.4748	38.4084
16	340	4.0	40.0586	38.1189843	-5.0884	38.5141
17	530	0.5	40.0586	41.51114149	3.4990	40.9400
18	530	1.0	41.2791	41.65934598	0.9126	41.5284
19	530	1.5	43.7163	41.80755047	-4.5656	41.8765
20	530	2.0	41.2791	41.95575497	1.6127	42.1253
21	530	2.5	41.2791	42.10395946	1.9590	42.3193
22	530	3.0	41.2791	42.25216395	2.3029	42.4784
23	530	3.5	41.2791	42.40036844	2.6444	42.6134
24	530	4.0	41.2791	42.54857272	2.9835	42.7307

Table 7.4 Temperature analysis with % error for PCD (tool) and aluminium (work)

READING NO.	CUTTING SPEED (m/min)	DEPTH OF CUT (mm)	CHIP-TOOL INTERFACE TEMPERATURE (°C)			
			EXPERIMENTAL TEMP.	PREDICTED TEMP.	PERCENTAGE ERROR	GA MODEL TEMP.
1	233	0.5	43.7163	54.98208066	20.4898	52.3213
2	233	1.0	47.3631	56.11009632	15.5888	54.9914
3	233	1.5	59.4555	57.23811198	-3.8740	56.6160
4	233	2.0	55.8366	58.36612764	4.3338	57.7978
5	233	2.5	59.4555	59.4941433	0.0648	58.7314
6	233	3.0	59.4555	60.62215896	1.9243	59.5054
7	233	3.5	58.2499	61.75012962	5.6683	60.1677
8	233	4.0	58.2499	62.8748378	7.3557	60.7474
9	340	0.5	73.8881	57.7471768	-27.9510	56.3631
10	340	1.0	63.0688	59.0033536	-6.8903	59.2395
11	340	1.5	66.6778	60.1395304	-10.8719	60.9897
12	340	2.0	65.4804	61.3357072	-6.7574	62.2627
13	340	2.5	65.4804	62.531884	-4.7153	63.2684
14	340	3.0	70.2838	63.7280608	-10.2871	64.1022
15	340	3.5	69.0821	64.9242376	-6.4041	64.8157
16	340	4.0	67.8801	66.1204144	-2.6613	65.4402
17	530	0.5	61.8649	62.6271606	1.2643	61.5117
18	530	1.0	63.0688	63.9743712	1.4154	64.6508
19	530	1.5	55.8366	65.2915818	14.4811	66.5609
20	530	2.0	63.0688	66.6087924	5.3144	67.9502
21	530	2.5	66.6778	67.926003	1.8374	69.0477
22	530	3.0	69.0821	69.2432166	0.2326	69.9577
23	530	3.5	70.2838	70.5604242	0.3919	70.7364
24	530	4.0	71.5560	71.87766348	0.4473	71.4179

Table 7.5 Temperature analysis with % error for high speed steel (tool) and aluminium(work)

READING NO.	CUTTING SPEED (m/min)	DEPTH OF CUT (mm)	CHIP-TOOL INTERFACE TEMPERATURE (°C)			
			EXPERIMENTAL TEMP.	PREDICTED TEMP.	PERCENTAGE ERROR (%)	GA MODEL TEMP.
1	233	0.5	33.9362	35.49122638	4.3814	32.6160
2	233	1.0	37.6317	37.43550276	-0.4761	37.1810
3	233	1.5	42.4983	39.37977914	-7.9191	40.1420
4	233	2.0	44.9330	41.32405552	-8.7335	42.3849
5	233	2.5	44.9330	43.2683319	-3.8475	44.2105
6	233	3.0	43.7163	45.21260828	3.3094	45.7603
7	233	3.5	46.1487	47.15688466	2.1379	47.1130
8	233	4.0	48.5765	49.10116104	1.0683	48.3171
9	340	0.5	35.1634	36.5576664	3.8137	34.8768
10	340	1.0	35.1634	38.9222238	9.6571	39.7582
11	340	1.5	38.8368	41.2867812	5.9339	42.9245
12	340	2.0	46.1487	43.6513386	-5.7211	45.3228
13	340	2.5	48.5765	46.015896	-5.5648	47.2750
14	340	3.0	44.9330	48.3804534	7.1255	48.9322
15	340	3.5	51.4133	50.7450108	-1.3169	50.3787
16	340	4.0	52.2111	53.1095682	1.6916	51.6662
17	530	0.5	40.0586	38.4513413	-4.1800	37.7336
18	530	1.0	43.7163	41.5621921	-5.1829	43.0148
19	530	1.5	44.9330	44.6730429	-0.5819	46.4404
20	530	2.0	47.3631	47.7838937	0.8804	49.0352
21	530	2.5	48.5765	50.8947445	4.5541	51.1472
22	530	3.0	49.7889	54.0055953	7.8077	52.9403
23	530	3.5	60.6605	57.1164461	-6.2050	54.5052
24	530	4.0	61.8649	60.2272969	-2.7191	55.8982

Table 7.6 Temperature analysis with % error for high speed steel (tool) and brass (work)

READING NO.	CUTTING SPEED (m/min)	DEPTH OF CUT (mm)	CHIP-TOOL INTERFACE TEMPERATURE (°C)			
			EXPERIMENTAL TEMP.	PREDICTED TEMP.	PERCENTAGE ERROR (%)	GA MODEL TEMP.
1	233	0.5	40.0586	47.1024755	14.9542	39.8873
2	233	1.0	52.2111	47.9107815	-8.9757	44.7173
3	233	1.5	52.2111	48.72904825	-7.1457	47.8024
4	233	2.0	52.2111	49.547315	-5.3762	50.1229
5	233	2.5	52.2111	50.36558175	-3.6643	52.0001
6	233	3.0	52.2111	50.614513	-3.1544	53.5859
7	233	3.5	49.7889	52.00211525	4.2559	54.9644
8	233	4.0	49.7889	52.820382	5.7391	56.1871
9	340	0.5	36.3892	47.7588114	23.8061	42.4108
10	340	1.0	54.6288	49.2142364	-11.0020	47.5420
11	340	1.5	54.6288	50.6696614	-7.8136	50.8267
12	340	2.0	54.6288	52.1250864	-4.8032	53.2940
13	340	2.5	54.6288	53.5805114	-1.9564	55.2899
14	340	3.0	54.6288	55.0359364	0.7397	56.9791
15	340	3.5	55.8366	56.4914614	1.1592	58.4418
16	340	4.0	55.8366	57.9467864	3.6415	59.7419
17	530	0.5	32.7075	48.94195339	33.1707	45.5799
18	530	1.0	60.6605	51.52878089	-17.7217	51.0944
19	530	1.5	61.8649	54.11560839	-14.3200	54.6247
20	530	2.0	61.8649	56.70243589	-9.5398	57.2763
21	530	2.5	61.8649	59.28916339	-4.3445	59.1214
22	530	3.0	61.8649	61.30690089	-0.9103	61.2336
23	530	3.5	61.8649	64.46291839	4.0301	62.8088
24	530	4.0	61.8649	67.04974589	7.8701	64.2060

Table 7.7 Temperature analysis with % error for PCD (tool) and brass (work)

READING NO.	CUTTING SPEED (m/min)	DEPTH OF CUT (mm)	CHIP-TOOL INTERFACE TEMPERATURE (°C)			
			EXPERIMENTAL TEMP.	PREDICTED TEMP.	PERCENTAGE ERROR (%)	GA MODEL TEMP.
1	233	0.5	52.2111	54.76109665	4.6565	52.0256
2	233	1.0	59.4555	56.18738219	-5.8165	55.6431
3	233	1.5	59.4555	57.61366774	-3.1969	57.8747
4	233	2.0	59.4555	59.03995328	-0.7039	59.5121
5	233	2.5	59.4555	60.46623883	1.6714	60.8141
6	233	3.0	59.4555	61.89252437	3.9374	61.8989
7	233	3.5	59.4555	63.31880992	6.1012	62.8312
8	233	4.0	59.4555	64.74509546	8.1697	63.6508
9	340	0.5	51.4133	56.6117221	9.1825	55.0383
10	340	1.0	58.2499	58.2775662	0.0474	58.8653
11	340	1.5	58.2499	59.9434103	2.8251	61.2261
12	340	2.0	66.6778	61.6092544	5.4526	62.9583
13	340	2.5	66.6778	63.2750985	-5.3777	64.3356
14	340	3.0	69.0821	64.9409426	-6.4027	65.4833
15	340	3.5	71.5560	66.6067867	-7.4306	66.4696
16	340	4.0	72.6868	68.2726308	-6.4655	67.3360
17	530	0.5	61.8649	59.89787943	-3.2840	58.8009
18	530	1.0	66.6778	61.9891079	-7.5638	62.8895
19	530	1.5	64.2722	64.08033635	-0.2995	65.4117
20	530	2.0	53.4201	66.1715648	19.2707	67.2622
21	530	2.5	69.0821	68.26279325	-1.2002	68.7338
22	530	3.0	73.8881	70.3540217	-5.0233	69.9599
23	530	3.5	71.5560	72.44525015	1.2273	71.0137
24	530	4.0	71.5560	74.5364786	3.9985	71.9393

7.2 GRAPHICAL INTERPRETATION OF CHIP-TOOL INTERFACE TEMPERATURE

The following graphs were obtained for the chip-tool interface temperature depending on cutting speed and depth of cut for different tool-work material combinations. Further the interpretation of graphs was carried out to understand the effects of the cutting parameters on the response variable i.e. chip tool interface temperature.

TOOL MATERIAL - Tungsten carbide WORK MATERIAL - Mild Steel

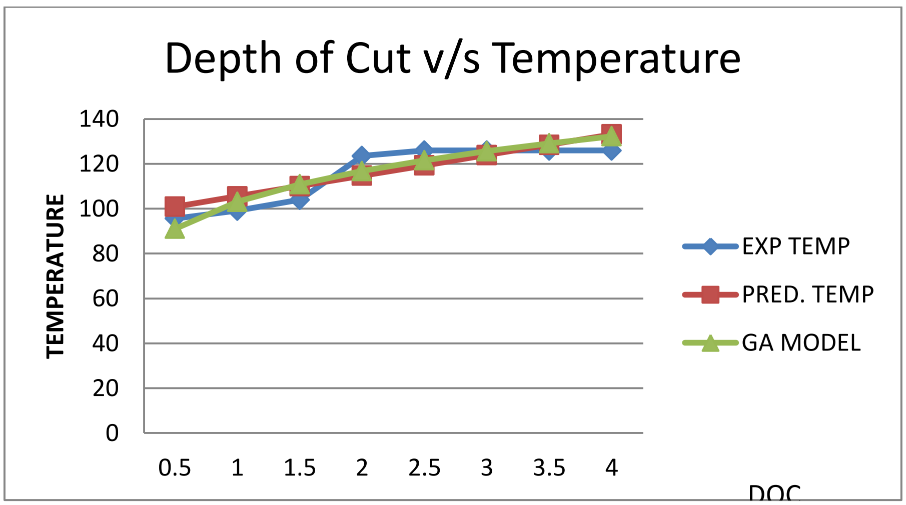


Figure 7.1 The variation of the temperature with the depth of cut (Cutting speed = 233m/min)

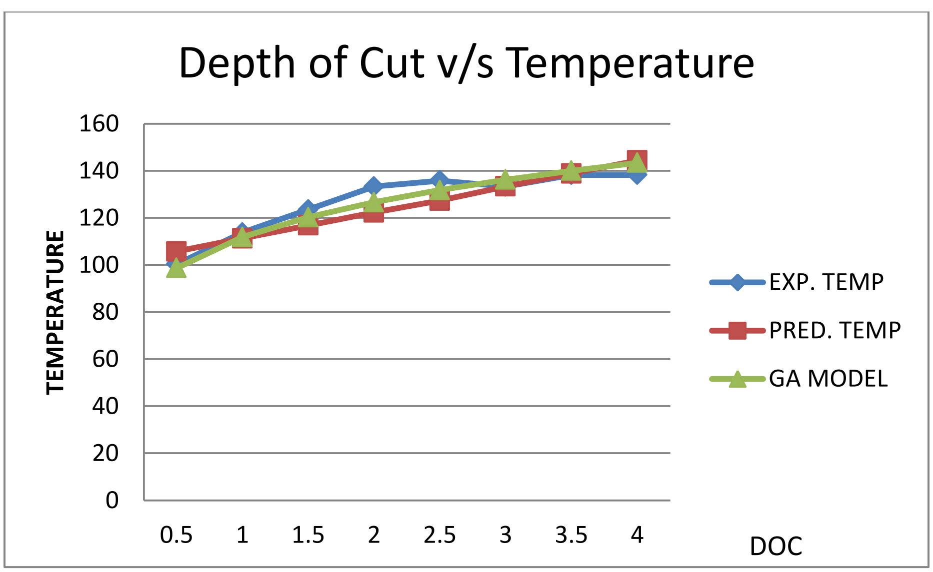


Figure 7.2 The variation of the temperature with the depth of cut (Cutting speed = 340 m/min)

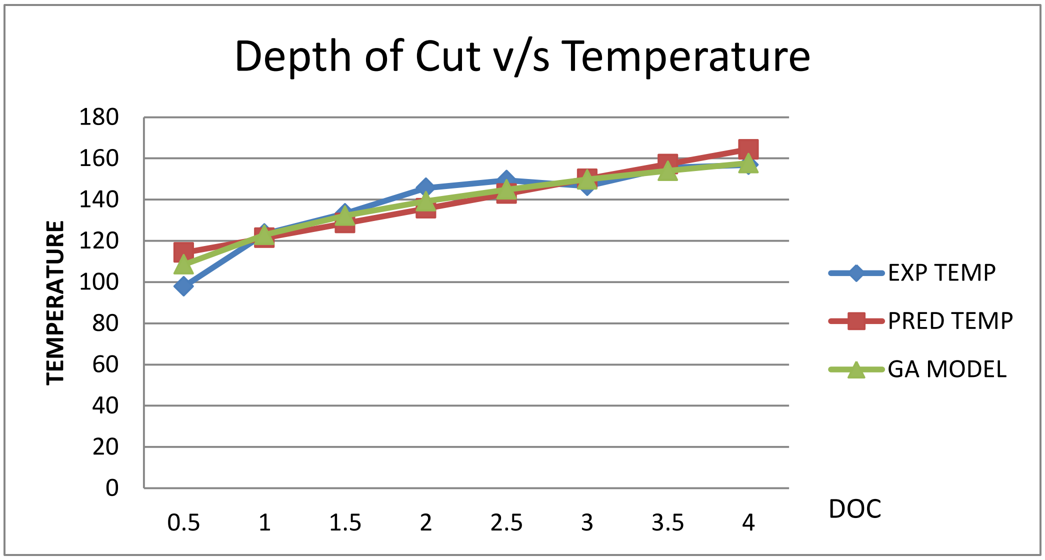


Figure 7.3 The variation of the temperature with the depth of cut (Cutting speed = 530 m/min)

The above graphs show the variation of chip-tool interface temperature with depth of cut at three different cutting speeds. The temperature measured experimentally and calculated theoretically shows an increase with the increase in the depth of cut. The measured values of temperature lie within the range of experimental error.

TOOL MATERIAL – Tungsten carbide WORK MATERIAL – Aluminium

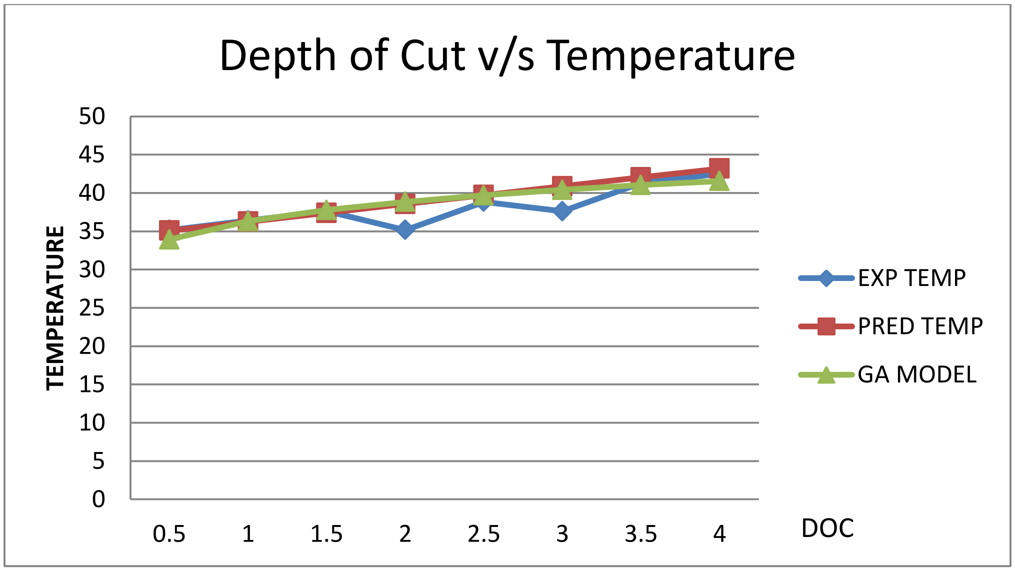


Figure 7.4 The variation of the temperature with the depth of cut (Cutting speed = 233 m/min)

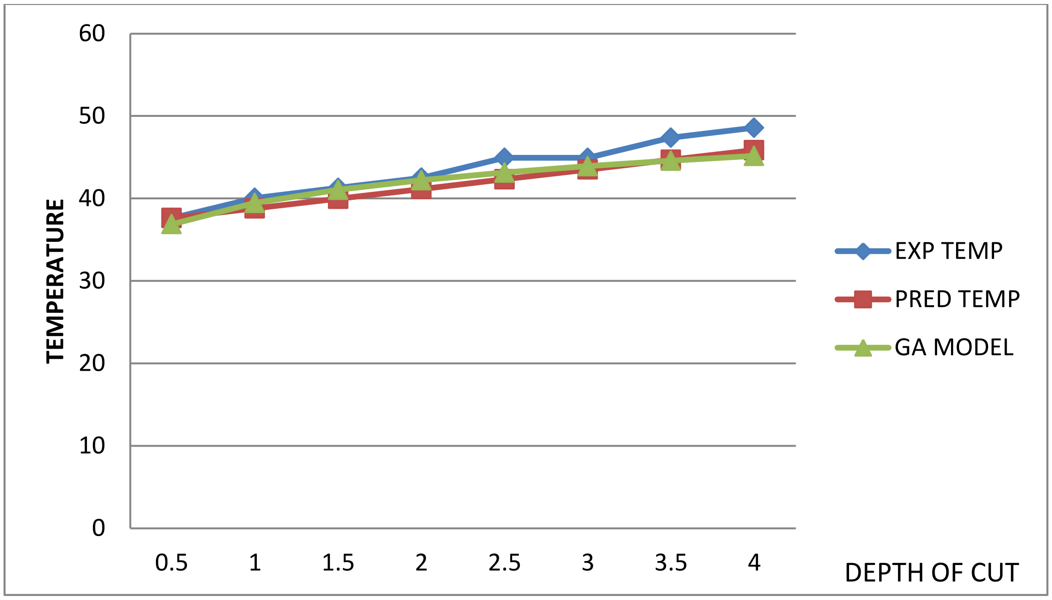


Figure 7.5 The variation of the temperature with the depth of cut (Cutting speed = 340 m/min)

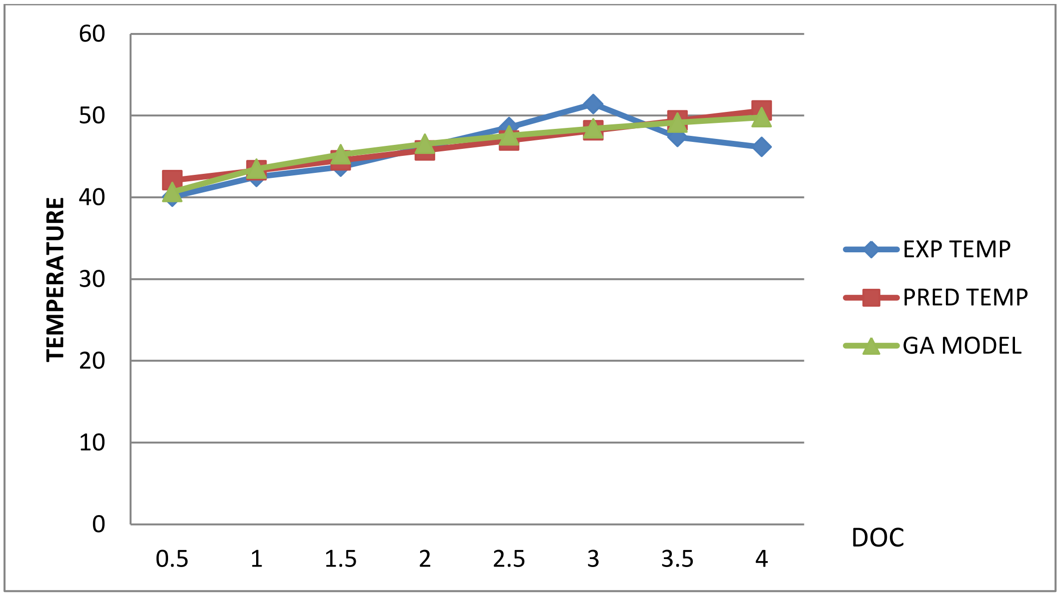


Figure 7.6 The variation of the temperature with the depth of cut (Cutting speed = 530 m/min)

The above graphs show the variation of chip-tool interface temperature with depth of cut at three different cutting speeds. The temperature measured experimentally and calculated theoretically shows an increase with the increase in the depth of cut but after 3.0 mm depth of cut a decrease in temperature is observed. The measured values of temperature lie within the range of experimental error.

TOOL MATERIAL – Tungsten carbide WORK MATERIAL – Brass

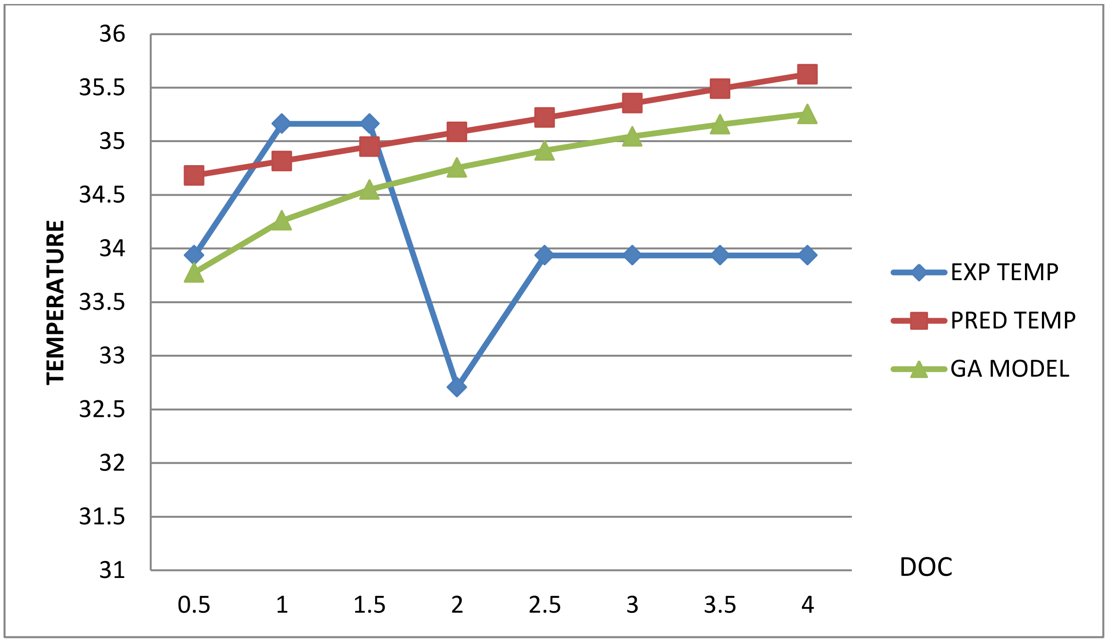


Figure 7.7 The variation of the temperature with the depth of cut (Cutting speed = 233 m/min)

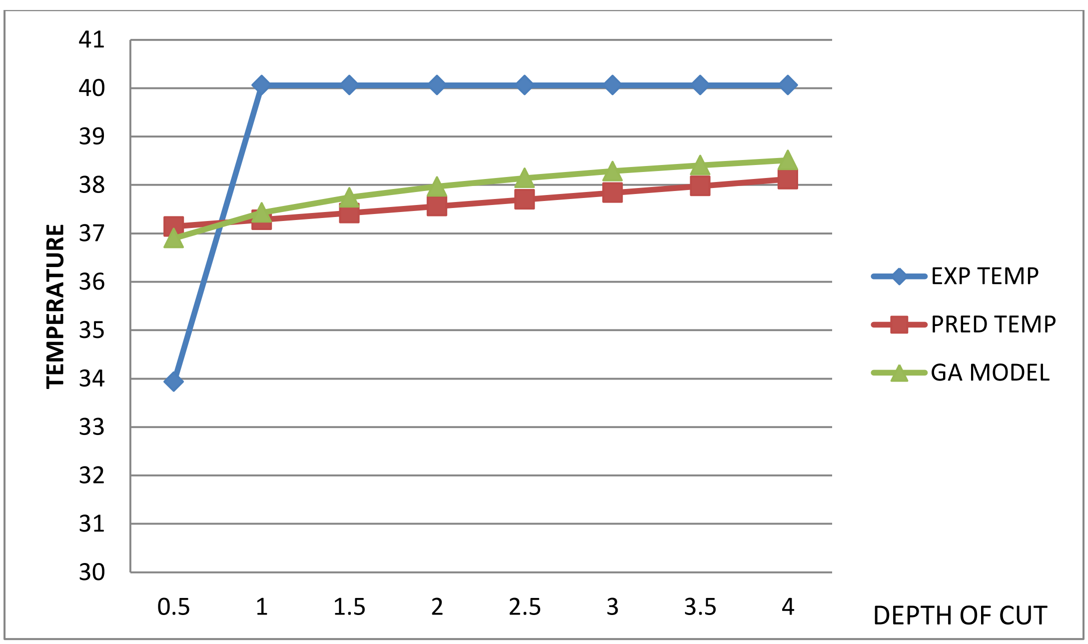


Figure 7.8 The variation of the temperature with the depth of cut (Cutting speed = 340 m/min)

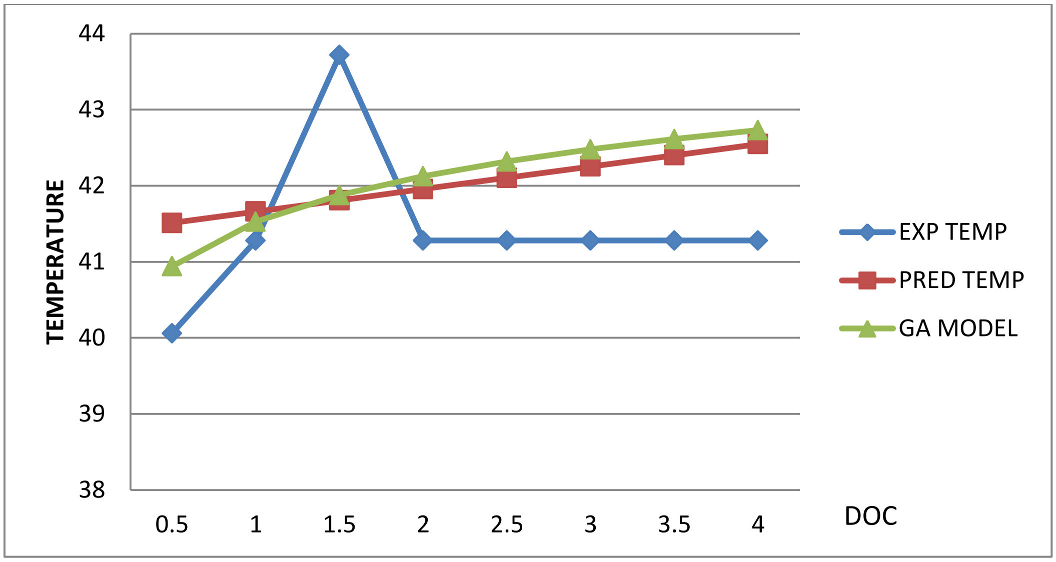


Figure 7.9 The variation of the temperature with the depth of cut (Cutting speed = 530 m/min)

The above graphs show the variation of chip-tool interface temperature with depth of cut at three different cutting speeds. The temperature measured experimentally shows an increase with the increase in the depth of cut upto a certain value after which a decrease is experienced but the theoretically calculated value shows a continuous increase in temperature with the increase in the value of depth of cut.

TOOL MATERIAL – PCD WORK MATERIAL – Aluminium

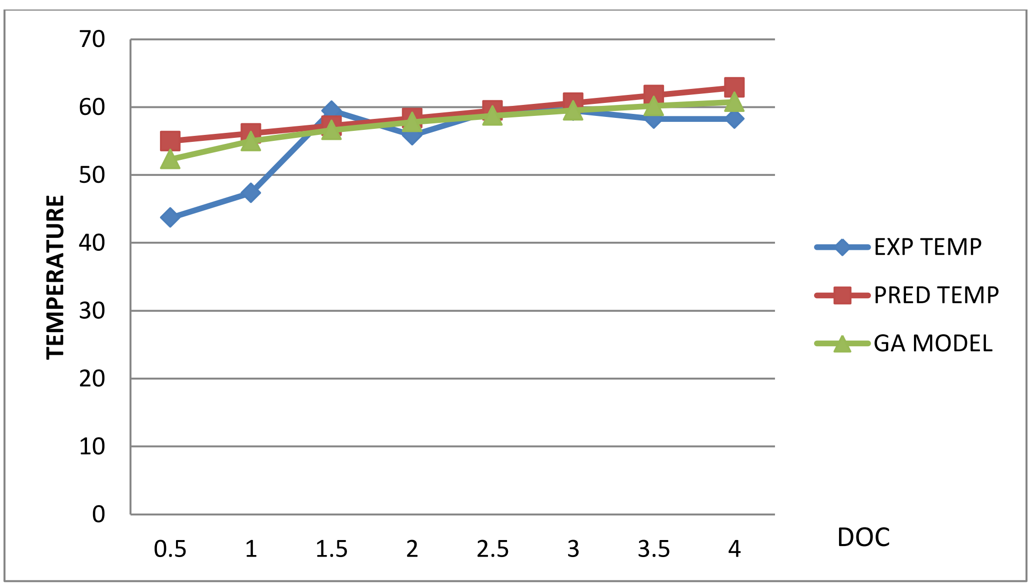


Figure 7.10 The variation of the temperature with the depth of cut (Cutting speed = 233 m/min)

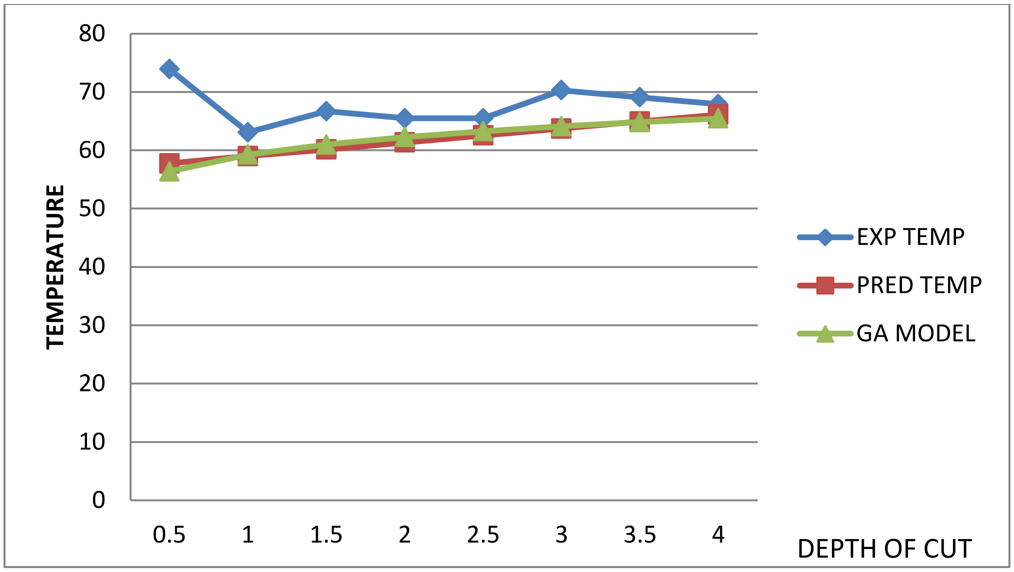


Figure 7.11 The variation of the temperature with the depth of cut (Cutting speed = 340 m/min)

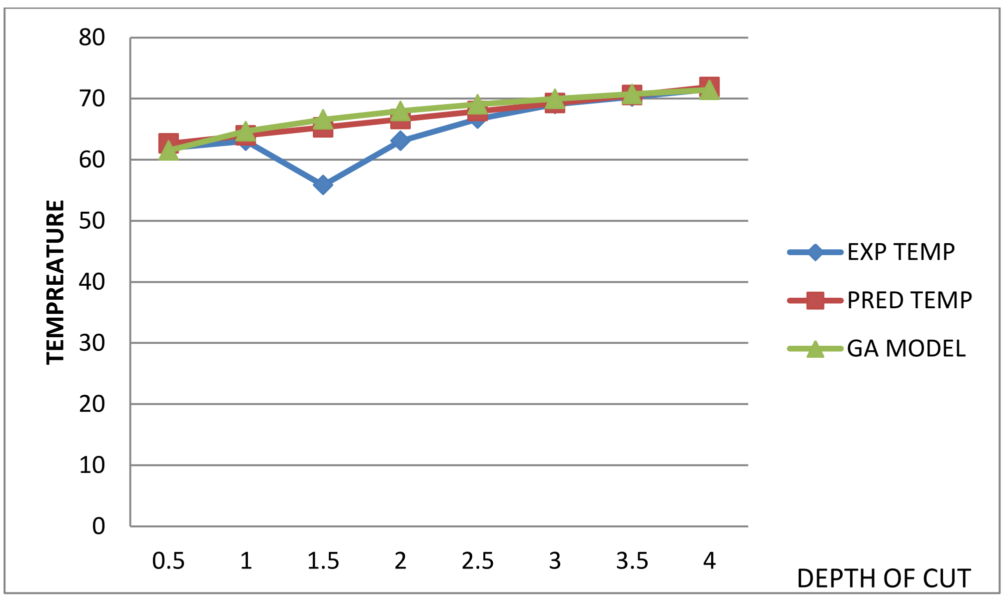


Figure 7.12 The variation of the temperature with the depth of cut (Cutting speed = 530 m/min)

The above graphs show the variation of chip-tool interface temperature with depth of cut at three different cutting speeds. The temperature measured experimentally and calculated theoretically shows an increase with the increase in the depth of cut but a slight decrease at some values in between is observed. The measured values of temperature lie within the range of experimental error.

TOOL MATERIAL – High speed steel WORK MATERIAL – Aluminium

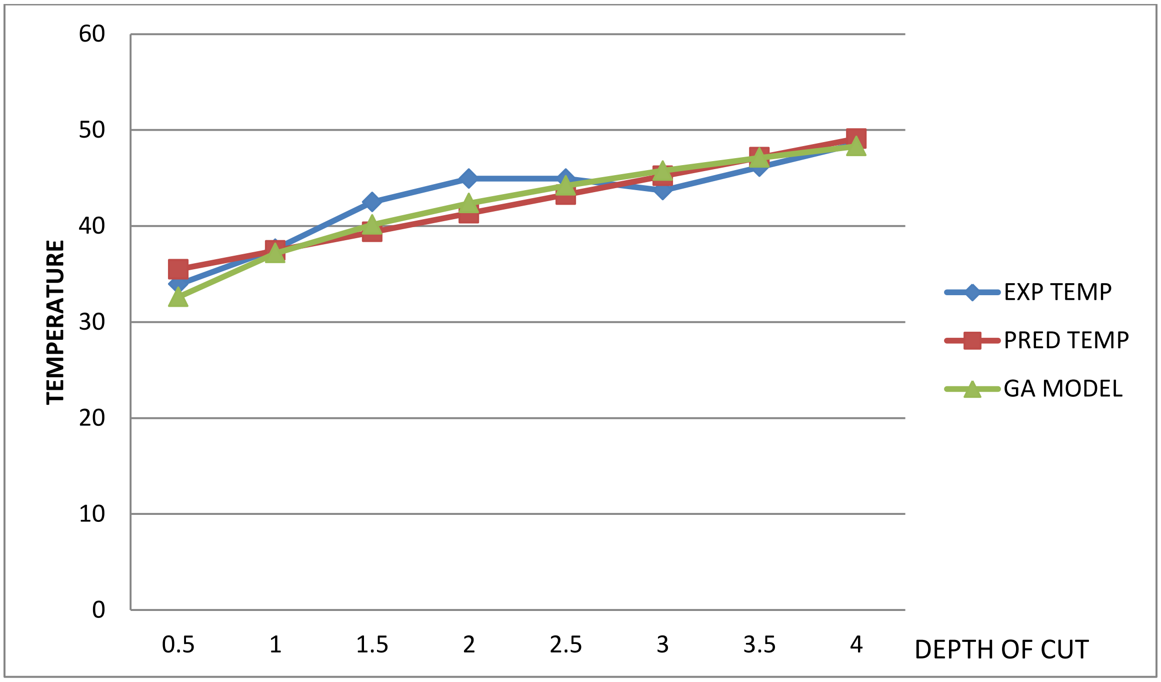


Figure 7.13 The variation of the temperature with the depth of cut (Cutting speed = 233 m/min)

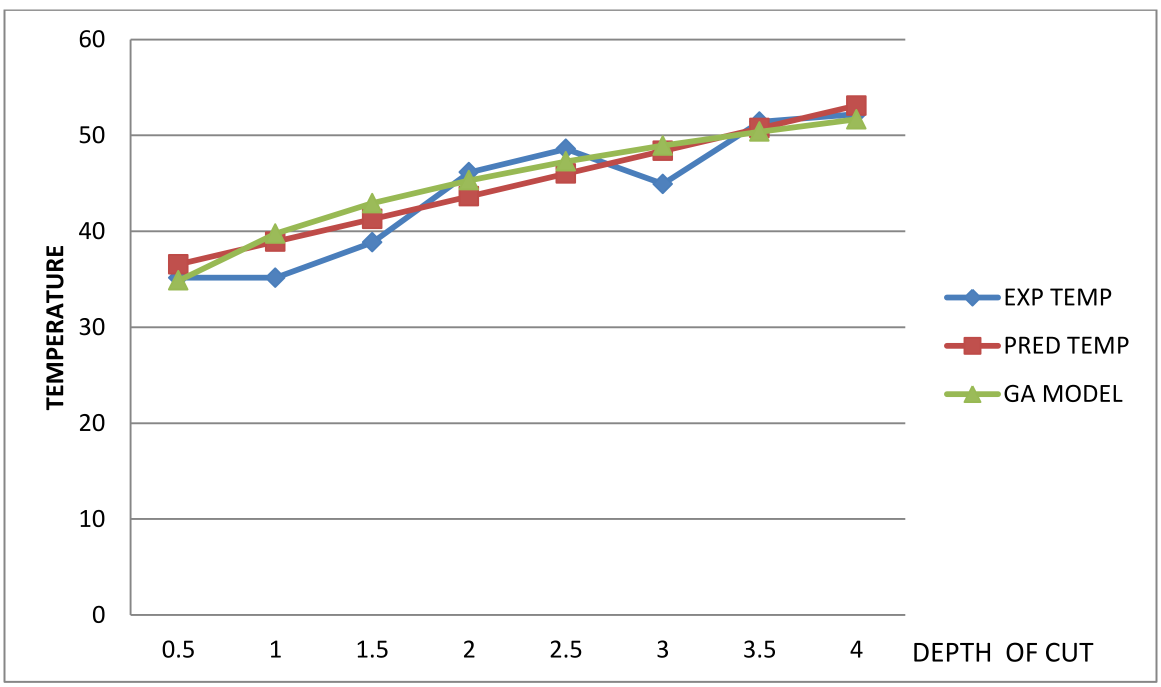


Figure 7.14 The variation of the temperature with the depth of cut (Cutting speed = 340 m/min)

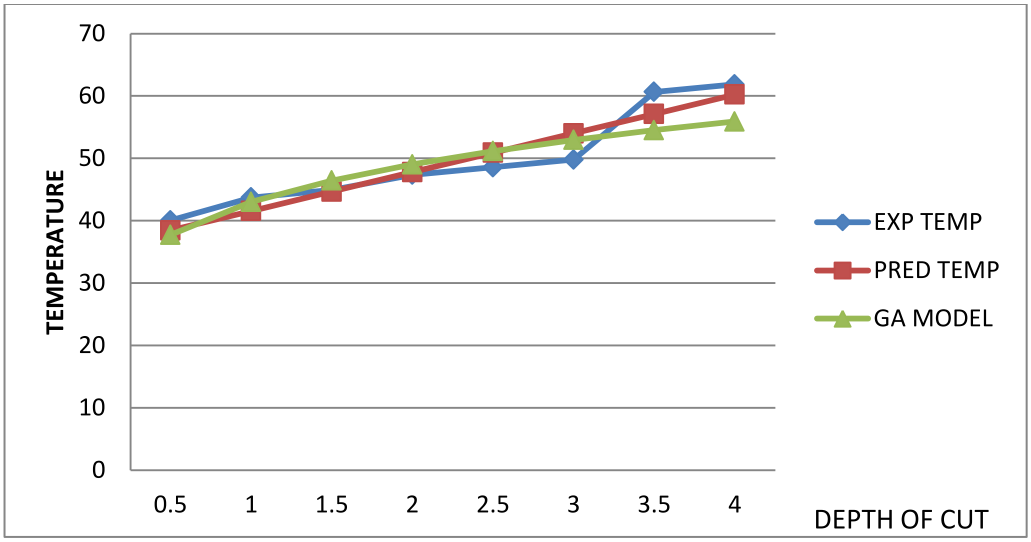


Figure 7.15 The variation of the temperature with the depth of cut (Cutting speed = 530 m/min)

The above graphs show the variation of chip-tool interface temperature with depth of cut at three different cutting speeds. The temperature measured experimentally and calculated theoretically shows an increase with the increase in the depth of cut but a slight decrease at some values in between is observed at all the three cutting speed due to some experimental error. The measured values of temperature lie within the range of experimental error.

TOOL MATERIAL – High speed steel WORK MATERIAL – Brass

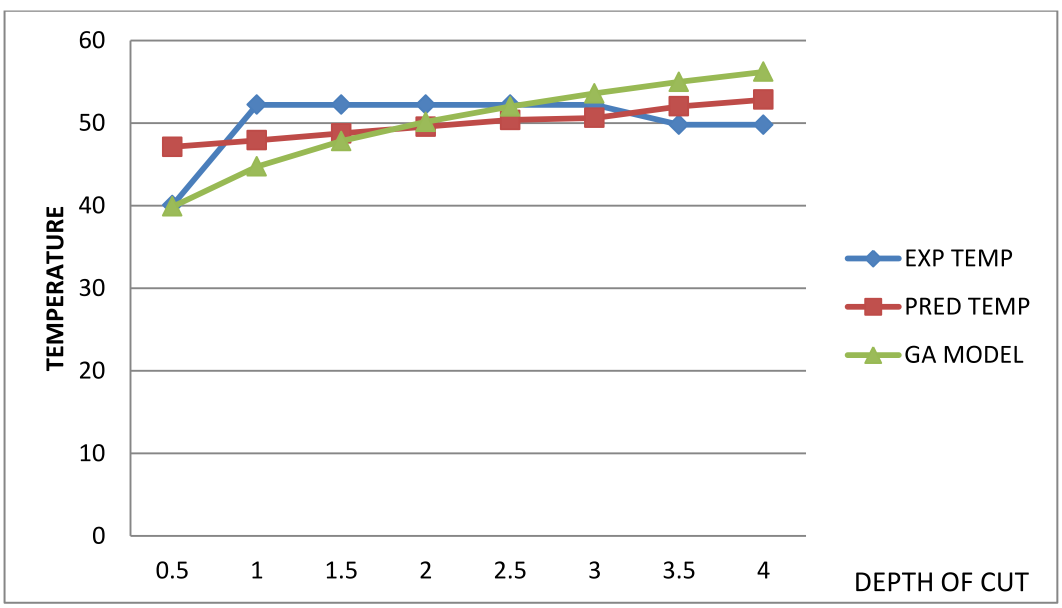


Figure 7.16 The variation of the temperature with the depth of cut (Cutting speed = 233 m/min)

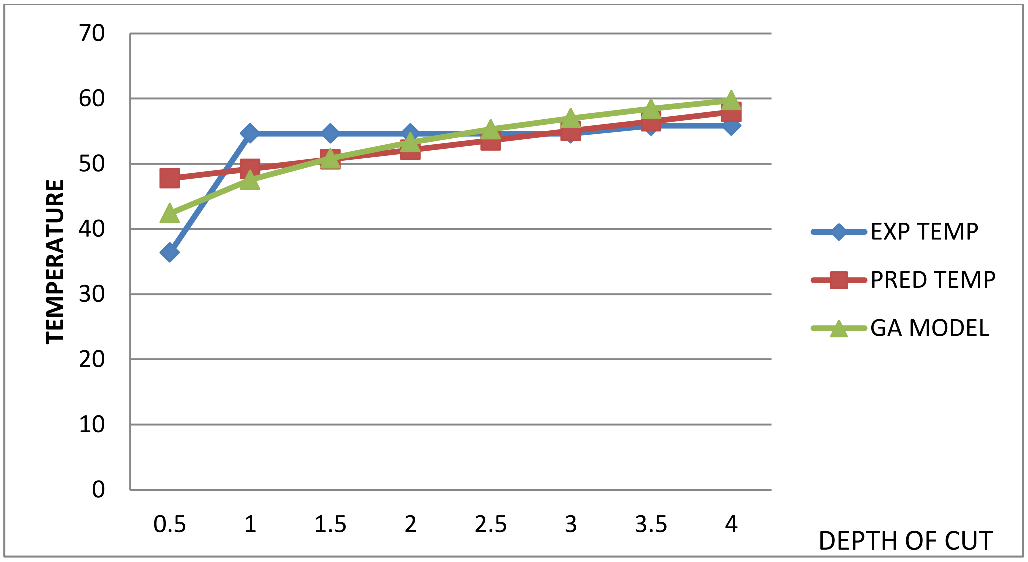


Figure 7.17 The variation of the temperature with the depth of cut (Cutting speed = 340 m/min)

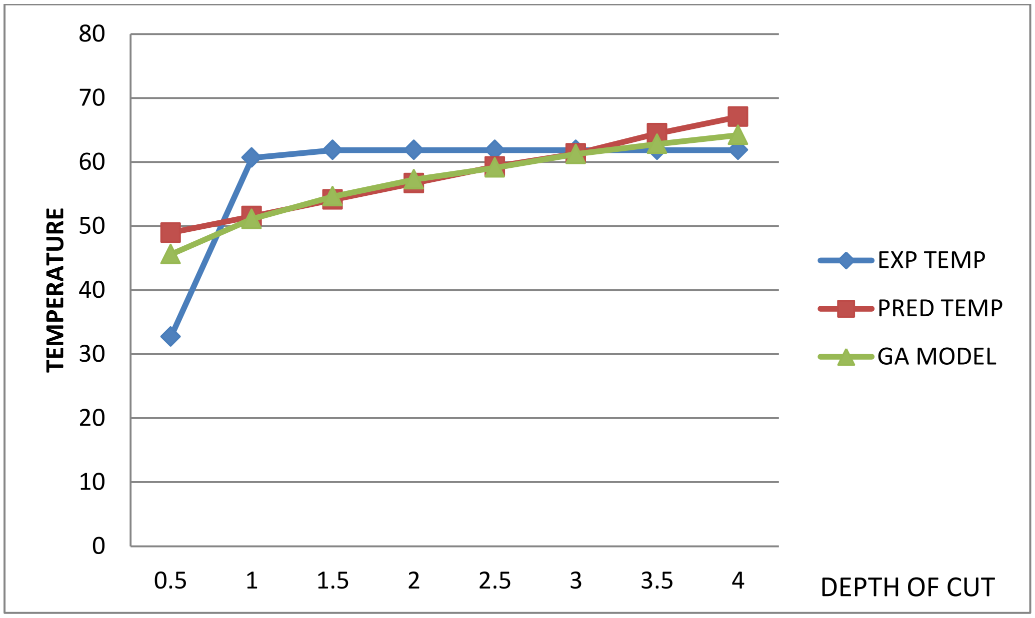


Figure 7.18 The variation of the temperature with the depth of cut (Cutting speed = 530 m/min)

The above graphs show the variation of chip-tool interface temperature with depth of cut at three different cutting speeds. The temperature measured experimentally and calculated theoretically shows an increase with the increase in the depth of cut. The measured values of temperature lie within the range of experimental error.

TOOL MATERIAL – PCD WORK MATERIAL – Brass

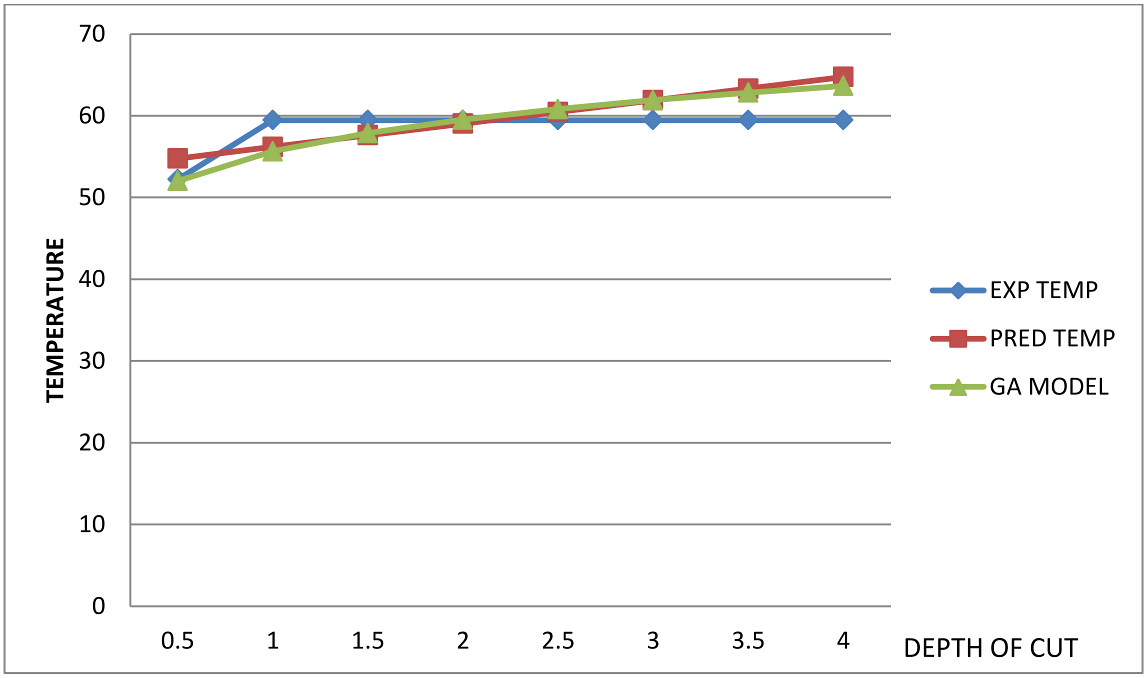


Figure 7.19 The variation of the temperature with the depth of cut (Cutting speed = 233 m/min)

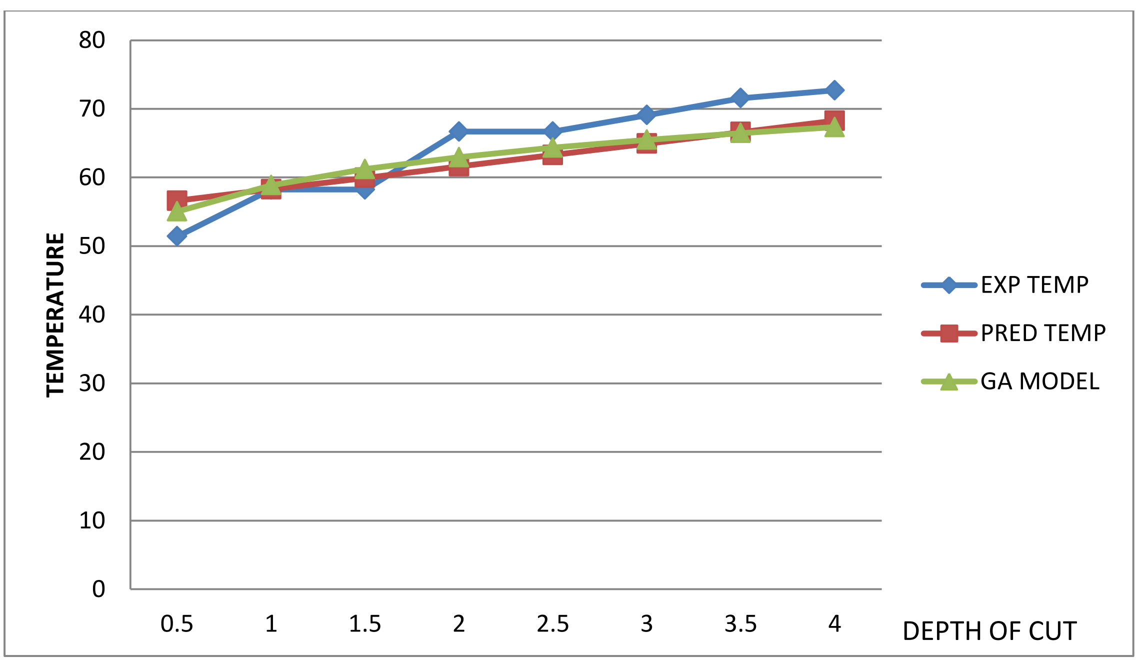


Figure 7.20 The variation of the temperature with the depth of cut (Cutting speed = 340 m/min)

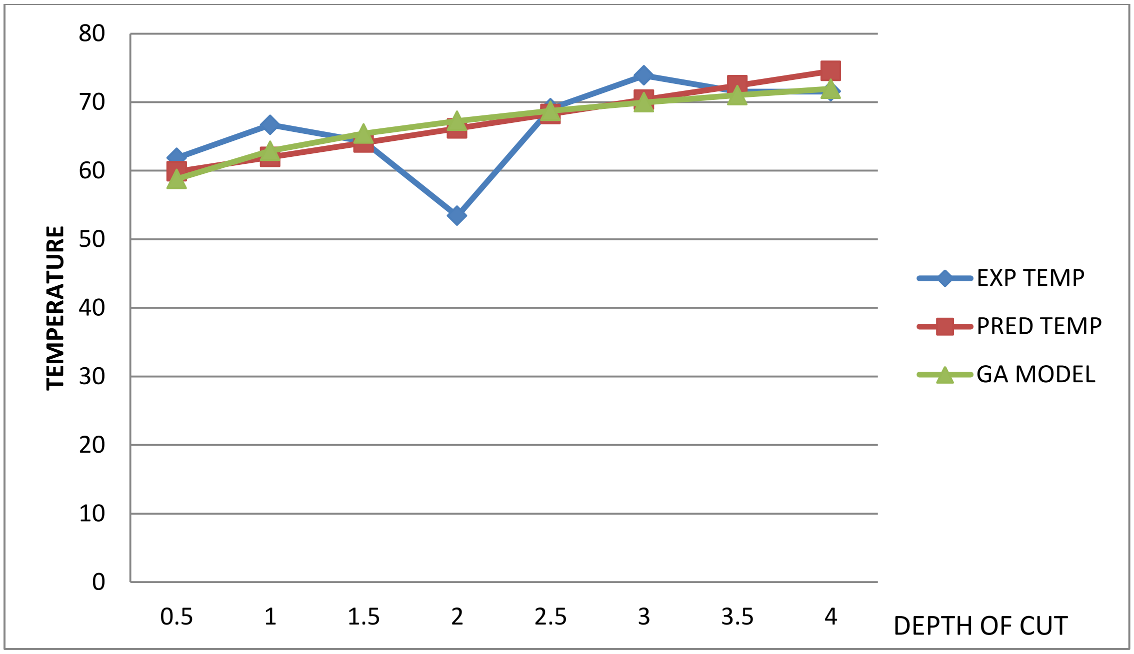


Figure 7.21 The variation of the temperature with the depth of cut (Cutting speed = 530 m/min)

The above graphs show the variation of chip-tool interface temperature with depth of cut at three different cutting speeds. The temperature measured experimentally and calculated theoretically shows an increase with the increase in the depth of cut. At cutting speed 530 m/min a decrease in temperature is observed as the depth of cut is increased from 1mm while further increase in depth of cut increases the chip-tool interface temperature. The measured values of temperature lie within the range of experimental error.

Chapter 8

CONCLUSIONS AND FUTURE SCOPE

8.1 CONCLUSIONS

Temperature and wear of cutting tools are investigated by means of cutting experiments and numerical analysis. The purpose of the temperature analysis is twofold: to propose a simple model which will predict temperature changes and to verify the propriety of the temperature measurement [49]. The cutting temperature during metal cutting processes has been recognized as one of the major factors influencing the tool performance and workpiece geometry accuracy [50]. Temperature on the chip-tool interface is an important parameter in the analysis and control of machining process. Total tool wear rate and crater wear on the rake face are strongly influenced by the temperature at chip-tool interface. The amount of heat generated varies with the type of material being machined, cutting parameters, contact length between tool and chip, cutting forces and friction between tool and workpiece material. To measure the tool temperature at the tool chip interface many experimental methods have been developed. The main techniques used to evaluate the cutting temperature during machining are tool-work thermocouple, embedded thermocouple and thermal radiation method [51].

The average chip-tool interface temperature was measured in turning process and the measured results were compared with the calculated (predicted) values. The effects of cutting speeds and depth of cuts were further studied and analyzed for different tool and work material combinations. The following conclusions and observations were drawn from the experiment performed and the analytical model predicted.

1. Theoretical methods and empirical approach were developed depending upon the regression analysis method and the response surface methodology (RSM).
2. The empirical equations derived from the orthogonal cutting process were used for temperature calculation and in order to obtain reliable results, the factors for each set of cutting parameters were re-evaluated.

3. Under the cutting conditions specified in this investigation, the chip-tool interface temperature was measured and compared with the calculated results. It was found that the maximum percentage error with different used combination of tool and work material was 30% occurring due to the error in the performance of the machine tool, milli voltmeter, environmental condition, human error etc.
4. When the cutting speed and the depth of cut were increased the chip-tool interface temperature increased.
5. It was observed that the cutting speed has a significant effect on the chip-tool interface temperature in comparison to the effect of depth of cut. These conclusions were verified by the correlation coefficients.
6. Further a model was formulated to optimize the chip-tool interface temperature considering the technological and material constraints. The heuristic technique used was genetic algorithm which is based on the mechanics of biological evolution.
7. The results obtained from the simulation model have presented a fast and suitable solution for automatic selection of the machining parameters.

8.2 FUTURE WORK

The tools and techniques used in this investigation can be applied in future to other cutting processes with different cutting parameter ranges. It can be shown that the effect of independent variables considered – cutting speed, cutting feed and radial cutting depth - as well as its interactions, on temperature can be compared with other traditional methods of optimization [52]. The approaches for modeling the prediction of the temperature distribution at the interface can be done with number of the commercial package such as DEFORM 3D [53] and also with other techniques such as SQP, ANN etc.

The proposed model can be extended and many other cutting variables can be included in order to optimize the cutting process. Integration of the proposed approach with an intelligent manufacturing system will lead to reduction in the chip-tool interface temperature and other parameters such as production cost, reduction in production time, flexibility in machining parameter selection, and improvement of product quality.

This genetic algorithm-based approach and simulation model can find the application in complex machining systems and automated process planning system. Further this approach can be compared with a number of other emerging optimization techniques. Since the genetic algorithm-based approach can obtain near optimal solution, the formulated model can be further enhanced and applied to other machining process such as milling, threading, grinding etc.

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